Appendix 3.2:
Peak demand forecast for period 2018 - 2027

Regulatory proposal for the ACT electricity distribution network 2019-24
January 2018

evoenergy

Evoenergy

Peak Demand Forecast for period: 2018 – 2027

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1 Introduction

This report provides the ActewAGL Distribution (AAD) peak demand forecast for the period 2018-2027. The forecast includes both a total system forecast and Zone Substation forecast.

The report covers the following areas:

- Detail on the modelling/forecasting principles adhered to, methodology and important notes on the model;

- The data used in the modelling and its sources;

- Structural changes and other post model adjustments;

- Forecast outcomes – the system and Zone Substation forecast seasonal average demand model, tables and graphs.

2 Method for Development of Forecast

This section is a brief summary of the approach taken to forecast the peak demand. More details are included in the following sections.

2.1 Method – Bottom-up demand forecast

Forecasts for each Zone Substation are developed using a bottom-up forecast. The Monash Electricity Forecasting Model (MEFM) has been used to determine the underlying trend and base load. Known proposed new customer block loads are added to the Zone Substation forecasts.

2.2 Method – Top-down (econometric) demand forecast

The development of the System demand forecast is done using a similar method to the Zone Substation bottom-up demand forecasts, with the inclusion of selected econometric and demographic variables. The purpose of the top-down forecast is to provide a comparison and check that the reconciled bottom-up zone substation forecasts' overall level and trend is consistent with overall expectations for the ACT region. Statistically significant variables only (e.g. population development, state final demand, electricity prices) are considered. Block loads are not included in the top-down forecast as these are inherent in economic growth factors.

2.3 Reconciliation between bottom-up and top-down forecasts

A bottom-up System demand forecast is obtained by applying a diversity factor to the individually forecasted Zone Substation demand peaks. This bottom-up System demand forecast is then compared with the top-down System demand forecast.

Figure 2.3.1 and 2.3.2 illustrated the comparison between the top-down forecast and the bottom-up forecast for both summer and winter.

Table 2.3.1 shows the discrepancy between top-down and bottom-up POE forecast for both summer and winter are between 1% and 5%, which is considered as an acceptable range for the purpose of forecast reconciliation.

The discrepancy can be explained by the following reasons:

1) The future diversity factor cannot be predicted. The estimated average diversity factors in Appendix 6.4.21 and 6.4.2.2 may not be 100% accurate;

2) It is plausible that the confidence interval of the accumulated ZSS forecasts is wider since this is built up from multiple individual models, while top-down is just 1 model. In addition, since the 10% POE is very close this should provide us with confidence that we are not over/underestimating the demand within the 90% confidence level.

Table 2.3.1: Forecast reconciliation discrepancy summary

Year	Summer POE 50	Summer POE 10	Winter POE 50	Winter POE 10
2018	-1%	2%	-4%	-1%
2019	-1%	5%	-4%	0%
2020	0%	5%	-3%	1%
2021	0%	4%	-3%	0%
2022	-1%	2%	-4%	0%
2023	-2%	2%	-5%	-1%
2024	-2%	2%	-5%	-1%
2025	-3%	2%	-5%	-1%
2026	-2%	1%	-5%	-1%
2027	-2%	1%	-5%	-2%
Average	**-1%**	**3%**	**-4%**	**-1%**

Figure 6.4.1: Summer Demand Forecast Reconciliation
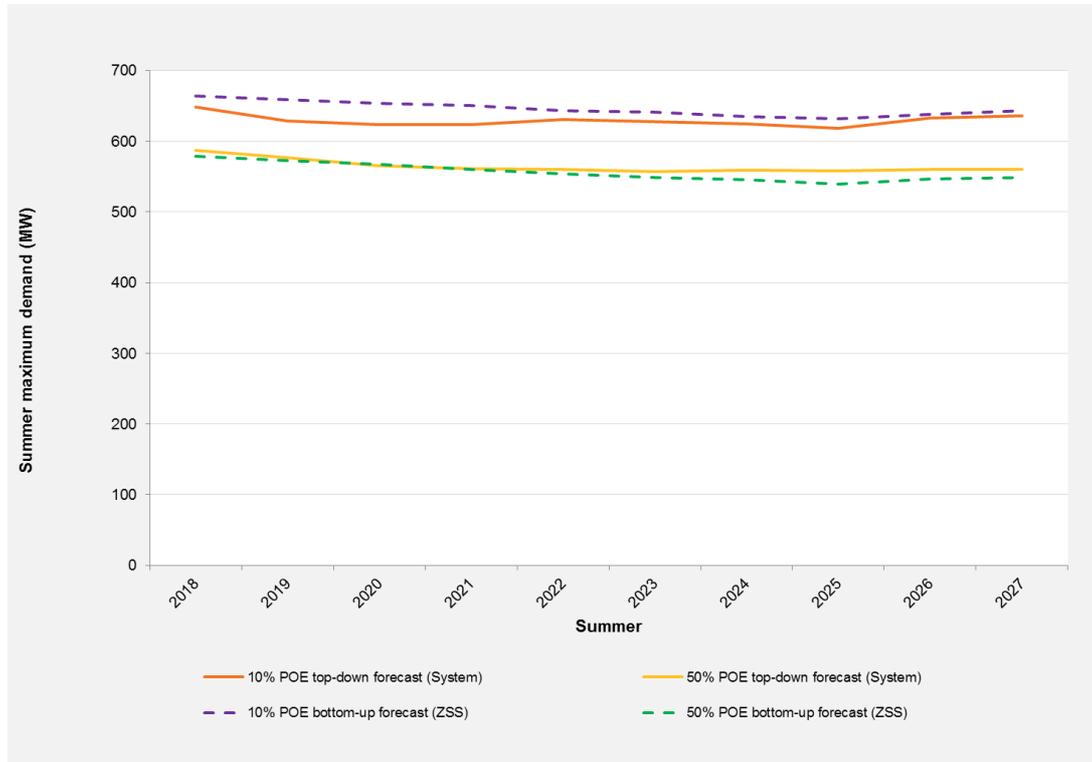
Figure 6.4.2: Winter Demand Forecast Reconciliation
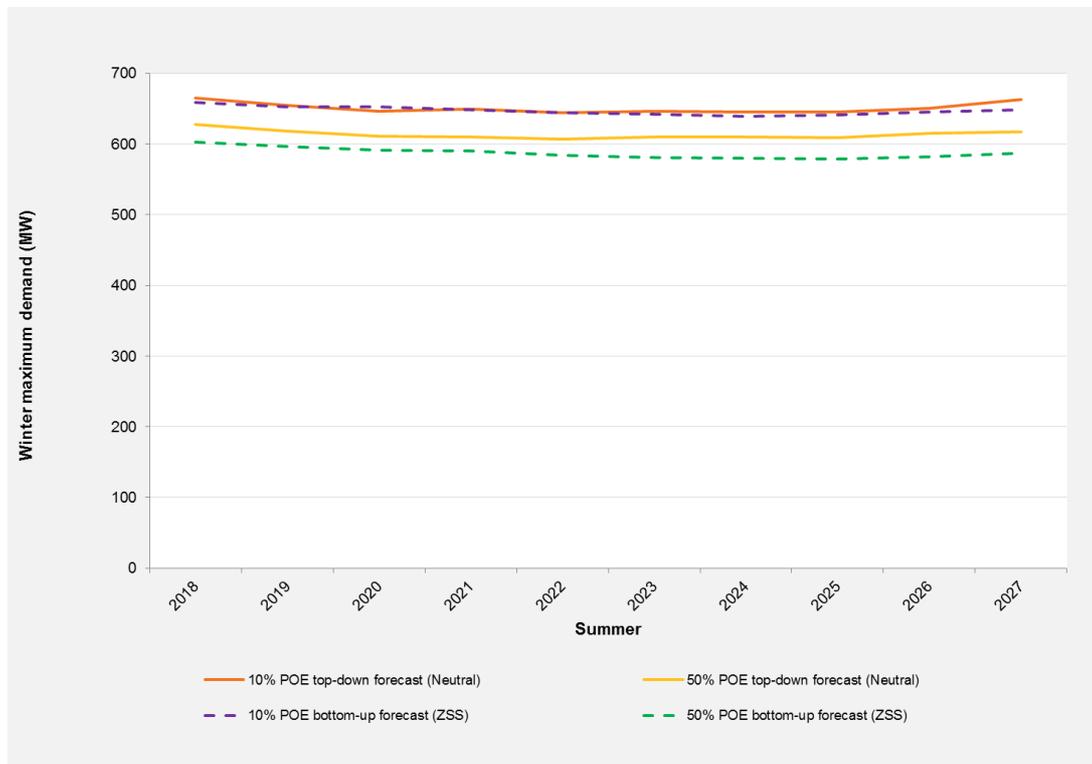
3 Modelling/Forecasting Principles followed

The best-practice modelling/forecasting principles that AAD adheres to are described in the table below.

	Principle	Description
1	Data	Obtain reliable and unbiased data from reputable sources, conduct data checks to remove/repair erroneous data and manage data effectively. Where similar data is used in more than one model, it must be consistently applied and care taken not to double count impacts.
2	Model calibration	Use appropriate statistical estimation methods.
3	Parsimony	Use only as many parameters as necessary to fit the model, to maximise information output from the model and improve forecast efficiency.
4	Fit to theory	Choose models that are supported by relevant theory.
5	Fit to evidence	Show that the model adequately accounts for history used in calibration (conduct back-casting).
6	Logical model	Explanatory variables in the model should have theoretical basis, and have theoretically correct signs.
7	Model validation	Analyse the statistical significance of variables, accuracy of fit, diagnostic checking of residuals etc.
8	Model documentation	Detailed and thorough documentation of modelling process to ensure transparency and repeatability.
9	Version source control	Track changes made to models.

4 Forecasting Methodology: Integrated MEFM

4.1 Overview of Current Approach

ActewAGL has adopted and implemented AEMO's maximum demand forecast methodology which uses the Monash Electricity Forecasting Model (MEFM) which is based on the paper by Hyndman and Fan (2010)[1].

Figure 4.1.1: Block diagram of the Monash Electricity Forecasting Model.
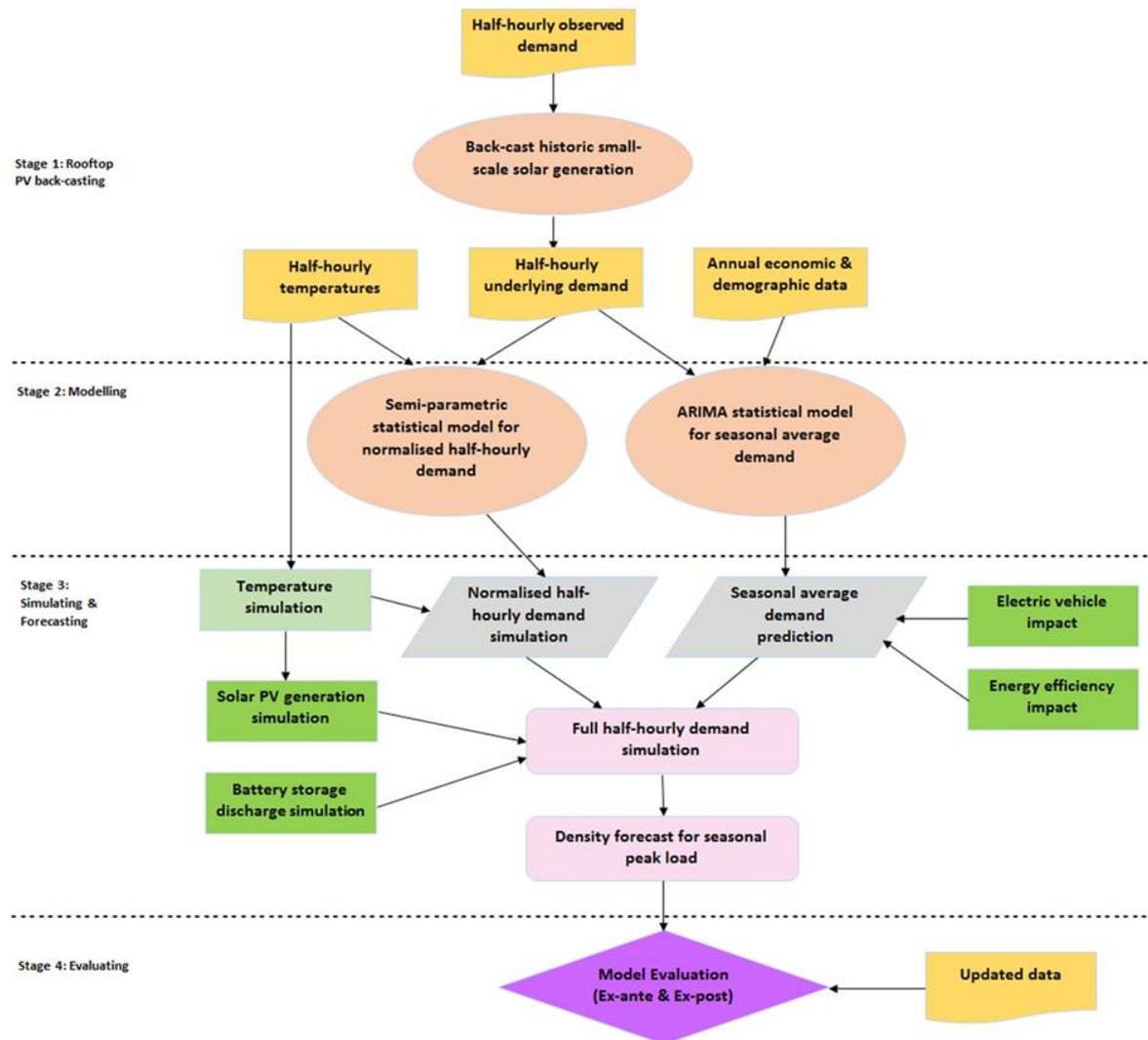
Source: Monash Electricity Forecasting Model Technical Report

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[1] R. J. Hyndman and S. Fan (2010) "Density Forecasting for Long-term Peak Electricity Demand", IEEE Trans. Power Systems, 25(2), 1142–1153. http://robjhyndman.com/papers/peak-electricity-demand/

Table 4.1.1 provides an overview of all the steps of the integrated MEFM load forecasting methodology. The key steps of the methodology are:

Step1: Estimate historical half hourly small and medium scale solar PV generation, battery and electric vehicle generation and combine with observed/operational demand to calculate underlying demand (Described in detail in Section 4.2);

Step 2: Apply Stage 2 and Stage 3 of MEFM process in Figure 4.1.1 to underlying demand (Section 4.3 to 4.6);

Step 3: Stage 4 of MEFM (Section 4.7): Forecast evaluation.

4.2   Solar PV Modelling Approach

This section outlines how the solar PV model was developed, and how both the historic estimates of underlying demand and forecast production of PV systems were integrated into the overall forecasting methodology.

The process has three stages:

1. **Develop model of historic solar generation against weather;**

2. **Back-cast historic small-scale solar generation; and**

3. **Integrate the solar PV model into demand forecasting by modelling combined solar PV and demand[2].**

These stages are described in the following subsections.

4.2.1.1   Stage 1: Develop Model of Historic Solar Generation against Weather

The major challenge in modelling small-scale solar generation is estimating how much energy is being produced by small scale systems, on an hourly or half-hourly basis. This estimate is challenging because:

- Information on gross output of PV systems is not typically shared with ActewAGL, and happens 'behind the meter'.
- There is considerable variation in the operating parameters of small-scale systems, with differing PV panel efficiencies, inverter ratios, orientations and shading characteristics.
- There is some uncertainty in estimating the installed capacity. The Clean Energy Regulator (CER) collects information on PV system capacity at a postcode level in order to manage certificate schemes. This is expected to capture the vast majority of installed systems, but does not give any information on when systems are removed, or how large the panel sizes are in relation to inverter sizes. ActewAGL (and other DNSPs) also collect information on PV systems as part of connection agreements.

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[2] This step ensures that a consistent history is used for modelling purposes. This is necessary because timing of solar PV generation can distort demand estimates across different hours of each day

Although care is taken when entering system sizes, there may be inconsistencies. In addition, this information is difficult to verify.

- PV system output is a function of solar exposure, which is affected by seasonality, time of day, and cloud cover. PV systems still produce some energy in modestly overcast conditions.

- There is significant uncertainty as to how the behaviour of groups of PV systems spread over a large geographic area compares with single systems. During days of consistent cloud cover the majority of all systems in the ACT may experience reduced production, while intermittent cloud cover may affect individual systems but not all systems at the same time. The total output across the ACT of PV systems will therefore be 'smoother' than any individual system output.

In order to develop a useful model, we need to be able to estimate PV system output as a function of weather, as this allows us to produce estimates of PV output in our forecasting simulations. Therefore, the PV model was developed in two stages (see Figure 4.2.1).

1. Using metered output from the Royalla Solar Farm to develop a statistical model of output as a function of weather; and

2. Using residential PV system data released publically by Ausgrid to estimate how average residential systems perform compared with optimally sited and orientated systems like the Royalla Solar Farm.

We have used Royalla Solar Farm to develop the solar model because this is a site for which interval metered data is available, and which can be assumed to have panels oriented in an optimal way for solar exposure and to be free from shading effects. While we have several series of gross metered residential PV system data, there are too few of these to infer a statistically significant representation of all residential systems, and there is no guarantee that these systems are optimally sited and oriented, which is a necessary requirement for the second stage of the solar model creation.

The weather model is developed using a similar statistical model to the half-hourly demand. Solar output is modelled as a non-linear function of temperature. In addition, separate statistical models were created for each half hourly period of the day, and for each season of the year. Residuals of this model are preserved in the model development, as these are resampled when forecasting solar output to reflect the statistical prediction power of the weather model.

After the weather model based on Royalla's output was developed, we made two adjustments to reflect residential system characteristics.

We first determined factors to adjust the predicted output in every month and half-hourly period to reflect the performance of the average small-scale system compared with an optimal one. We derived these ratios by examining a dataset of 300 residential NSW PV systems output (released publically by Ausgrid). These system profiles represent a range of system configurations – we compared the mean output by hour of all systems in this

dataset to the output of the best systems in the data set to better understand the loss in performance of the average system compared with the best system.

The adjustment factors were then applied to the Royalla solar farm output which was considered to be analogous to an optimally configured system. Figure 4.2.1 illustrates the ratios calculated in this way.

Figure 4.2.1: Illustration of Solar Model development
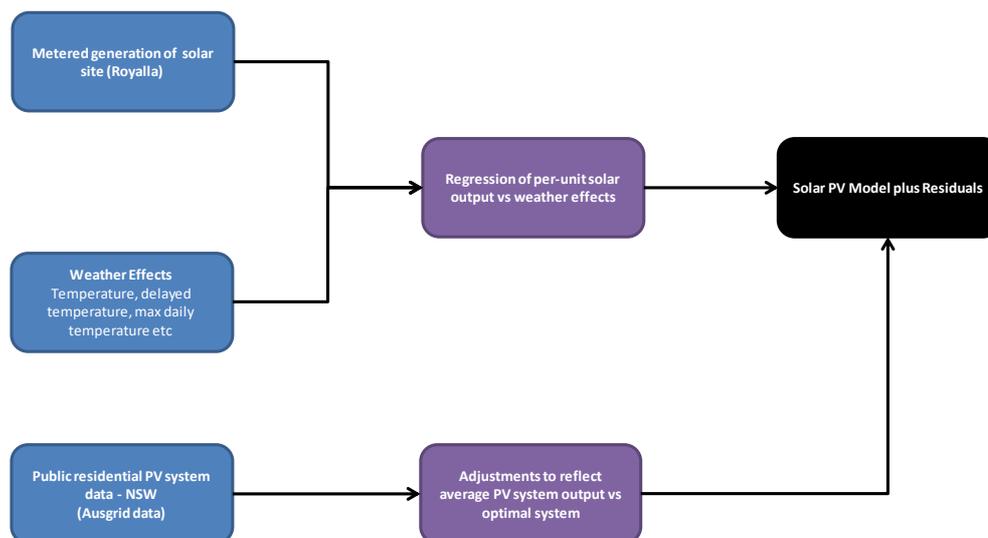
Figure *4.2.1*

The average system output during peak solar production generally ranges from 60% to 80% of optimally sited systems, depending on the time of the day and the season. We applied these ratios to the forecast output of the solar model, which is based on an optimally orientated system.

We also applied an adjustment to reflect the smoothing effect on system output of having multiple, geographically diverse systems generating. We used a moving average function to smooth the model forecasts, with the moving average applied over three periods from the period before the forecast to the period after. That is:

$$P_i^* = \frac{P_{i-1} + P_i + P_{i+1}}{3}$$

Where:

$P_i^* = smoothed\ production\ in\ period\ i$

$P_i = model\ output\ production\ in\ period\ i$

Figure 4.2.1: Average to Optimal System performance, January
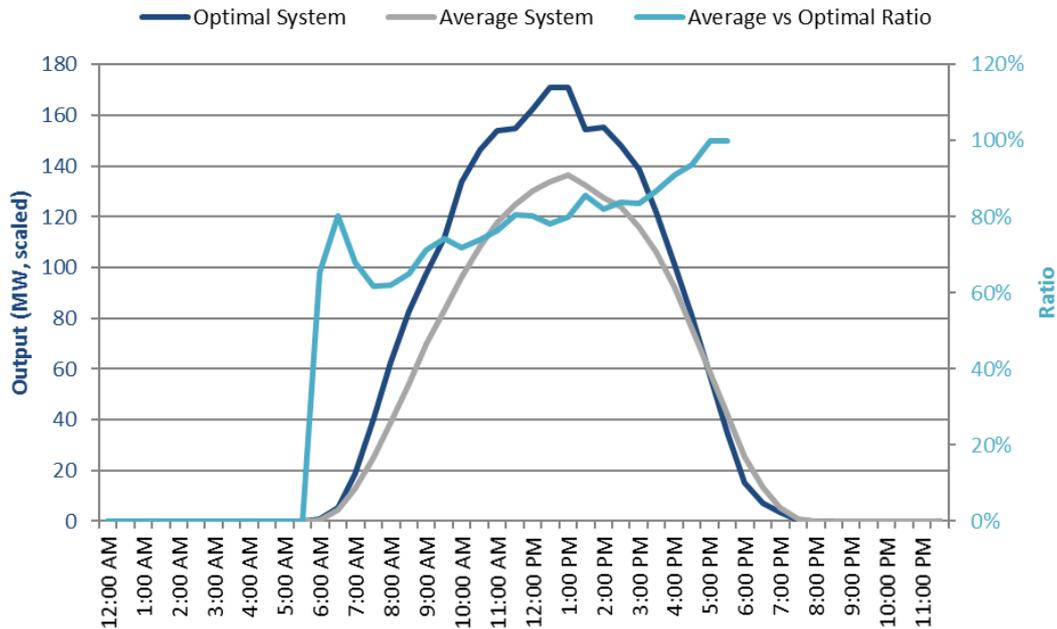
The 3-period centred moving average function was chosen on the basis of a variance test. We examined the variance statistics of single systems and the aggregate performance of multiple systems using the Ausgrid PV dataset. We examined the volatility of system performance over several periods, and chose the 3-period moving average function on the basis that this function best transformed the variance distribution of a single system into the variance distribution of the aggregate system performance.

The result of this process is a statistical model that predicts the output of small-scale PV systems on a half-hourly basis as a function of weather and temperature variables (which are used as a proxy for solar exposure). The model produces its results on a per-MW basis, which enables adjustment of the historic or forecast installed small-scale capacity of solar PV.

4.2.1.2   Stage 2: Back-cast of Historic Small-Scale Solar Production

In Stage 2 of the process a half-hourly estimate of small-scale production was produced to create an estimate of historic underlying demand. This is done by using historic weather observations to predict historic small-scale PV system production on a per-MW basis, then multiplying this back-cast by the installed capacity of PV systems in the ACT over time.

This process is illustrated in Figure 4.2.2.

ActewAGL historic PV installed capacity by month was used to develop the back-cast. The date indicated that PV uptake only begins to become significant after 2012, as prior to this only a small number of systems were installed.

When back-casting historic PV generation, it is difficult to verify outputs, as we do not have access to metered output from large numbers of residential systems with which to benchmark the model.[3] We therefore do not add residuals of the model onto our back-casts. However, we can test whether our model explains the observed decline in average energy use during daylight hours, which can provide us the confidence that the model is calibrated adequately. This test is discussed in detail in Section 4.5.1.

The half-hourly trace of estimated solar PV is then added to the half-hourly trace of observed system demand to produce the underlying demand back-cast. The underlying demand trace is used as the main basis of the MEFM demand forecasting model.

Figure 4.2.2: Illustration of solar back-cast process
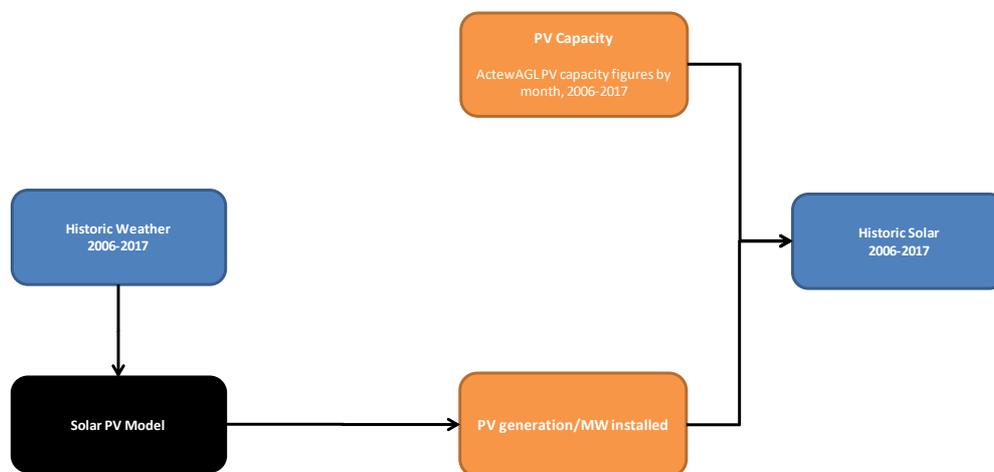
4.2.1.3   Stage 3: Integrate the Solar PV Model into Demand Forecasting

The final stage in the PV modelling process is to integrate the PV forecasts into the demand forecasting process. As the forecasts are on the basis of underlying demand, the developed forecast of solar PV is subtracted from the MEFM demand forecasting results in order to accurately forecast the observed demand on the network.

The key challenge in this process is ensuring that the solar forecasts are consistent with the temperature simulations used in the demand modelling. The MEFM involves a process of simulating multiple temperature profiles, which are used to estimate the probability of different demand conditions. When we produce solar forecasts, which are a function of weather conditions, we need to ensure that both the underlying demand simulation and the solar PV simulation are produced using the same temperature profiles.

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[3] One would typically use a process of adding on residuals from the model to our back-casts to assess the confidence intervals of our back-cast against actual outcomes, but in this case there are no benchmark data to assess against.

This process is illustrated visually in Figure 3.2.4

Figure 3.2.4: Illustration of solar PV integration into demand forecasting
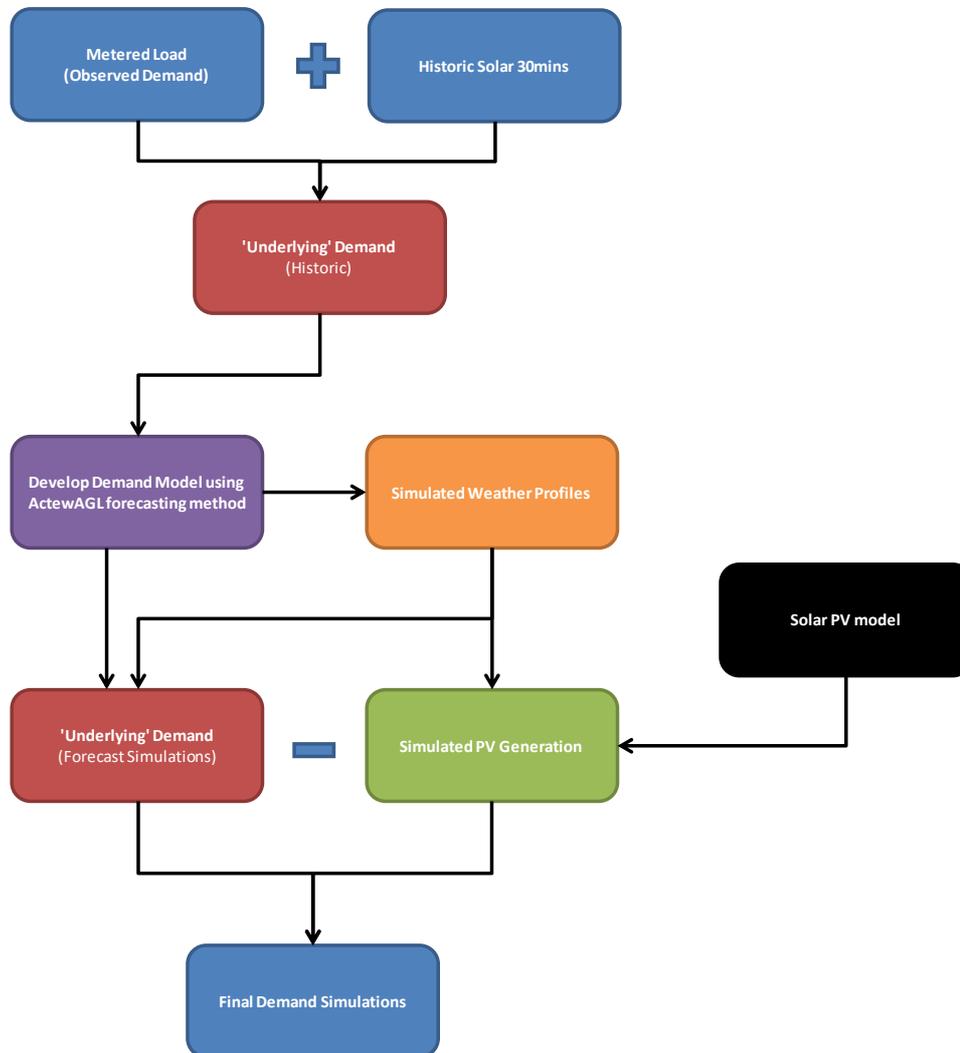
The integration proceeds as follows:

1. The solar PV back-cast is added to the historic trace of observed system demand to produce the 'underlying' demand trace;

2. The underlying demand trace is used within the existing forecasting methodology to create a demand model using the MEFM;

3. When the MEFM produces demand forecasts based on simulated temperature series, the temperature profiles are extracted and fed into an equivalent series of n PV simulations, which use forecast installed capacities of small-scale PV. For each PV simulation we add on a series of model residuals, which are resampled using a seasonal block bootstrapping approach derived from the MEFM method;

4. Each PV simulation is subtracted from the equivalent simulation of underlying demand to produce a simulation of observed demand; and

5. These observed demand simulations are used as the basis of the reported demand forecasts.

4.3 Half Hourly Demand Model

4.3.1 Model Inputs

The half hourly demand model (HH model) requires three key inputs (refer Table 4.4.1):

1) Normalised half hourly demand: that is, each half hourly underlying demand scaled by Average Demand;
2) Temperature Variables: temperatures from the last 3 hours and the same period from the last six days; and
3) Calendar Variables such as day of the week, holiday effect and time of year.

4.3.2 Variables selection

There are 48 half-hourly demand models included in the MEFM. For each model, the temperature and calendar variables are selected through a cross-validation procedure. That is, the data has been separated into training and validation sets, and then the input variables are selected by minimizing the accumulated prediction errors for the validation data set. Here the mean squared error (MSE) is used as the selection criterion, and only time periods between 12 noon and 8:30 pm are included in the MSE calculations, since the major concern is the peak load. To select the input variables for the half-hourly demand model, we began with the full model including all temperature and calendar variables. The predictive value of each variable in the model was tested independently by dropping each term from the model while retaining all other terms. Omitted variables that led to a decrease in MSE were left out of the model in subsequent tests. Thus, a step-wise variable selection procedure was carried out based on out-of-sample predictive accuracy.

4.4 Seasonal average demand model

We have accepted Jacobs' recommendation to develop a seasonal average demand model. This recommendation was made to increase the amount of data available for modelling and consequently improve the statistical confidence in the modelling results. An ARIMA model with external regressors based on demographic and economic

variables (refer Table 4.4.1 for all tested variables) was adopted to forecast the future seasonal average demand.

4.4.1 Definition of seasonal average demand

Each year was divided into four seasonal quarters: summer (Dec, Jan and Feb), autumn (Mar, Apr and May), winter (Jun, Jul and Aug) and spring (Sep, Oct and Nov). The seasonal average demand is the average half-hourly demand for each seasonal quarter. Estimating seasonal average demand is therefore critical to the overall approach.

4.4.2 Model and variable selection

The Akaike information criterion (AIC) was used to select the best model. In statistical literature, the AIC which has the lowest value maximises the information available in the model subject to parsimony principles in that models with too many variables are penalised. The rule of thumb is the lower the value of the AIC, the better the model.

Table 4.4.1: Summary of input variables for half-hourly and seasonal average demand model

		Half-hourly model	Seasonal average demand model
Level	**Forecast Approach**	**Forecast Drivers**	**Forecast Drivers**
System	Top-down	1. Current temperature; 2. Temperatures from the last 3 hours and the same period from the last six days; 3. The current temperature differential and the temperature differential from the last 6 hours; 4. The temperature differential from the same time period over the last six days; 5. The maximum temperature in the last 24 hours;	1. Estimated residential population; 2. Persons per household; 3. Number of households; 4. Canberra CPI; 5. Seasonal CDDs and HDDs[4]; 6. Household sector per capita disposable income, in dollars; 7. GSP chain volume estimates, in millions of dollars; 8. Seasonal cooling/heating degree days;

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[4] A Heating degree day (HDD) is a transformation of temperature that reflects how much colder the temperature is in a given hour below a threshold temperature (usually 18 degrees but other thresholds can be used). Because cold temperature conditions prompt use of heating equipment, it is an appropriate independent variable for use in a regression which is designed to quantify the demand for energy needed to heat a building.

A similar measurement, the cooling degree day (CDD), is a transformation of temperature that reflects how much warmer the temperature is in a given hour relative to a threshold temperature (usually 21 degrees but other thresholds can be used). It is an appropriate independent variable for use in a regression which is designed to quantify the demand for energy used to cool a home or business.

		6. The minimum temperature in the last 24 hours; 7. The average temperature over the last seven days; 8. The day of the week; 9. The holiday effect; 10. The day of summer/winter effect.	9. Average electricity price (residential), in cents/kWh; 10. Supply charge (residential), in cents/kWh; 11. Consumption charge (residential), in cents/kWh; 12. Canberra Wage Index.
Zone Substations	Bottom-up	Same as System	1. Trend growth; 2. Significant block loads; 3. Seasonal CDDs and HDDs.

To develop an average demand model, the 'Forecast' package in the R statistical modelling software was used. The 'auto.arima' command was applied to select the most appropriate ARIMA model because it enables the automatic selection of the most appropriate ARIMA model with a selection of external regressors. The best model was chosen by selecting the model with the lowest AIC and where:

- the regression coefficients were statistically significant
- the regression coefficients were of the appropriate sign (positive / negative)
- the model passed a statistical 'goodness of fit' test
- the residuals displayed no remaining patterns as checked through examination of an ACF and PACF plot

Zone Substation average demand models were developed by Jacobs. Please refer to Jacobs' report for details.

4.5 Structural Changes

Structural change technologies such as solar PV, battery storage, electric vehicle and energy efficiency can have a significant impact on the maximum demand forecast. The treatment for each of these structural change technologies is described below:

1) Rooftop PV and battery storage have now been integrated into half-hourly demand simulation, so that underlying demand (which considers behind the meter generation) is modelled rather than metered demand;

2) Seasonal average demand forecasts have been adjusted for electric vehicles using AEMO estimates of NSW and ACT electric vehicle proportions. This adjustment is made at Stage 3 of Integrated MEFM process; and

3) Energy efficiency is treated as one of the average demand model inputs where applicable and relevant.[5]

4.5.1   Solar PV Behind the Meter

The uptake of small scale photovoltaic systems over the past decade has had a material impact on the load characteristics of the ACT electricity distribution system. The peak demand as observed by the network has moved to later in the day, as self-consumption by solar PV owners reduces the load demand on the grid during the middle of the day.

Accounting for the increased penetration of residential PV systems is becoming increasingly important for accurate demand forecasting. However, we are unable to directly measure how much load is being supplied by residential solar generation, as this load is consumed 'behind the meter' and is only available to a DNSP when gross metering is installed and PV generation data is collected by the DNSP.[6] The impact of PV generation can to an extent be inferred by the observed changes in daily load shape, but impacts on load caused by residential PV can be difficult to separate from impacts caused by temperature sensitivity and other changes over time.

We can analyse how the load shape is changing over time by looking at the average load observed in each hour of the day. To compare this shape over time, we first have to correct for general load growth – the result of this correction is the 'normalized' load shape, which is shown in Figure 4.5.1.1.

Over time, the average demand observed by the network during daylight hours has declined. The 'hollowing out' of the load shape in the middle of the day is consistent with an increasing penetration of residential solar PV, but causes challenges in preparing the demand forecasts.

As the ActewAGL demand forecasting approach is based on the MEFM, it blends a long-term model that captures growth in overall demand over years with a short-term model that predicts how temperature effects and other short term phenomena affect the half-hourly load shape. One of the assumptions of this model is that the normalised demand profile used does not change in any structural manner over time.

However, the PV effect challenges this assumption. PV generation has both a long term component (with increasing installed capacity over time) as well as short term impact (PV

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[5] The quality of energy efficiency data available is poor relative to the level of solar insolation data. Given this, the modellers decided to use this as an input variable rather than treat it as a structural demand adjustment. Jacobs has modelled the average demand for each zone substation, for details please refer to the Jacobs report.

[6] ActewAGL currently only has a handful of gross metered connections with Solar PV, which is not sufficient to produce reliable estimates on solar generation behind the meter.

output depends on weather, the season and the time of day). We therefore need to explicitly correct for the PV impact in our modelling.

We have done so by adding the residential solar production to the historically observed demand profile, and modelling the 'underlying' demand for energy by consumers rather than the demand observed by the network (see section 4.2 for the methodology). The load shape characteristics of underlying demand are more stable over time, and therefore are more suitable for use with the forecasting methodology.

Figure 4.5.2 shows the normalized demand profile of underlying demand, with the contribution by small-scale PV added.

The resulting normalized load shapes are much more stable over time and more suitable for use in the forecasting model.

Figure 4.5.1: Normalized Observed Demand, 2006-2016
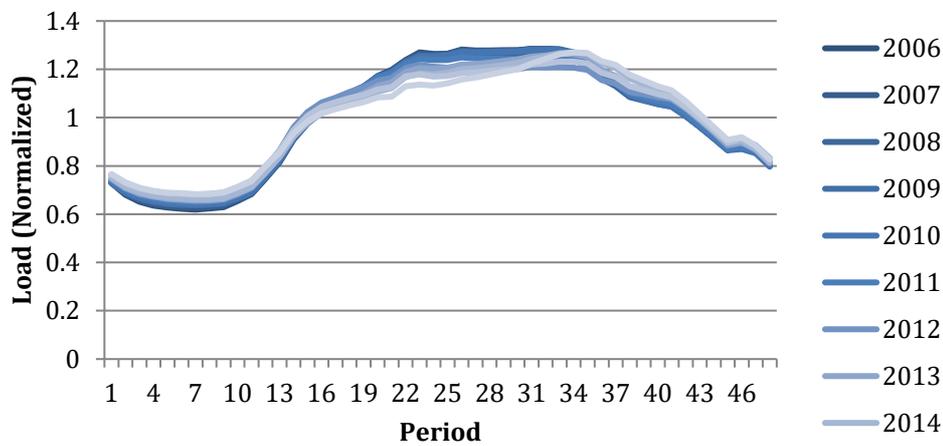
Figure 4.5.2: Normalized Underlying Demand, 2006-2016
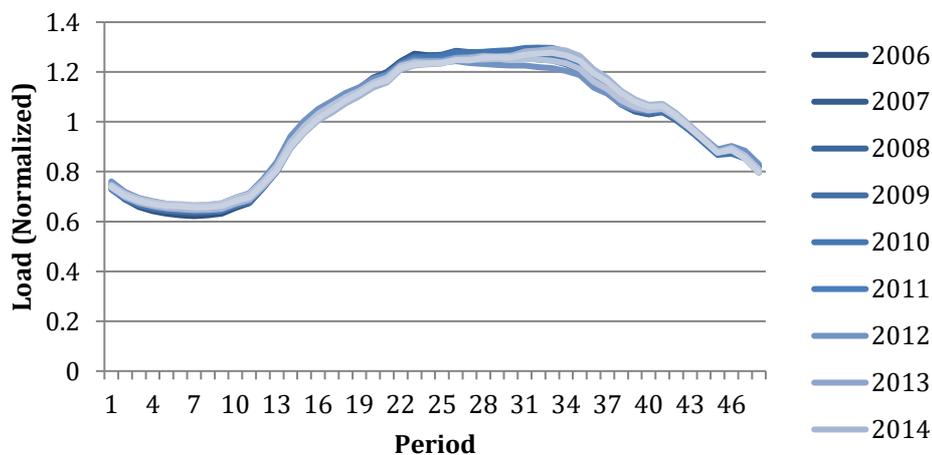
4.5.2   Battery Storage

Similar to AEMO's battery model, we assume that batteries will be of the lithium-ion variety, and limited to 90% depth of discharge. The impact of battery storage on peak demand will be muted by the average discharge profile, which is shown by Figure 4.5.3.

In the absence of actual operational data from batteries, the Figure 4.5.3 profile is based on assumptions about how customers will use their battery system. It is anticipated that most of the early uptake will be by customers with PV systems, so use of the battery should be based around maximising self-consumption of PV generation.

We also assume batteries that all discharge at the same time in order to reduce system or substation peak demand would have a more material impact. There are two key facts about battery storage impact based on our assumed scenarios;

1) Battery storage has major Impact on the winter peak demand whereas summer peak demand can be partially offset by Solar PV alone or a combination of Solar PV and battery storage;

2) Battery storage impact is at its minimum for those commercial zone substations whose peak time is normally between 1 PM and 3 PM based on Figure 4.5.3. Direct offset from rooftop solar PV may be much more economic and effective for commercial zones and feeders.

Figure 4.5.3: Assumed battery storage charge and discharge profile.
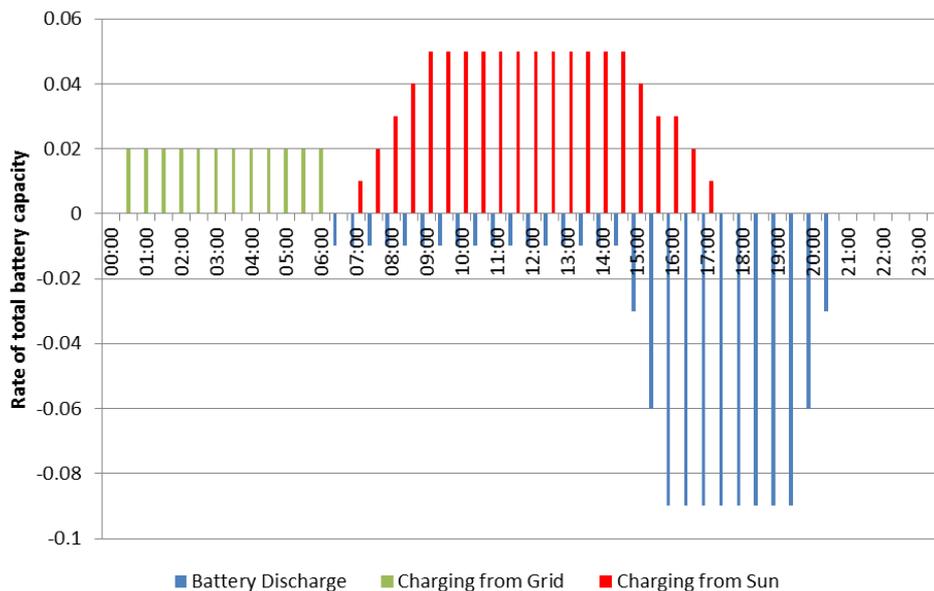
The battery impact is integrated into the MEFM process along with solar PV during full half-hourly demand simulation.

4.5.3   Energy Efficiency

Quantifying the impact of energy efficiency is a challenging task because energy efficiency is difficult to measure and validate. We used AEMO's energy efficiency assumptions and projections which are provided for a combined ACT and NSW regional zone and separated into business and residential data sets. In addition, we have scaled the data to reflect the ACT population. We also assumed that the proportion of energy efficiency for the residential combined NSW and ACT data set adequately explains residential energy efficiency for the ACT, and similarly this also applies to the business sector, even though the business sector is relatively smaller in the ACT. Energy efficiency has been used and tested as one of the seasonal average demand input variables. For more details, please refer to Jacobs' implementation report.

4.5.4 Electric Vehicles

Electric vehicles are not yet materially prevalent in the ACT grid, but a small percentage of additional demand from electric vehicles is expected to arise towards the end of the period. Therefore, it is not appropriate to apply a structural adjustment to historical demand as was done for solar PV and batteries, but a more appropriate approach is to undertake a post modelling adjustment for EV instead. AEMO projections of electric vehicle demand ratios were therefore applied to residential demand at the end of the process for the NSW and ACT areas. For further details about EV projections, please refer to Jacob's implementation report.

4.5.5 Changing Tariff Structures

We are currently proposing new capacity and time-of-use based tariff structures for residential customers. The new tariffs will be offered on an opt-out basis only to new customers and existing customers receiving a new smart meter. However, the expectation is that take-up of these tariff structures will not be significant in the next regulatory period (2019-2024). Therefore, we have not considered the impact of these new tariff structures on demand.

4.6 Treatment of Block Loads

4.6.1 Source of Block Load

There are two main sources of block load information:

a) ACT government land development agency's annual **indicative land release program** (ILRP) for the next four financial years; and

b) Connection requests provided directly from customers. An estimated diversified maximum demand is calculated by our customer connection staff based on the type of connection and size of building or complex. The details of diversified maximum demand calculations can be provided on request.

4.6.2 Key Assumptions

Figure 4.6 provides an overview of the rules we applied for the block load allocation and below we summarised the key assumptions we implemented.

- ILRP is the base source of block loads for Greenfield new estates such as Gungahlin, Molonglo Valley, West Belconnen and Parkwood developments.

These are currently or planned to be supplied by Gold Creek, Latham, and Woden zone substations and proposed new zone substations at Molonglo and Strathnairn;

- Direct customer requests are the source of block loads for brownfield developments. Load growth in such areas is slow and driven by customer requests;

Figure 4.6: Rules for block load allocation
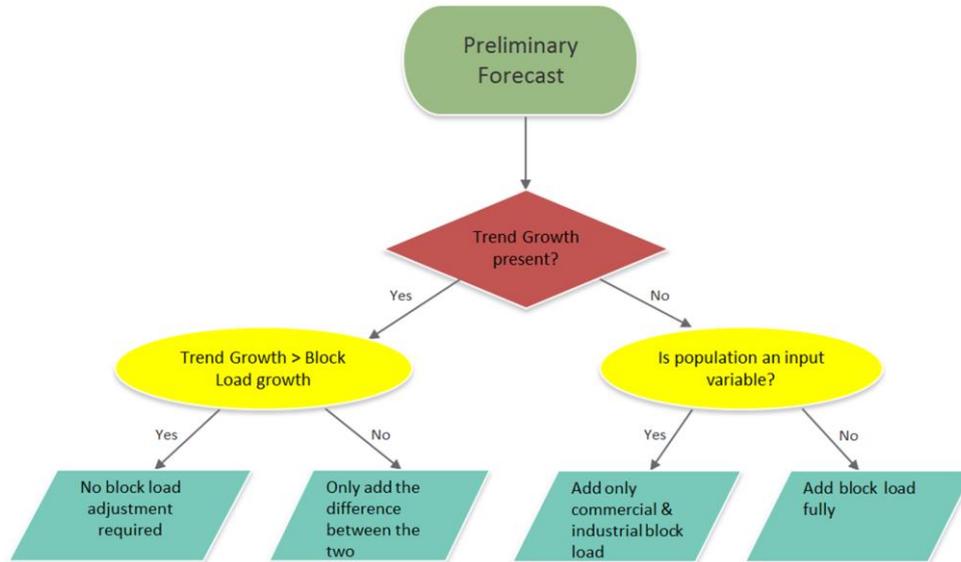
Table 4.9.1: Block load probability adjustment rate by completion year

Completion Year (Financial Year)	Probability of Project going ahead
2018	100%
2019	70%
2020	50%
2021	30%
2022	10%
2023	10%
2024	10%
2025	10%
2026	10%
2027	10%

- Mixed use developments such as multi-storey buildings are split into the following ratios: 67% residential and 33% commercial;

- Block load adjustment is undertaken as a post model adjustment. The zone substation's preliminary forecast requires adjustment based on the rules given in Figure 4.6;
- Probability adjusted based on expected completion date and consideration of past customer experience except the following two categories:
  1) New estate highlighted in ILRP;
  2) Government initiated projects, schools and hospitals;
- 50 % load discount is applied to all data centre customers' load projections based on their historical load growth pattern (except Metronode Data Centre).
- Probability adjustment rates in Table 4.9.1 were calculated from customer experience.

4.7 Forecast Accuracy Review Process

4.7.1 System forecast evaluation

To evaluate the forecasting performance, the actual demand of the most recent period has been compared with two different types of predictions: ex-ante forecasts and ex-post forecasts.

Ex-ante forecasts are those that are made using only the information that is available in advance; consequently, Year t's demands are calculated using economic conditions as assumed in Year t-1 and simulated temperatures based on models for data up to Year t-1.

Ex-post forecasts are those that are made using known information on the "driver variables". In this evaluation, ex-post forecasts for *Year t* are calculated using known economic conditions and known temperatures in *Year t*. Data from the forecast period are not used for the model estimation or variable selection. Ex-post forecasts can assume knowledge of the input or driver variables, but should not assume knowledge of the data that are to be forecast.

The difference between the ex-ante and ex post forecasts will provide a measure of the effectiveness of the model for forecasting (removing the effect of forecast errors in the input variables) relative to the effectiveness of the forecasted input variables.

The system forecast evaluations can be found at sections 5.1.3 and 5.1.4.

4.7.2 Zone Substation forecast evaluation

Zone Substation average demand models were prepared and developed by Jacobs. Please refer to Jacobs' report for details on the zone substation forecast evaluation.

4.8 Review of Forecasting Methodology

4.8.1 General Approach

Each year, we conduct a review of the forecasting methodology by the following three steps:

Step one: "Actual vs Predicted" – evaluate actual demands against 10%, 50% and 90% POE forecasts

Investigate those models whose actual demand is outside the POE forecast range and then redesign models to improve forecast accuracy by re-evaluating ex-post and ex-ante forecasts.

Step two: Identify and research the impact of emerging technologies.

Focus on emerging technologies such as battery storage, EVs, and hydrogen storage.

Step three: Evaluate comments/suggestions from external stakeholders and consultants

Respond to and evaluate all external comments or recommendations and implement relevant suggestions accordingly.

4.8.2   Review by Independent Consultant
The forecast methodology is scheduled to be reviewed by an independent consultant such as Jacobs every five years prior to regulatory submissions.

4.8.3   Collaboration with Industry
It is important to share, discuss and review forecast methodology with industry participants such as AEMO, TransGrid and other DNSPs. We interact annually with all relevant parties to examine the demand forecast methodology and its outcomes as follows:

- Face to face Forecast Methodology workshop: Annual event organized by AEMO with all DNSPs;
- Annual Planning Report Discussion Forum held every year; and
- AEMO Canberra region demand forecast review.

5 Forecast Results

5.1 System Forecast

5.1.1 Seasonal average demand

Seasonal average demand can be expressed as a product of per capita average demand and population. The dependent variable used for modelling is per capita average demand.

5.1.1.1 Model Summary

A summary of the R output from the final chosen model for projecting per capita average demand is presented below in Model output 1. The output summary presents a large range of statistical information. For reference purposes we have included a description of each element in this output in **Error! Reference source not found.**. Output presented later on in this report would be similarly interpreted.

The model presented is preferred because it presented:

- The lowest AIC statistic;
- Correct logical sign of coefficient of external regressors;
- An appropriate selection of independent variables, based on theoretical assumptions; and
- A set of residuals passing statistical tests for model adequacy (refer to section 5.1.1.2);

Model output 1 - per capita average demand

```
Regression with ARIMA(2,0,0)(1,0,0)[4] errors
Box Cox transformation: lambda= 0

Coefficients:
          ar1     ar2     sar1   intercept  CanHDD  CanCDD   Eff_Res   PRICE_RES
      -0.0015  0.6130   0.5801    -0.1917     4e-04   3e-04    -6e-04      -1e-04
s.e.   0.1100  0.0758      NaN     0.0154    0e+00   0e+00     3e-04       2e-04

sigma^2 estimated as 0.0001964:  log likelihood=136.5
AIC=-254.99    AICc=-250.13   BIC=-238.34
```

The table below includes a detailed description of the above model outputs.

Table 5.1.1: Description of model output parameters

Model output parameter	Description
`ARIMA(2,0,0)(1,0,0)[4]`	ARIMA model structure. In this case, projected values are a function of the values from the two preceding time periods (the ar1 and ar2 parameters in the coefficients table) and the value from the same quarter one year earlier (the sar1 parameter in the coefficients table). The seasonality, denoted by [4] has been set to 4 because there are four quarters per year.

Model output parameter	Description
`Box Cox transformation: l ambda= 0`	A log transformation has been applied

`Coefficients:`
`        Variable`
`        s.e.`
	The coefficient of each variable an the standard error for the relevant coefficient. In the case above the model includes the following variables:
	
	ar1 (value of dependent variable one time period prior)
	ar2 (value of dependent variable two time periods prior)
	sar1 (value of dependent variable one year prior)
	intercept (a constant value)
	canHDD (heating degree days in Canberra)
	canCDD (cooling degree days in Canberra)
	Eff_res (energy efficiency for residential sector)
	Price_res (retail prices for residential sector)

`sigma^2 estimated as 0.00 01964` `AIC=-254.99   AICc=-250.1 3   BIC=-238.34`	Model variance
`log likelihood=136.5`	A statistical parameter which describes the amount of information provided by a given model such that models with a larger value are preferred
`AIC, AICC and BIC`	AIC (Akaike information criterion) AICC (Akaike information criterion) BIC (Bayes information criterion) Each of the above are statistical parameters which describe the amount of information provided by a given model, adjusted by the number of parameters included in that model. Models with lower value are preferred because they maximise the amount of information provided using the fewest independent variables for efficiency.
`Training set error measur es`	Statistics describing quality of fit for the model on the given training set. Lower values indicate a better model fit. The various statistics include: ME – mean error RMSE – root mean square error MAE – mean average error MPE – mean percentage error MAPE – mean average percentage error MASE – mean average standard error ACF1 – autocorrelation at lag 1

5.1.1.2 Residual Diagnostics

The diagrams presented in Figure 5.1.1 indicate that no discernible patterns exist in the data that would invalidate the use of the statistical models applied. The ACF and PACF indicates that the residuals are most likely independently distributed (no serial correlation) and the histogram indicates that the assumption that errors are normally distributed is reasonable.

Figure 5.1.1: Four residual diagnostic plots
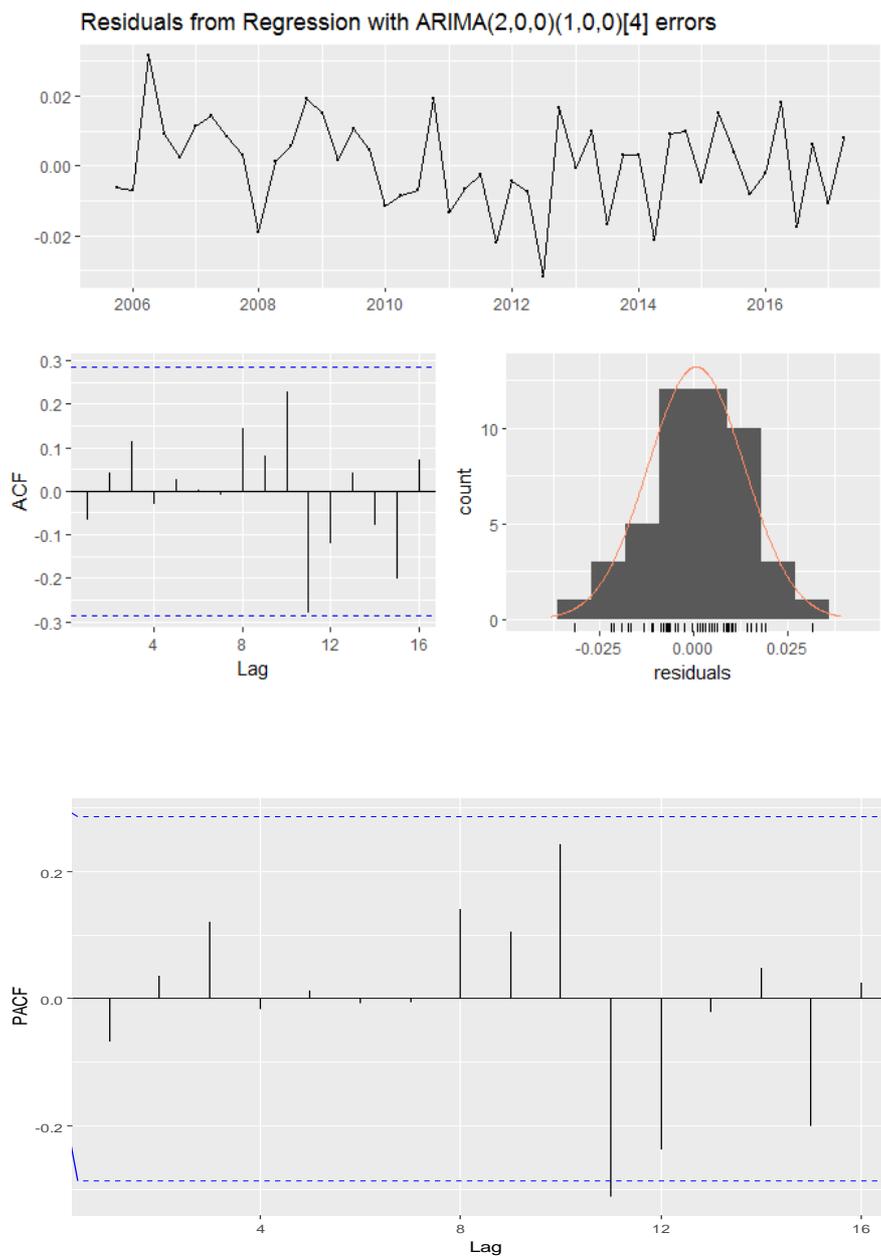
5.1.1.3 Population forecast

The ACT government's spatial population forecast have been used as one of key forecast input variables for system and zone substation seasonal average demand models and was provided by Jacobs in order to align with their volume and customer number forecast. For further details about the population forecast, please refer to Jacobs' reports.

5.1.1.4 Scenarios for selected input variables

Residential retail price and residential energy efficiency were selected for average demand per capita model and strong, neutral and weak scenarios were chosen to be consistent with the AEMO NEFR 2017 report.

Table 5.1.2: Average demand model scenarios

Driver	Weak scenario	Neutral scenario	Strong scenario
Population growth	ACT Government spatial projection		
Electricity retail costs	High	Medium	Low
Energy efficiency uptake	High	Medium	Low

Figure 5.1.2 shows historical and forecast residential retail prices for the ACT under the strong, neutral and weak scenarios projected by Jacobs. For further detail on how this was developed please refer to Jacobs' report.

Figure 5.1.2: Residential Retail Prices – Historical and Forecast trend by Scenario
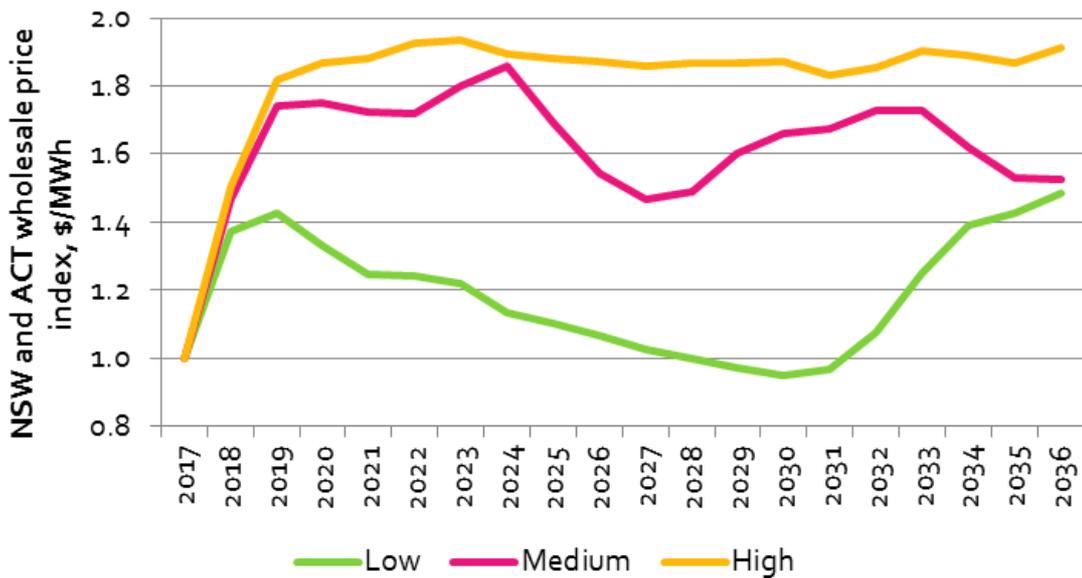
Figure 5.1.3: Residential energy efficnency – Historical and Forecast trend by Scenario
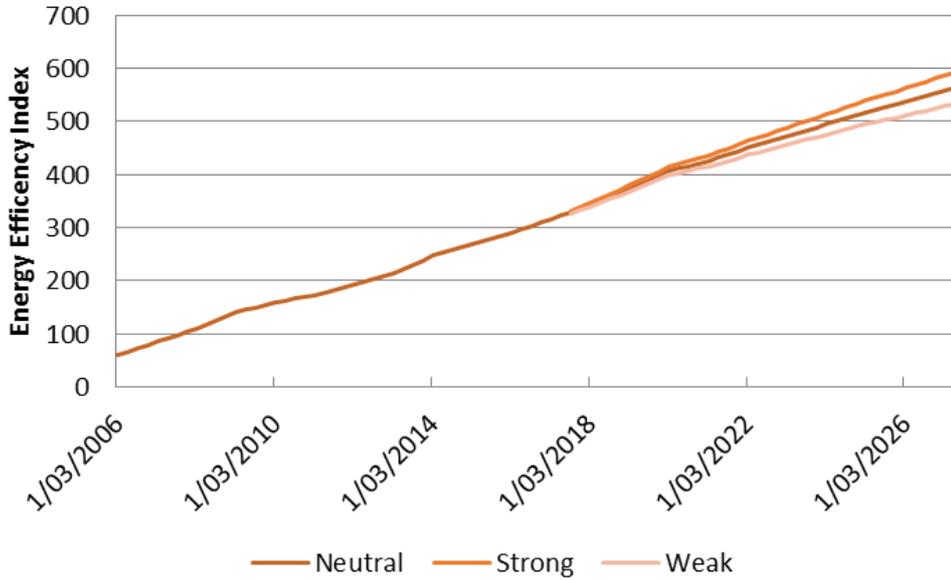
Figure 5.1.3 shows historical and forecast energy efficiency index figures for the ACT under the strong, neutral and weak scenarios collected by Jacobs from AEMO NEFR 2017 projections for the NSW and ACT region. Please refer to Jacobs' report for more details about retail price and energy efficiency projections.

5.1.2 Half-hourly model

An example of a half hourly model for each season is presented in Appendix 6.1.1.1 and 6.1.1.2. A description of each parameter is provided in Table 5.1.3, which is applicable to all half-hourly models. A list of selected weather and calendar variables is provided in Table 5.1.4.

Table 5.1.3: Description of model output parameters

Model output parameter	Description
`Residuals summary`	Description of minimum and maximum residual, as well as median and first and third quartile values of residuals
`Coefficients summary`	Table displaying value of coefficients, the standard error of the coefficient estimate, the t-statistic, and the probability that the coefficient is significant and should be included in the model. Any coefficient presenting one or more asterisks should be retained with confidence at the 5% level. Coefficients included are: Various day type variables – that is, day of week, public holiday, etc

Model output parameter	Description
	Various temperature related variables in current or prior time periods
`Residual standard error, R-squared values, F-statitics and degrees of freedom`	Statistics representing the models goodness of fit. Residual standard error values should be small in good models while R-squared values should be high/close to 1. Degrees of freedom should be appropriately large for testing purposes.

Table 5.1.4: The following weather and calendar variables were selected by cross validation stepwise procedure for summer and winter season

Summer	Winter
• the current temperature and temperatures 1 h, 1.5 h and 3 h ago; • temperatures from the same time period for the previous day; • the current temperature differential and the temperature differential 1.5 h ago; • the temperature differential from the same time period of the previous day and six days ago; • the maximum temperature in the last 24 h; • the minimum temperature in the last 24 h; • the average temperature in the last seven days; • the day of the week; • the holiday effect; • the day of summer effect.	• the current temperature and temperatures 0.5 h,1 h, 2 h and 3 h ago; • temperatures from the same time period for the last three days and six days ago; • the maximum temperature in the last 24 h; • the minimum temperature in the last 24 h; • the average temperature in the last seven days; • the day of the week; • the holiday effect; • the day of winter effect.

5.1.3   Summer Forecast (2018-2027)

5.1.3.1   Forecast Summary

The historical, weather corrected historical and POE scenario forecast are demonstrated in Figure 5.1.4

Key findings from Figure 5.1.4 are:

1) 2012 and 2015 summer peak demand were below 90% POE due to mild summer weather and it implies that ACT summer maximum demand is heavily driven by weather;

2) Figure 5.1.4 shows a clear downward trend for all POE forecasts from 2018 to 2026 when rooftop PV impact is expected to exceed the load growth driven by

population growth. However, from 2026 onwards, a slow upward trend is projected due to increasing forecast uptake of EVs in the ACT;

3) The variations between the strong, neutral and weak scenarios are very small, which indicates that the economic varaibles such as energy price and energy efiiciency have some minor impact on average demand. For instance, The coefficient of the price variable was -6.48 x 10-5. That is, annual per capita demand decreases by 0.0061% for every additional dollar/kWh that price increases. The coefficient of energy effciency was -5.738 × 10-4 .That is, seasonal average per capita demand decreases by 5.58% for every additional 100 energy effeciency index points.

Figure 5.1.4: line graph (Horizontal) 10-year summer forecast (Operational Demand)
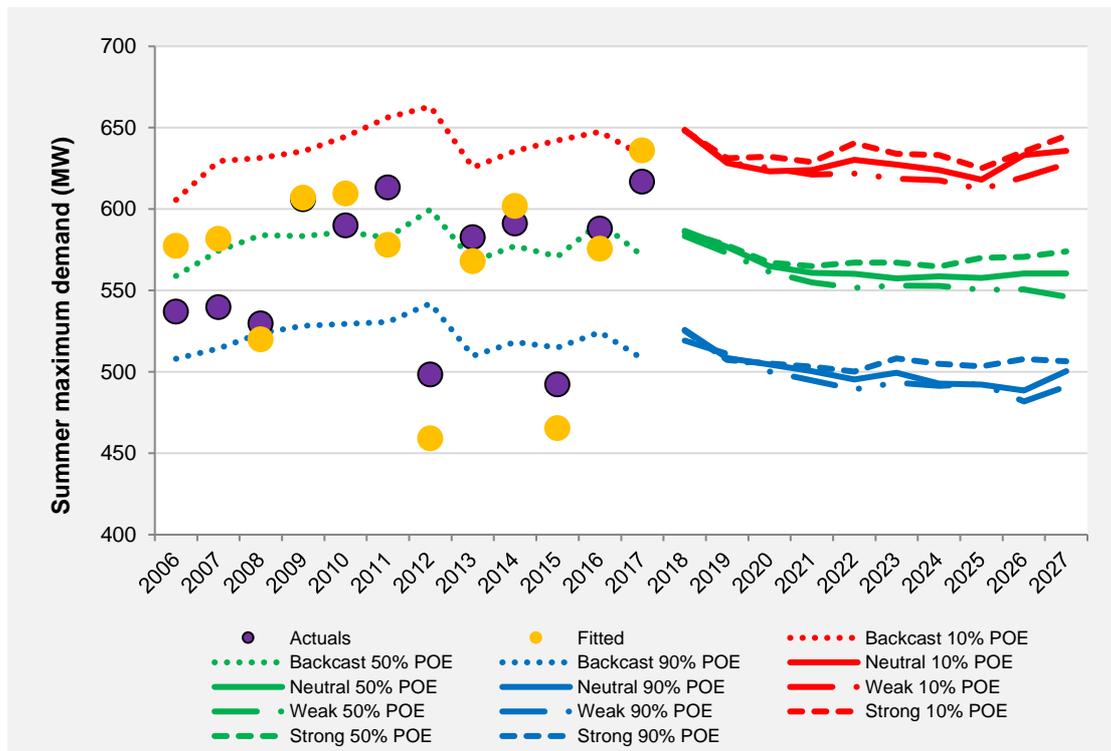
5.1.3.2 POE Forecast breakdown by structure change technology – Vertical analysis (Neutral Scenario)

Figure 5.1.5 and 5.1.6 demonstrates the vertical analysis of POE forecast. Both charts show the combined impact from rooftop PV and battery storage demand, and is expected to grow gradually in next ten years as more PV and battery systems are projected to be installed across the network. The EV impact on summer demand is minor but noticeable after 2022. Finally, the import from TransGrid is projected to be trending downward because of increase impact from solar PV and battery storage, but the rate of declining is expected to slow down due to more EV uptake from 2023 onwards.

Figure 5.1.5: 50% POE 10-year summer demand forecast stack charts
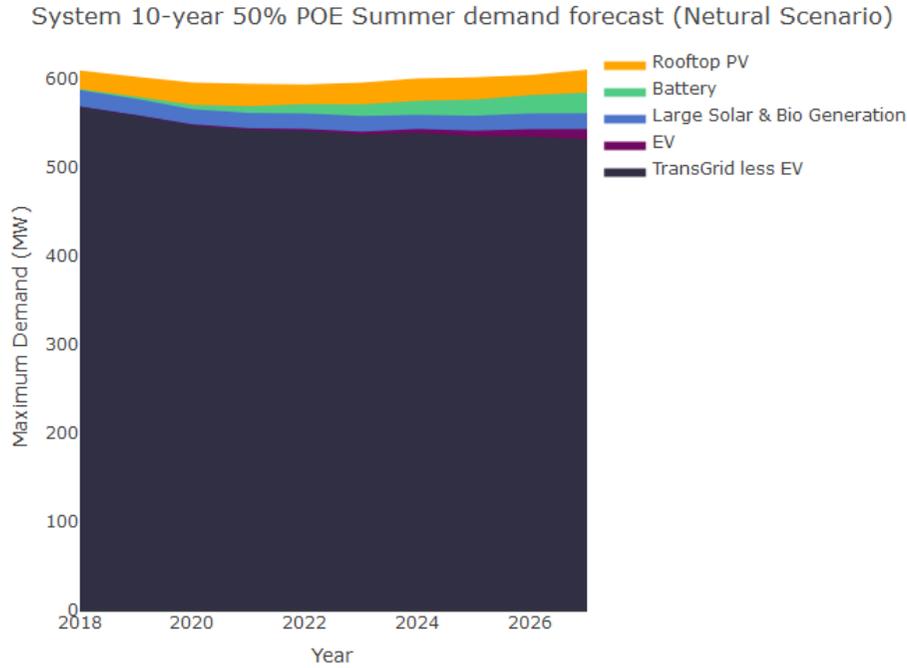
Figure 5.1.6: 10% POE 10-year summer demand forecast stack charts

System 10-year 50% POE Summer demand forecast (Netural Scenario)

- Rooftop PV
- Battery
- Large Solar & Bio Generation
- EV
- TransGrid less EV

System 10-year 10% POE Summer demand forecast (Netural Scenario)

- Rooftop PV
- Battery
- Large Solar & Bio Generation
- EV
- TransGrid less EV
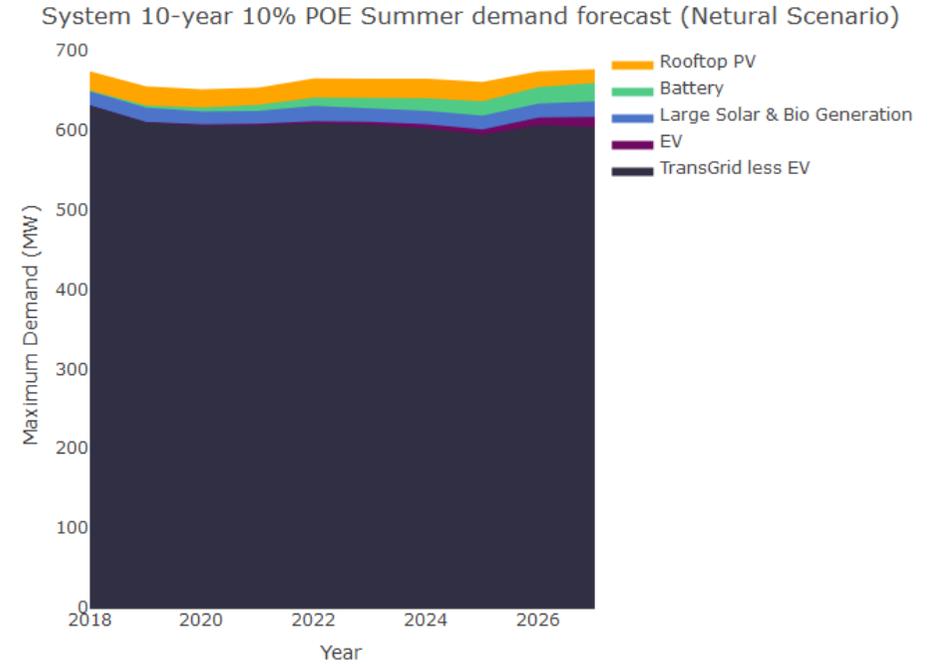
5.1.3.3 Historical and forecast outcomes for Figure 5.1.4, 5.1.5 and 5.1.6

Table 5.1.5: Summer maximum demand historical and forecast POE trend by scenario

Year	Actual	Fitted	Back-cast 90%	Back-cast 50%	Back-cast 10%	Weak 90%	Weak 50%	Weak 10%	Neutral 90%	Neutral 50%	Neutral 10%	Strong 90%	Strong 50%	Strong 10%
2006	537	577	508	559	606									
2007	540	582	514	574	629									
2008	530	520	524	584	632									
2009	606	607	528	583	636									
2010	590	609	529	586	645									
2011	613	578	531	582	656									
2012	498	459	542	600	663									
2013	583	568	510	568	626									
2014	591	602	518	577	636									
2015	492	465	515	571	642									
2016	588	576	524	592	647									
2017	617	636	508	571	633									
2018						519	583	648	526	587	649	525	586	648
2019						511	573	628	509	577	628	507	578	631
2020						500	561	625	504	565	623	505	567	632
2021						495	555	621	500	561	624	503	565	629
2022						489	552	622	495	560	630	500	567	640
2023						493	553	619	500	557	627	508	567	634
2024						491	553	618	493	559	624	505	565	633
2025						493	550	612	492	558	618	503	570	625
2026						482	551	620	489	560	633	508	571	635
2027						491	546	628	500	560	636	506	574	645

Table 5.1.6: Summer maximum demand POE forecast vertical breakdown (neutral scenario)

Summer Year	TG less EV POE50	TG less EV POE10	Plus EV (TG Import) POE50	Plus EV (TG Import) POE10	Plus Large Solar& Bio Gen (Operational demand) POE50	Plus Large Solar& Bio Gen (Operational demand) POE10	Plus Battery POE50	Plus Battery POE10	Plus Rooftop Solar (Underlying demand) POE50	Plus Rooftop Solar (Underlying demand) POE10
2018	568	631	568	631	587	649	588	650	609	674
2019	558	610	559	610	577	628	579	631	602	655
2020	547	606	548	607	565	623	570	628	595	651
2021	542	606	544	608	561	624	569	632	594	653
2022	541	609	543	611	560	630	571	641	593	665
2023	537	607	540	610	557	627	571	640	595	665
2024	538	602	543	607	559	624	575	640	600	665
2025	535	594	541	601	558	618	576	636	601	660
2026	534	606	543	616	560	633	581	654	604	674
2027	531	604	543	616	560	636	584	659	610	676

5.1.3.4 Forecast Evaluation:

Figure 5.1.7 illustrates the ex-ante forecast density function for maximum weekly demand and maximum annual demand for 2006–2016. These graphs demonstrate that the actual demands fit the ex-ante forecast distributions remarkably well. The upper chart from Figure 5.1.7 provides the best evidence of the performance of the model. In this case, the 12 actual weekly maximum demand values all fall within the region predicted from the ex-ante forecast distribution. Although there is only one annual maximum demand observed, the bottom chart shows that this also falls well within the predicted region.

Figure 5.1.7: Ex ante probability density functions for weekly maximum demand and annual maximum demand. Actual values and ex post forecast are also shown.

Density of summer 2017 weekly maximum demand
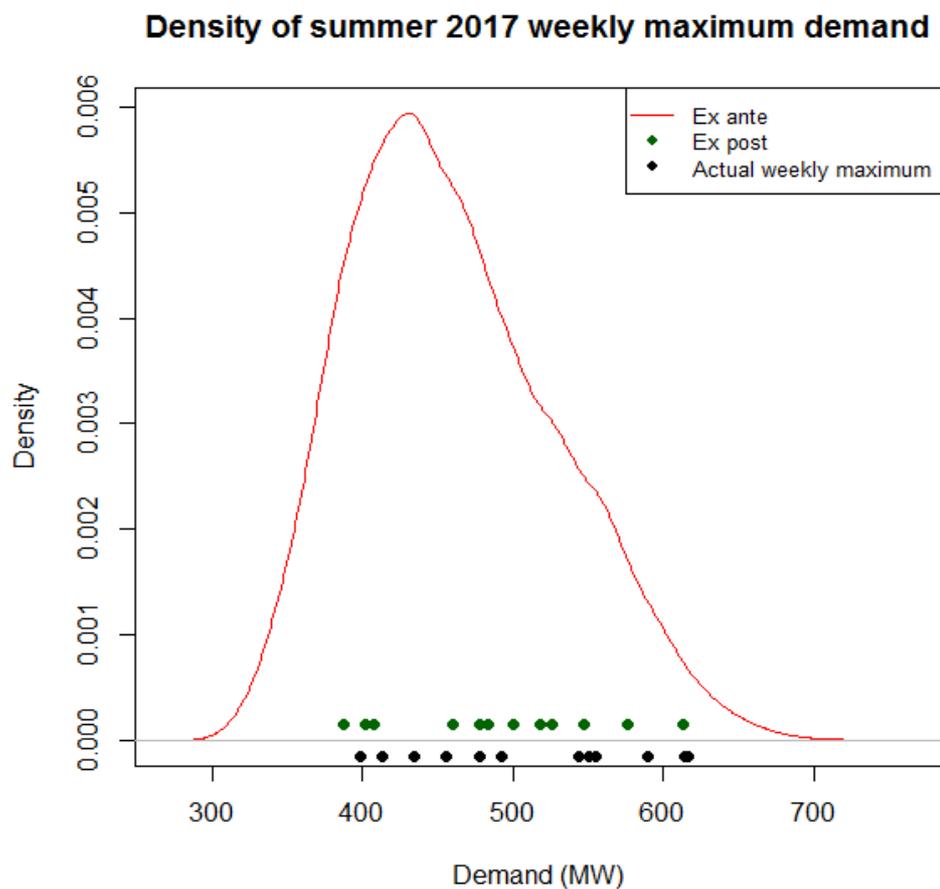
Density of summer 2017 annual maximum demand
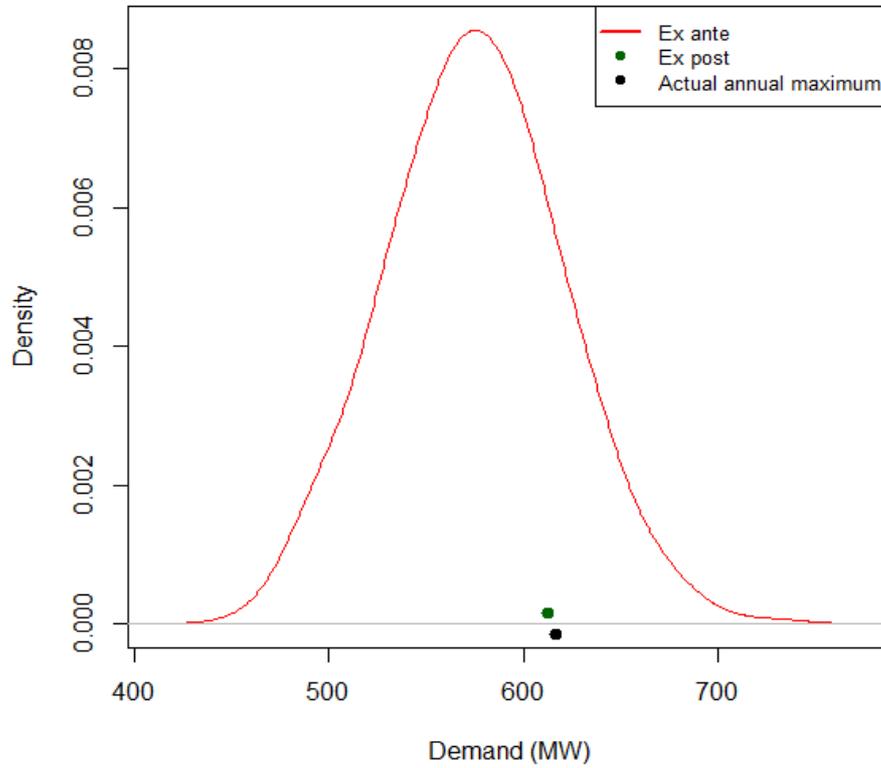
5.1.4 Winter Forecast (2018 – 2027)

5.1.4.1 Forecast Summary

The historical, weather corrected historical and POE scenario winter forecast are demonstrated in Figure 5.1.8.

Figure 5.1.8: line graph (Horizontal) 10-year winter forecast (Operational Demand)
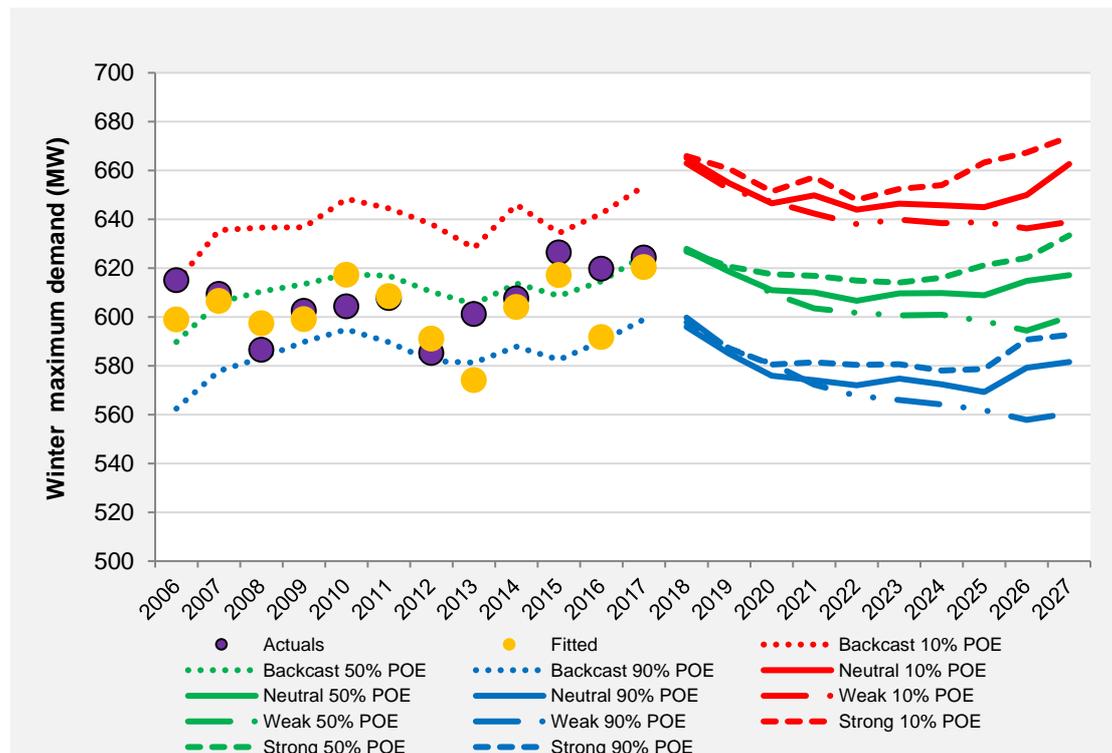
Key findings from Figure 5.1.8 are:

1) Historically, the winter peak demands have always been above 600 MW except 2008 and 2012 due to warm climate;

2) Roof top PV has less impact to the winter demand than the summer demand because the sun has already gone down before the peak has hit (Figure 5.1.5 vs Figure 5.1.9) and Figure 5.1.9 and Figure 5.1.10 demonstrates the battery storage impact is growing and is expected to be influential in winter demand at the end of 10-year period;

3) Similar to summer forecast, the load growth is expected to start gradually accelerating from 2026 onwards due to higher uptake of EV; and

4) Figure 5.1.8 also shows that the economic variables have much greater impact on winter demand than summer demand as the scenario spreads are much wider than those in Figure 5.1.4.

5.1.4.2 POE Forecast breakdown by structure change technology – Vertical analysis (Neutral Scenario)

Vertical analysis by stack chart breaks down the POE demand forecast by structure change technology. Below two charts show nearly zero impact from solar whereas gradually increase influnence of battery storage. The electrcity demand from EV is forecast to be small but noticable when more EVs are projected to be connected to Grid, which consequently drvies up TransGrid import at the end of 10-year period.

*Figure 5.1.9: 50% POE 10-year winter demand forecast stack charts*
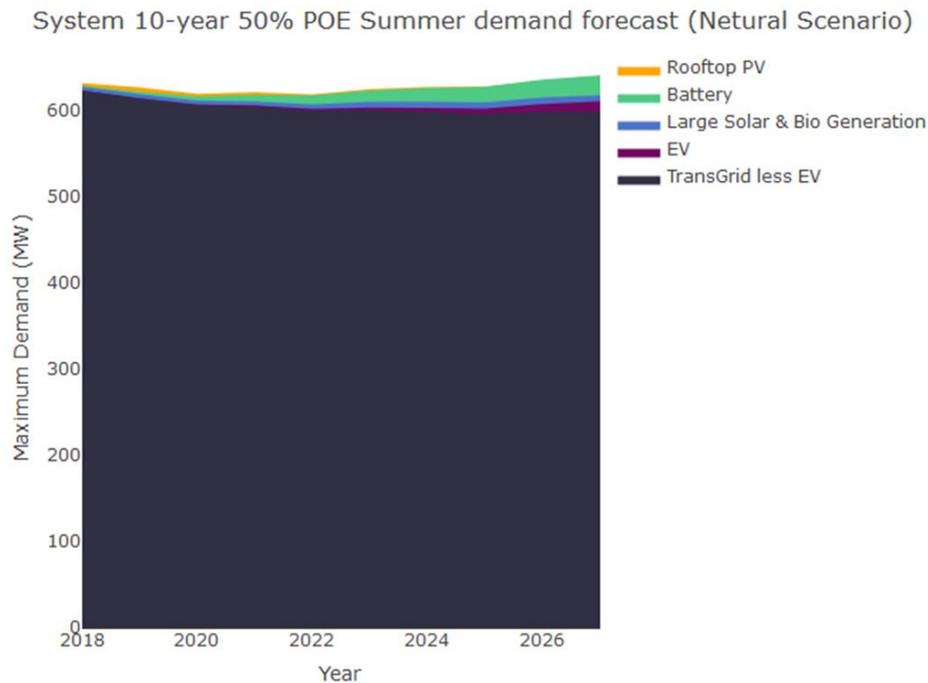
Figure 5.1.10: 10% POE 10-year winter demand forecast stack charts
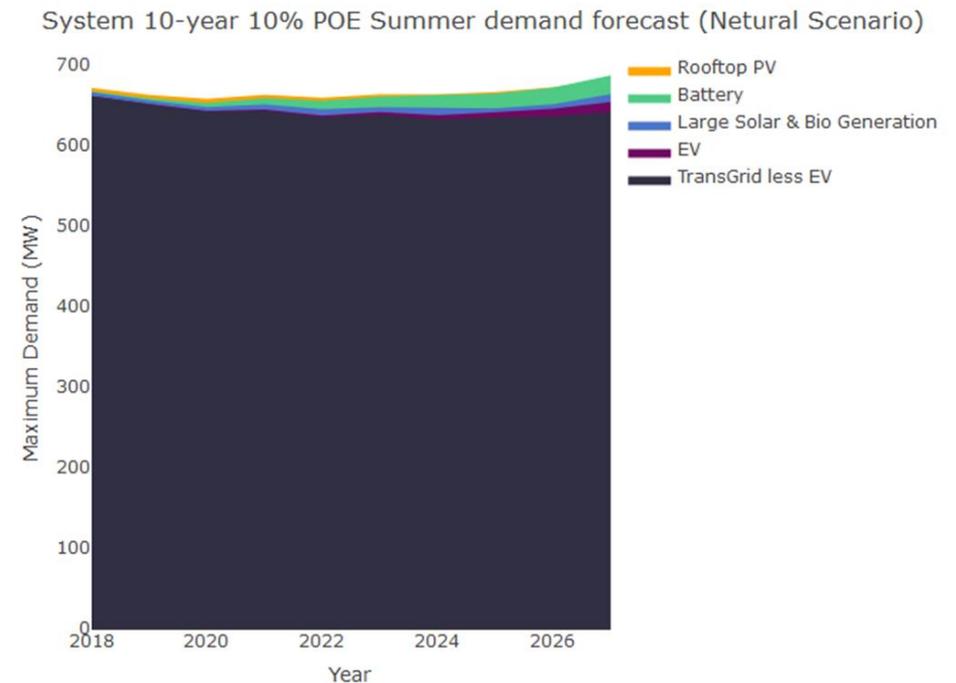
5.1.4.3 Historical and forecast outcomes for Figure 5.1.8, 5.1.9 and 5.1.10

Table 5.1.7: Winter maximum demand historical and forecast POE trend by scenario

Year	Actual	Fitted	Back-cast 90%	Back-cast 50%	Back-cast 10%	Weak 90%	Weak 50%	Weak 10%	Neutral 90%	Neutral 50%	Neutral 10%	Strong 90%	Strong 50%	Strong 10%
2006	615	599	562	590	614									
2007	609	607	578	606	636									
2008	587	597	583	611	637									
2009	603	599	590	613	637									
2010	604	617	595	618	648									
2011	608	608	590	617	645									
2012	585	591	582	610	638									
2013	601	574	581	605	628									
2014	608	604	588	614	646									
2015	626	617	582	609	634									
2016	620	592	590	615	642									
2017	624	620	599	625	654									
2018						600	628	663	596	627	665	598	627	666
2019						587	620	652	585	619	655	587	621	661
2020						581	610	647	576	611	647	581	617	651
2021						572	604	642	574	610	650	581	617	657
2022						568	602	638	572	607	644	580	615	648
2023						566	601	640	575	610	646	581	614	652
2024						564	601	638	572	610	646	578	616	654
2025						562	598	639	569	609	645	579	621	663
2026						558	594	636	579	615	650	591	624	667
2027						560	600	639	582	617	663	593	633	674

Table 5.1.8: Winter maximum demand POE forecast vertical breakdown (neutral scenario)

Summer	TG less EV		Plus EV (TG Import)		Plus Large Solar& Bio Gen (Operational demand)		Plus Battery		Plus Rooftop Solar (Underlying demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	623	660	623	660	627	665	628	666	631	670
2019	613	650	614	650	619	655	621	657	626	662
2020	606	641	607	642	611	647	616	652	619	657
2021	604	642	606	644	610	650	618	658	621	662
2022	599	634	601	636	607	644	617	654	618	658
2023	600	637	603	640	610	646	623	660	624	662
2024	598	631	603	636	610	646	626	662	627	662
2025	596	634	602	640	609	645	627	663	627	665
2026	598	635	607	644	615	650	635	671	635	671
2027	598	640	610	653	617	663	640	686	640	681

5.1.4.4 Forecast Evaluation

Figure 5.1.7 illustrates the ex-ante forecast density function for maximum weekly demand and maximum annual demand for 2006–2016. These graphs demonstrate that the actual demands fit the ex-ante forecast distributions remarkably well. The upper chart from Figure 5.1.7 provides the best evidence of the performance of the model. In this case, the 11 actual weekly maximum demand values all fall within the region predicted from the ex-ante forecast distribution. Although there is only one annual maximum demand observed, the bottom chart shows that this also falls well within the predicted region.

Figure 5.1.11: Ex ante probability density functions for weekly maximum demand and annual maximum demand. Actual values and ex post forecast are also shown.
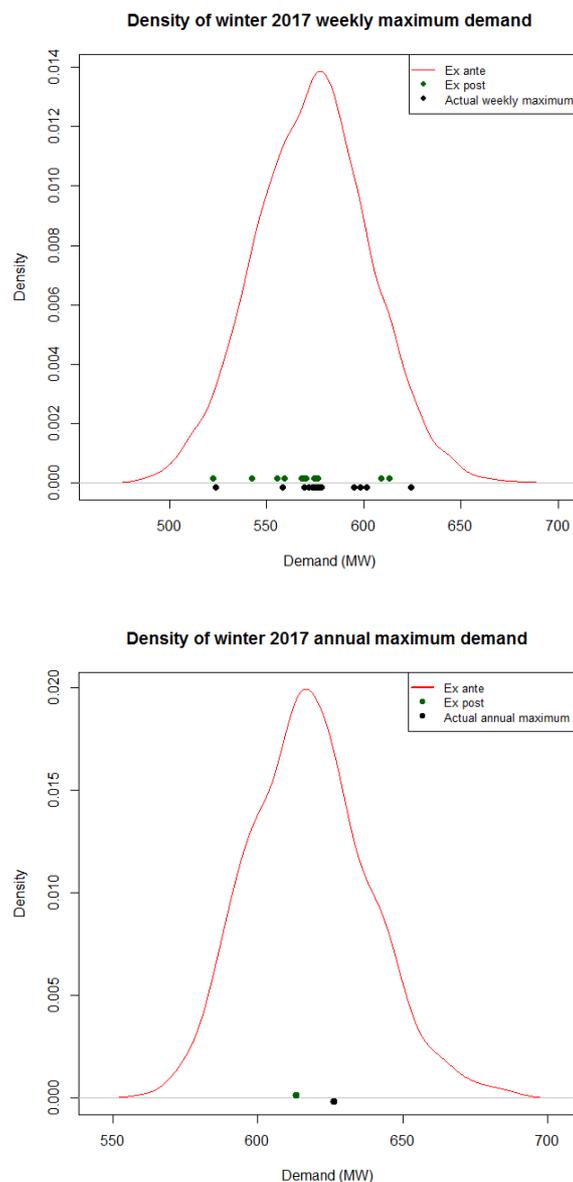
5.2 Zone Substation Forecasts

The zone substation forecasts section covers the following areas:

- Zone substation forecast summaries include both summer and winter 50% POE and 10% POE forecast for all current and proposed zone substations;
- Description of seasonal average demand model and normalised half-hourly model for each zone substation;
- Block load analysis and post-model adjustment for each zone substation;
- Forecast outcomes – Horizontal and vertical analysis of summer and winter POE forecast before and after block load adjustment and corresponding tables and graphs.

5.2.1 Zone Substation Forecast Summaries

5.2.1.1 Zone substation summer demand forecasts 2018 - 2027 (in MVA)

Zone Substation	Continuous Rating	Emergency two-hour Rating	PoE Forecast	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Belconnen	55	63	50%	58	62	62	65	65	65	66	66	68	69
			10%	65	69	70	73	73	74	73	74	76	77
City East	95	95	50%	75	78	80	73	74	74	73	72	73	73
			10%	86	88	90	84	84	85	85	83	84	83
Civic	110	114	50%	57	56	56	59	63	64	63	63	63	63
			10%	65	63	64	67	71	72	70	70	70	70
East Lake	24[1]	43[1]	50%	20	19	21	24	27	30	31	58	58	58
			10%	24	24	25	28	31	34	35	62	62	63
Fyshwick	28	28	50%	29	30	30	29	27	25	25	0	0	0
			10%	33	34	35	34	31	30	29	0	0	0

Zone Substation	Continuous Rating	Emergency two-hour Rating	PoE Forecast	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Gilmore	45	62	50%	34	36	37	37	36	38	38	38	38	39
			10%	42	44	44	46	46	47	46	47	47	48
Gold Creek	57	76	50%	60	64	67	70	72	72	73	74	78	78
			10%	73	76	81	84	85	89	90	92	95	95
Latham	95	95	50%	52	51	52	52	53	54	54	54	56	46
			10%	59	59	59	59	60	61	61	61	63	54
Strathnairn	55[2]	63[2]	50%	0	0	0	0	0	0	0	0	0	10
			10%	0	0	0	0	0	0	0	0	0	10
Telopea Park	100	114	50%	86	87	89	89	89	89	89	89	89	90
			10%	94	96	97	98	98	98	98	97	98	101
Tennent	15[3]	15[3]	50%	3	3	3	3	3	3	3	3	3	3
			10%	3	3	3	3	3	3	3	3	3	3
Theodore	45	62	50%	24	24	23	23	23	22	22	22	22	22
			10%	30	29	29	28	29	28	28	27	27	28
Wanniassa	95	95	50%	63	63	64	64	63	62	60	60	58	57
			10%	72	73	74	73	73	71	70	68	67	67
Woden	95	95	50%	76	78	80	82	82	80	78	75	74	72
			10%	86	88	90	92	92	89	86	84	82	80
Molonglo	12[4]	13[4]	50%	0	0	0	0	0	1	2	3	4	4
			10%	0	0	0	0	0	1	2	3	4	4

5.2.1.2 Zone substation winter demand forecasts 2018 - 2027 (in MVA)

Zone Substation	Continuous Rating	Emergency two-hour Rating	PoE Forecast	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Belconnen	55	76	50%	60	62	63	65	65	66	66	67	68	69
			10%	64	66	68	70	70	71	71	72	73	74
City East	95	112	50%	68	71	72	67	66	66	65	65	64	64
			10%	74	76	78	73	72	72	72	72	71	71
Civic	110	143	50%	49	48	49	56	57	57	56	56	56	56
			10%	54	54	56	61	63	63	63	62	63	62
East Lake	30[1]	54[1]	50%	20	21	24	27	30	32	32	55	56	57
			10%	24	25	28	31	34	36	36	59	60	61
Fyshwick	28	28	50%	23	24	24	22	21	20	20	0	0	0
			10%	27	28	28	26	24	24	24	0	0	0
Gilmore	45	69	50%	35	36	37	37	38	38	39	39	40	40
			10%	41	41	43	44	44	44	45	46	47	47
Gold Creek	57	76	50%	68	73	75	79	80	82	84	86	88	91
			10%	76	81	84	89	90	93	95	97	99	103
Latham	95	114	50%	68	68	69	70	69	70	71	72	64	64
			10%	73	74	74	75	75	75	76	77	70	70
Strathnairn	55[2]	76[2]	50%	0	0	0	0	0	0	0	0	9	10
			10%	0	0	0	0	0	0	0	0	9	10
Telopea Park	100	114	50%	84	86	88	88	88	88	88	88	89	89
			10%	89	90	92	92	92	92	93	93	93	93

![evoenergy logo]

Zone Substation	Continuous Rating	Emergency two-hour Rating	PoE Forecast	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Tennent	15³	15³	50%	3	3	3	3	3	3	3	3	3	3
			10%	3	3	3	3	3	3	3	3	3	3
Theodore	45	69	50%	29	28	28	28	27	27	27	27	27	27
			10%	33	32	32	31	31	31	30	30	30	30
Wanniassa	95	114	50%	77	78	77	77	75	74	74	72	71	71
			10%	83	83	84	83	82	81	79	78	78	77
Woden	95	114	50%	78	78	81	83	84	83	82	79	78	77
			10%	84	84	86	89	90	88	86	84	83	82
Molonglo	14⁴	16⁴	50%	0	0	0	0	0	1	2	3	4	4
			10%	0	0	0	0	0	1	2	3	4	4

Notes:

1 East Lake Zone Substation will be equipped initially with one transformer only (ie N security).

2 Strathnairn Zone Substation has one transformer only (ie N security).

3 Tennent Zone Substation has one transformer only (ie N security).

4 Molonglo Zone Substation will be equipped initially with the mobile substation with one transformer only (ie N security).

5.2.2 Strathnairn Zone Substation Forecast

A new zone substation is to be constructed to supply the West Belconnen area. It is proposed that the Strathnairn *Zone Substation will commence* supplying the West Belconnen and Parkwood area by June 2026.

The below table shows the deterministic demand forecast for Strathnairn Zone Substation by financial year:

Table 5.2.2: Strathnairn Zone Substation 10-year load forecast

Financial Year	Demand Forecast (in MVA)
2017/18	-
2018/19	-
2019/20	-
2020/21	-
2021/22	-
2022/23	-
2023/24	-
2024/25	-
2025/26	8.9
2026/27	9.8

5.2.3 Belconnen Zone Substation Forecast

5.2.3.1 Seasonal average model

5.2.3.1.1 Model Description

Jacobs produced the seasonal average demand model for Belconnen Zone Substation and found that the key drivers were weather, Belconnen regional population, retail price and unemployment. The model had an adjusted R-squared statistic of 95% and projections are displayed in Figure 5.2.3.1 – more detail in Jacobs report on the actual model.

5.2.3.1.2 Forecast trend and block load analysis

Figure 5.2.3.1: Belconnen ZSS seasonal average demand – Model Fit and Forecast
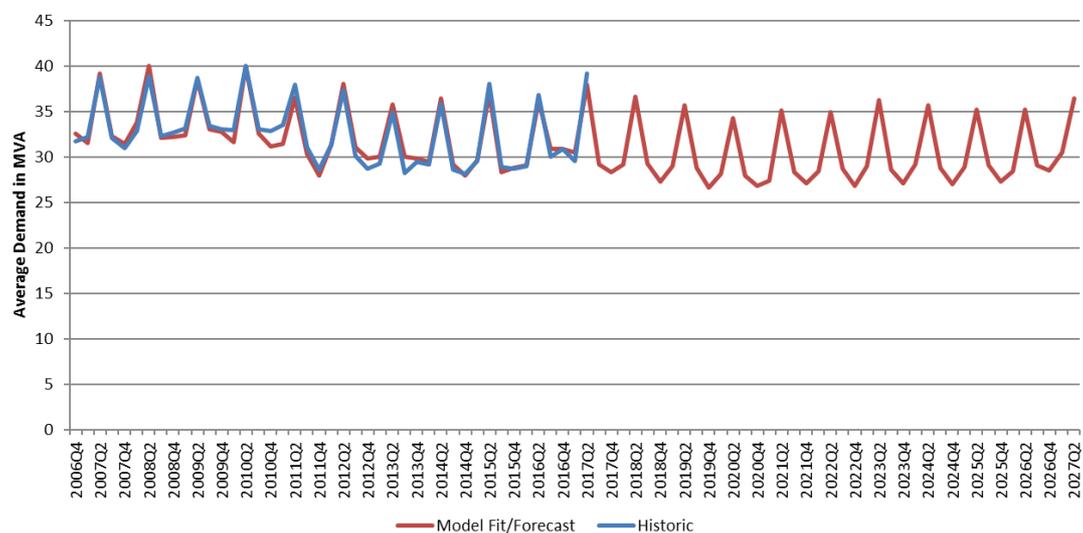
Block Load analysis:

1) Figure 5.3.2.1 shows no upward trend, therefore block load adjustment is required if any;
2) Belconnen regional population is a variable of model with a positive coefficient and forecast to grow in next ten year under ACT Government spatial projection. Thus, to avoid double accounting, the residential block load should be excluded from adjustment;
3) Detailed block load information can be found under Appendix 6.3.

5.2.3.2 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.1.

5.2.3.3 Summer and Winter Demand forecast

The final forecast results and historical analysis are presented using the following formats:

- Figure 5.2.3.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.3.3: Stack Chart by structure change impact;
- Table 5.2.3.1 to 5.2.3.4: Actual or forecast figures for Figure 5.2.3.2 and 5.2.3.3

Key findings from Figure 5.2.3.2 are:

1) Both summer and winter maximum demands has been fluctuating around the continuous rating for past 12 years;
2) Summer emergency rating has been breached twice during the 12-year period;
3) Strong commercial, industrial and high rise building spot loads[7] (e.g. Metronode data centre, new University of Canberra Hospital, expansion of Calvary Hospital, several Mixed developments and High rise apartment and so on) have been noted directly from key customers constantly from Belconnen area, which consequently drives the summer POE 10 forecast trending above emergency rating for next 10 years;
4) Summer POE 50 forecast is expected to exceed emergency rating by 2021 at the next regulatory period;
5) Solar PV impact has very little impact on winter peak demand as winter peak time is forecast to be 6:00 PM, beyond the daylight.

In conclusion, Belconnen Zone Substation network could be easily constrained by future extreme summer weather as experienced in February 2017 (3 consecutive days of hot weather). It is proposed to install a third 132/11 kV 30/55 MVA transformer at Belconnen Zone Substation in the 2019-24 Regulatory Control Period.

Figure 5.2.3.3 illustrates the vertical analysis of summer and winter POE forecast. Roof top PV has less impact on the winter demand than the summer demand because ZSS' summer peak time is typically around 4 PM whereas its winter peak normally occurs at 6:30 PM.

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[7] Appendix 6.3

Figure 5.2.3.2: Belconnen ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis
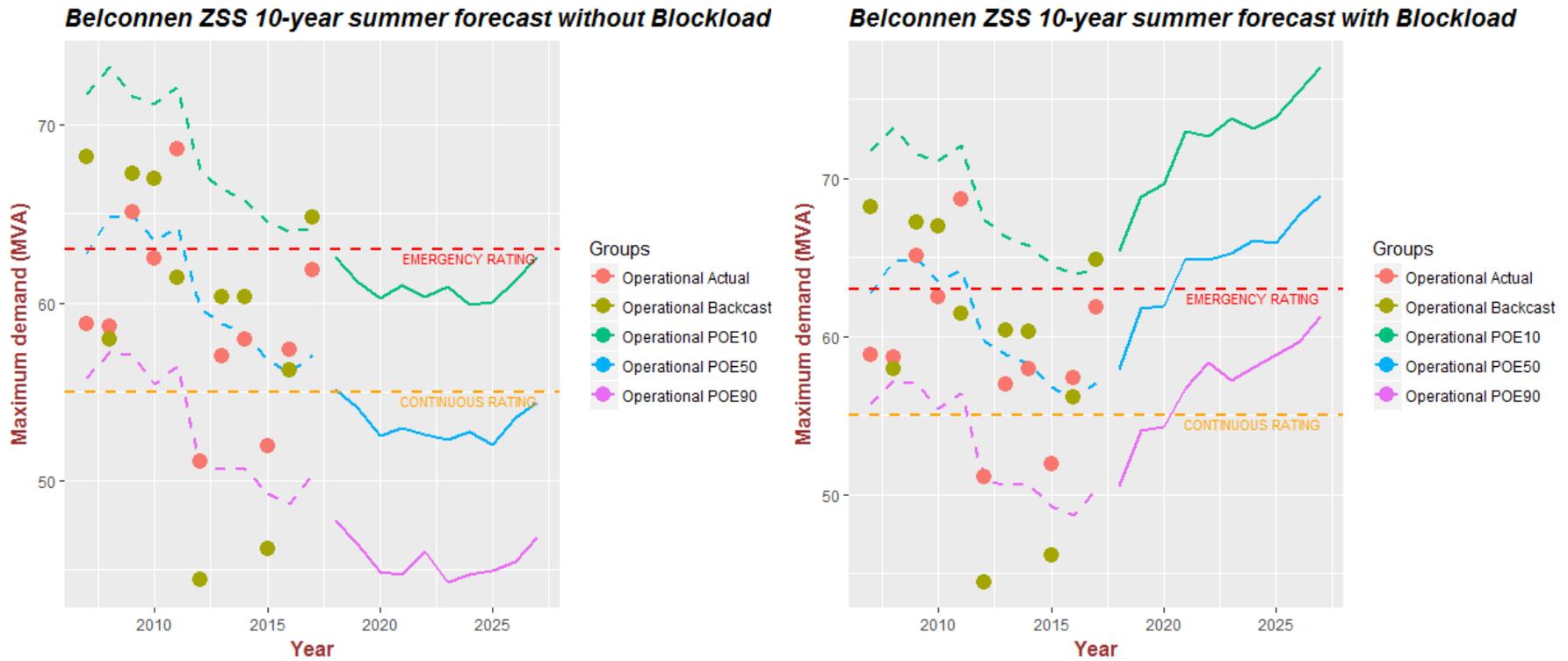
Figure 5.2.3.2: Belconnen ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.3.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

Belconnen ZSS 10-year summer demand forecast (50% POE)

Belconnen ZSS 10-year winter demand forecast (50% POE)

Legend (both charts):
- Rooftop PV
- Battery
- EV
- Operational Less EV

Y-axis: Maximum Demand (MVA)
X-axis: Year
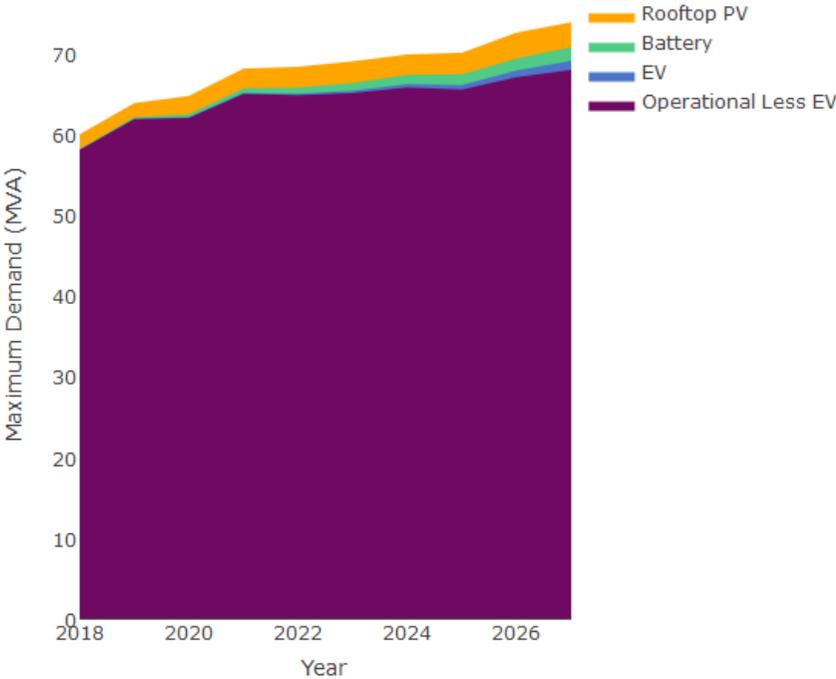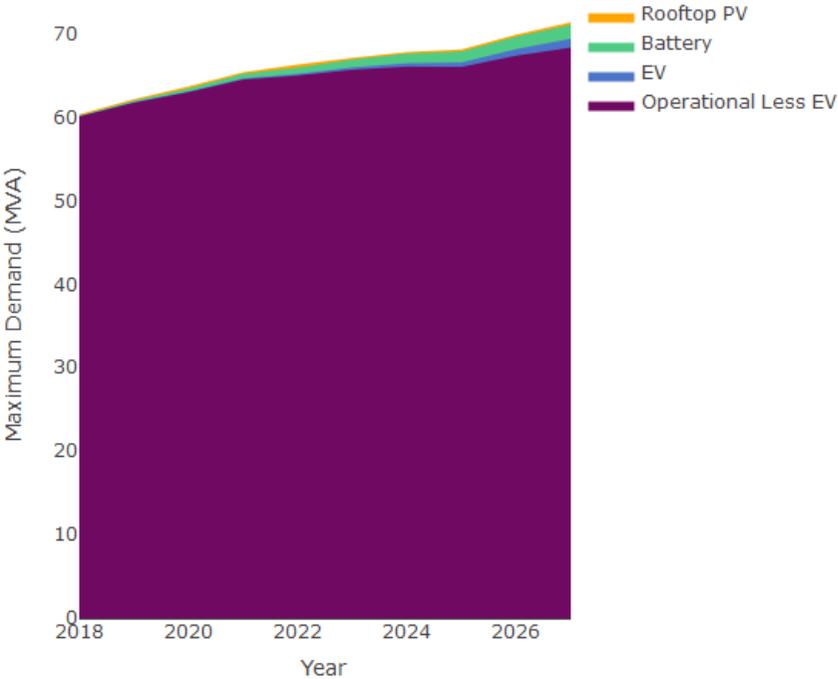
Figure 5.2.3.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Belconnen ZSS 10-year summer demand forecast (10% POE)

Winter POE Forecasts
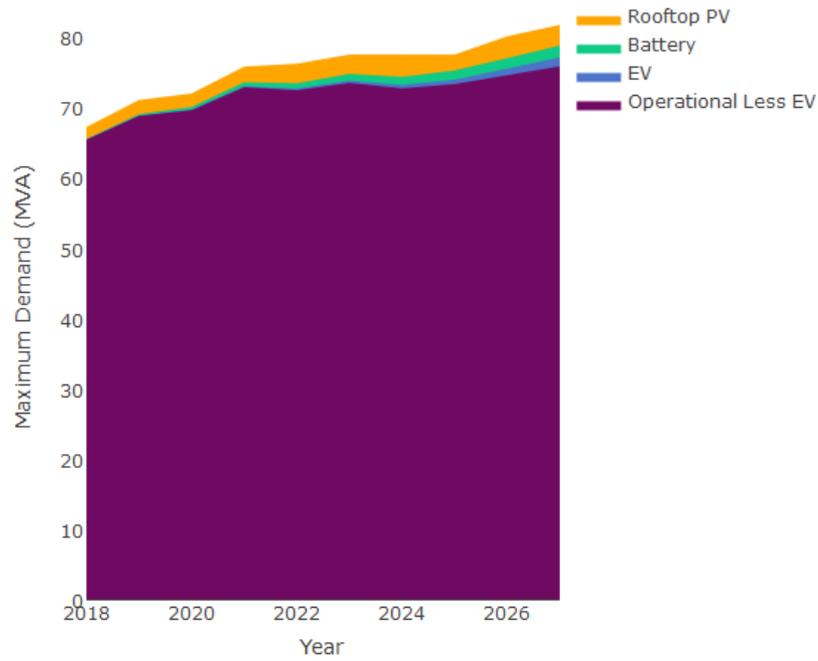
Belconnen ZSS 10-year winter demand forecast (10% POE)
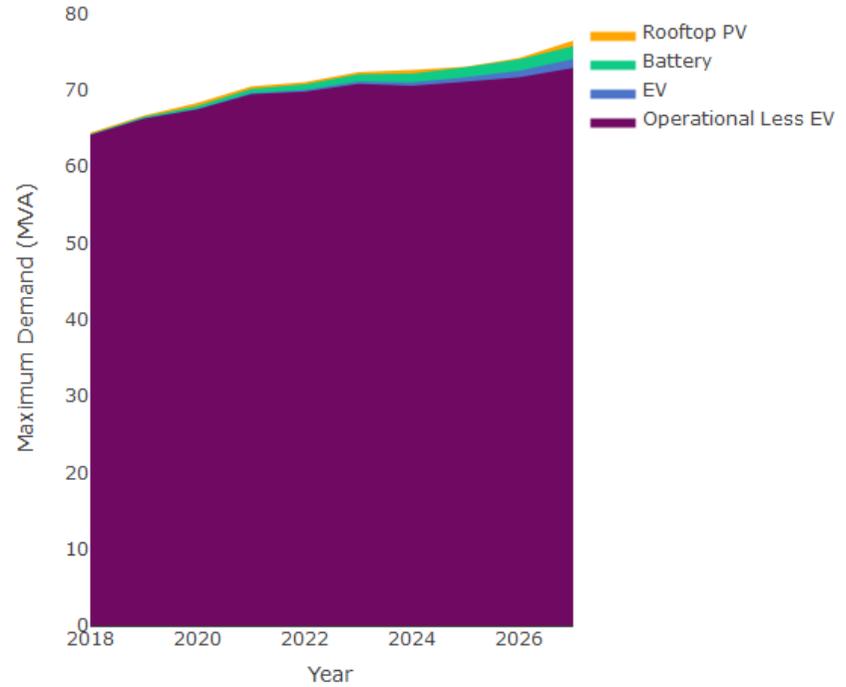
Table 5.2.3.1: Belconnen ZSS summer back-cast and weather correction in MVA

	Summer		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	59	68	56	63	72
2008	59	58	57	65	73
2009	65	67	57	65	72
2010	63	67	55	64	71
2011	69	61	56	64	72
2012	51	44	51	60	67
2013	57	60	51	59	66
2014	58	60	51	58	66
2015	52	46	49	57	65
2016	57	56	49	56	64
2017	62	65	50	57	64

Table 5.2.3.2: Belconnen ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	58	65	58	65	58	65	60	67
2019	62	69	62	69	62	69	64	71
2020	62	70	62	70	62	70	65	72
2021	65	73	65	73	66	74	68	76
2022	65	73	65	73	66	74	68	76
2023	65	74	65	74	66	75	69	77
2024	66	73	66	73	67	75	70	77
2025	66	74	66	74	68	76	70	77
2026	67	75	68	76	70	77	72	80
2027	68	76	69	77	71	79	74	82

Table 5.2.3.3: Belconnen ZSS winter back-cast and weather correction in MVA

| Year | Winter | | Weather Correction | | |
	Actual	Fitted	POE90	POE50	POE10
2007	58	59	56	61	65
2008	56	59	58	62	66
2009	58	59	57	60	65
2010	58	60	57	60	65
2011	58	55	52	56	61
2012	53	55	53	57	61
2013	53	53	53	56	60
2014	55	54	51	56	60
2015	58	55	51	55	60
2016	57	54	52	57	60
2017	60	56	52	56	60

Table 5.2.3.4: Belconnen ZSS winter forecast breakdown in MVA

| Winter | Operational Demand less EV | | Plus EV (Operational Demand) | | Plus Battery | | Plus Rooftop Solar (Underlying Demand) | |
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	60	64	60	64	60	64	60	64
2019	62	66	62	66	62	67	62	67
2020	63	67	63	68	63	68	64	68
2021	65	69	65	70	65	70	65	70
2022	65	70	65	70	66	71	66	71
2023	66	71	66	71	67	72	67	72
2024	66	71	66	71	68	72	68	73
2025	66	71	67	72	68	73	68	73
2026	67	72	68	73	70	74	70	74
2027	68	73	69	74	71	76	71	76

5.2.4   City East Zone Substation Forecast

5.2.4.1   Seasonal average model

5.2.4.1.1   Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, North Canberra regional population and business energy efficiency. The model had an adjusted R-squared statistic of 93% and projections are displayed in Figure 5.2.4.1 – more detail in Jacobs report on the actual model.

5.2.4.1.2   Forecast trend and block load analysis

Figure 5.2.4.1: City East ZSS seasonal average demand – Model Fit and Forecast
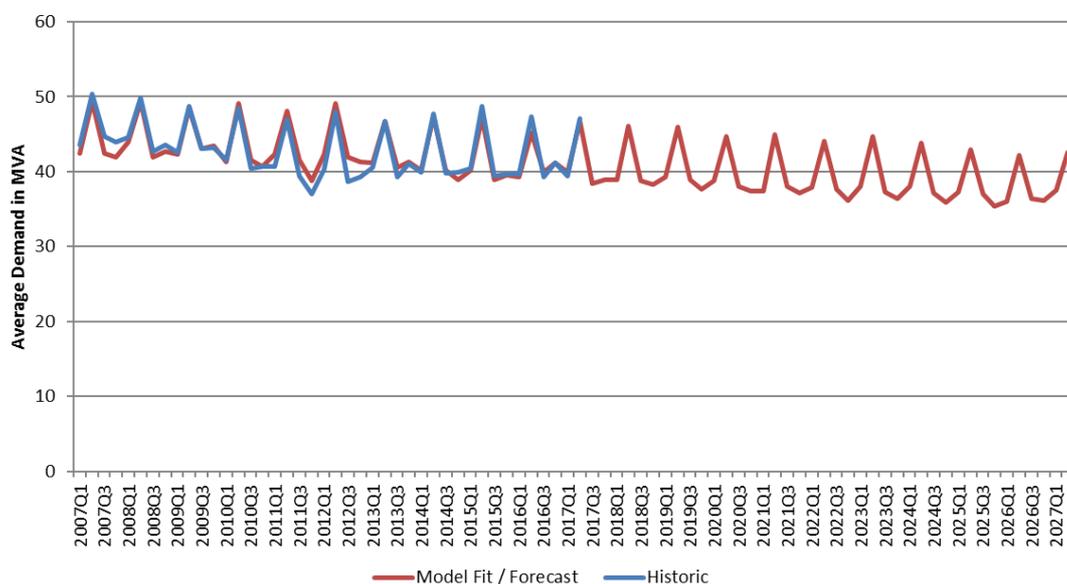
Block Load analysis:

- Figure 5.2.4.1 demonstrates a clear downward trend over the next ten years. Therefore, block load adjustment is required;
- In order to avoid double accounting, the residential block loads should be excluded from block load adjustment since North Canberra regional population is a variable of average demand model with a positive coefficient and the regional population is forecast to grow in next ten years;
- City East ZSS will supply all Canberra City and Dickson area's new block loads until a new feeder is commissioned from Civic ZSS by 1 July 2020;
- The new feeder from Civic ZSS will have a total capacity of 6 MVA, which means 6 MVA load will permanently transferred from City East to Civic by 1 July 2020;
- More block load information can be found under Appendix 6.3.

5.2.4.2 Half-hourly model: summer and winter

A total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.2.

5.2.4.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by the following formats:

- Figure 5.2.4.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.4.3: Stack Chart by structure change impact;
- Table 5.2.4.1 to 5.2.4.4: Actual or forecast figures for Figure 5.2.4.2 and 5.2.4.3.

Key findings from Figure 6.14 are:

- Both summer and winter historical actuals show a strong downward trend;
- The downward trend is possibly caused by a combination effect of rooftop PV and business energy efficiency;
- Business energy efficiency is a key input variable of City East ZSS seasonal average demand model;
- It seems City East ZSS has enough capacity to accommodate strong commercial and mixed use development demand in the eastern Canberra area as both summer and winter's POE 10 and POE 50 forecasts are expected to be trending below its continuous rating over the next ten years.

Figure 5.2.4.3 illustrates the vertical analysis of summer and winter POE forecast. Roof top PV has less impact on the winter demand than the summer demand because ZSS summer peak time is typically around 3 PM whereas its winter peak normally occurs either at 9 AM in the morning or at 6 PM in the evening.

Figure 5.2.4.2: City East ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis
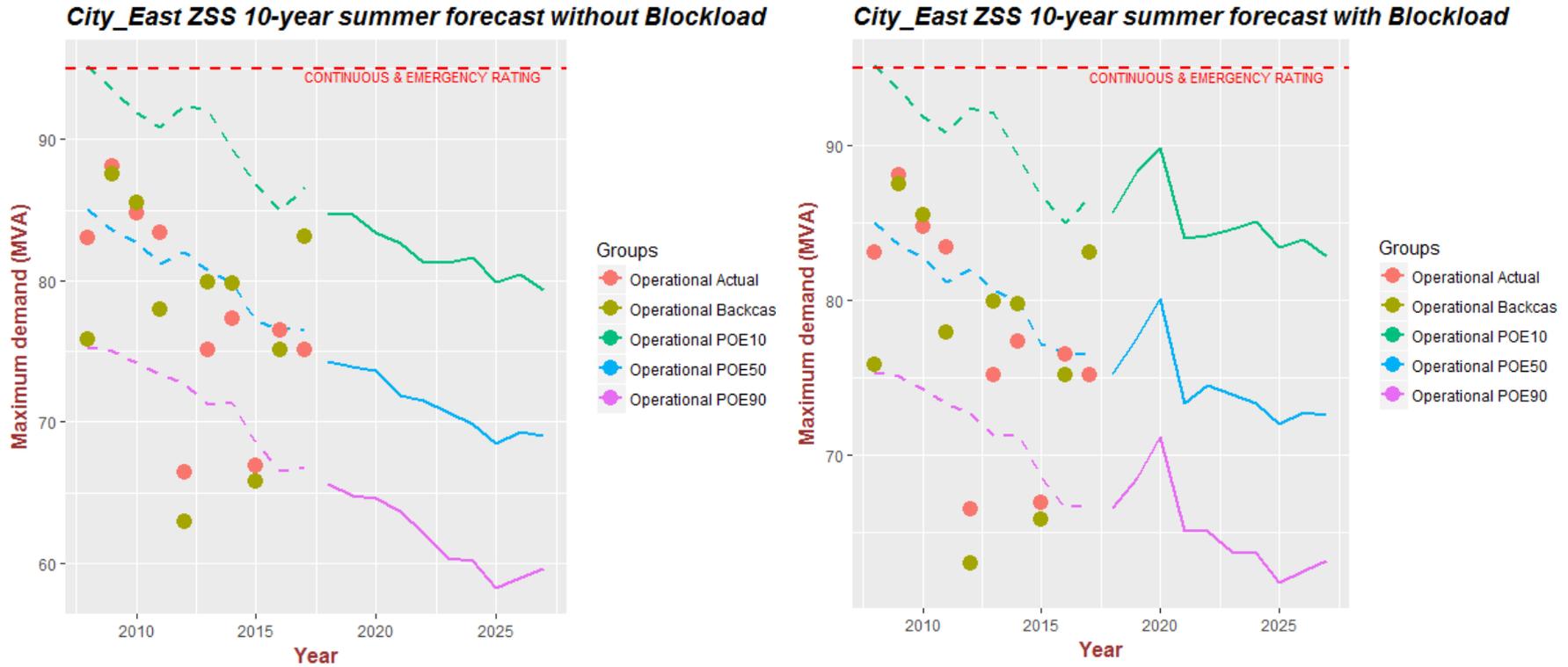
Figure 5.2.4.2: City East ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.4.3: POE Forecast breakdown by structure change technology – Vertical analysis

| Summer POE Forecasts | Winter POE Forecasts |

Belconnen ZSS 10-year summer demand forecast (50% POE)

Belconnen ZSS 10-year winter demand forecast (50% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV
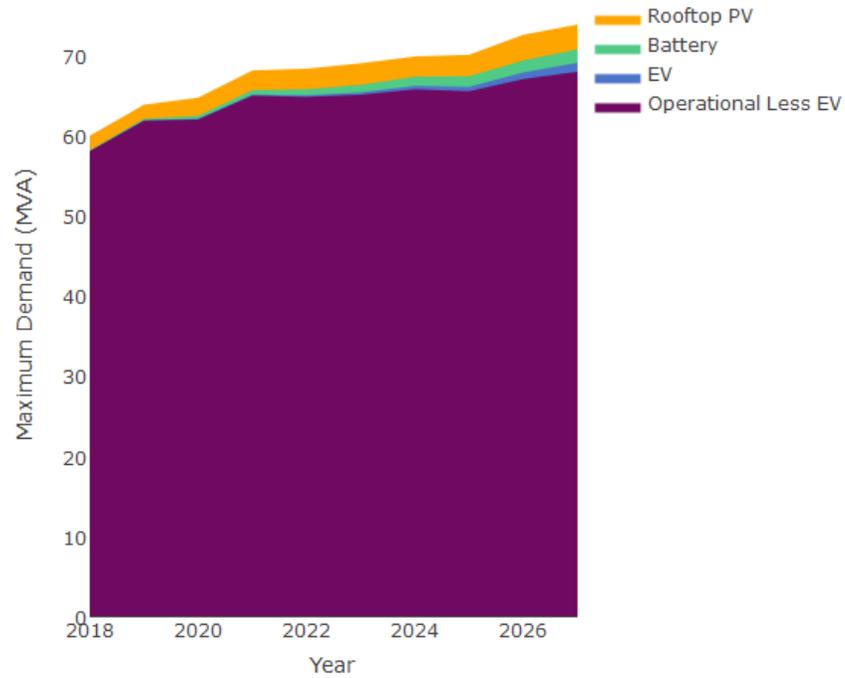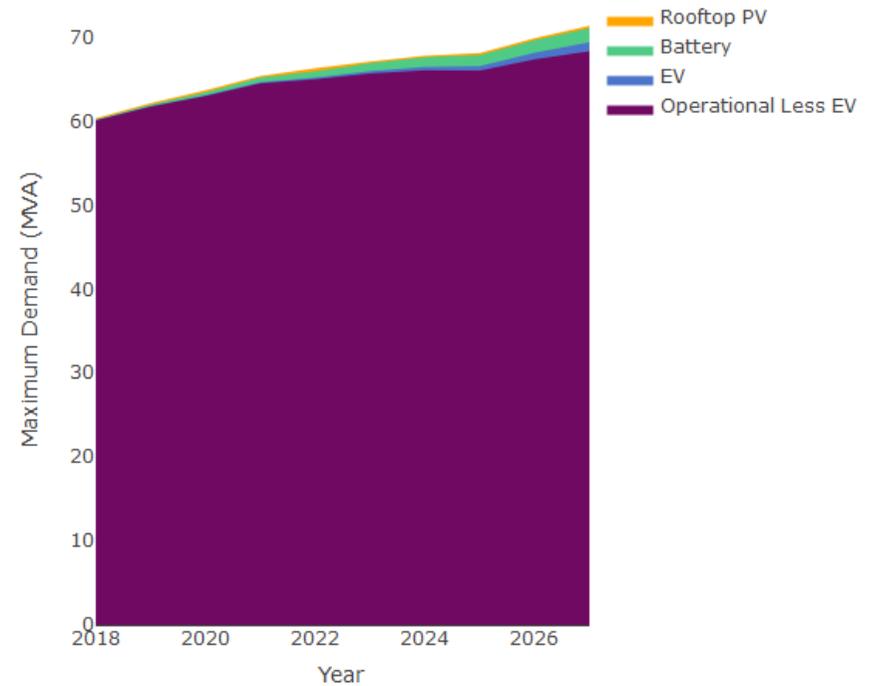
Figure 5.2.4.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Winter POE Forecasts

Belconnen ZSS 10-year summer demand forecast (10% POE)
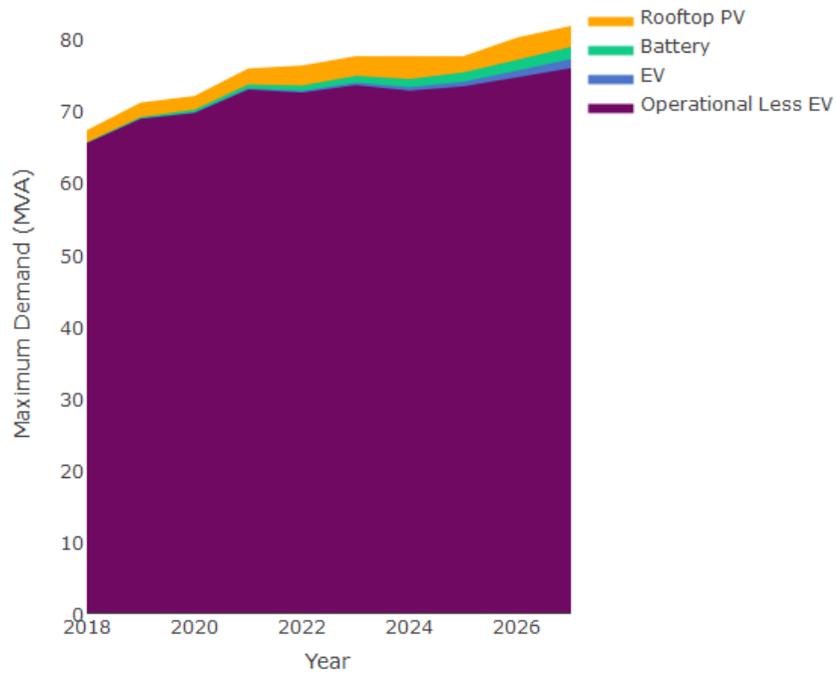
Belconnen ZSS 10-year winter demand forecast (10% POE)
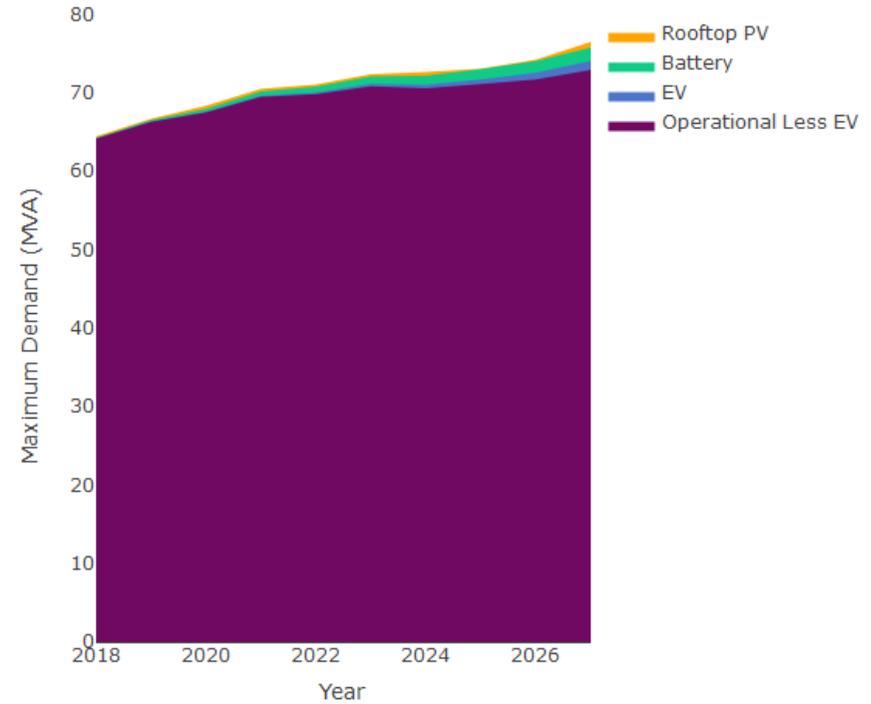
Table 5.2.4.1: City East ZSS summer back-cast and weather correction in MVA

| Year | Summer | | Weather Correction | | |
	Actual	Fitted	POE90	POE50	POE10
2008	83	76	75	85	95
2009	88	88	75	84	94
2010	85	86	74	83	92
2011	83	78	73	81	91
2012	67	63	73	82	92
2013	75	80	71	81	92
2014	77	80	71	80	89
2015	67	66	69	77	87
2016	77	75	67	77	85
2017	75	83	67	77	87

Table 5.2.4.2: City East ZSS summer forecast break down in MVA

| Summer | Operational Demand less EV | | Plus EV (Operational Demand) | | Plus Battery | | Plus Rooftop Solar (Underlying Demand) | |
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	75	86	75	86	75	86	77	88
2019	78	88	78	88	78	88	80	91
2020	80	90	80	90	80	90	83	92
2021	73	84	73	84	73	84	76	87
2022	74	84	74	84	75	84	78	87
2023	74	84	74	85	74	85	77	88
2024	73	84	73	85	74	85	77	89
2025	71	83	72	83	72	84	76	88
2026	72	83	73	84	73	84	77	88
2027	71	81	73	83	73	83	77	87

Table 5.2.4.3: City East ZSS winter back-cast and weather correction in MVA

Year	Winter Actual	Fitted	Weather Correction POE90	POE50	POE10
2007	76	75	69	74	79
2008	73	70	67	73	80
2009	74	72	68	73	79
2010	70	71	65	72	78
2011	70	73	66	71	78
2012	69	71	65	70	77
2013	69	67	65	70	76
2014	70	71	64	69	75
2015	70	68	62	68	74
2016	69	66	62	67	74
2017	69	70	62	66	72

Table 5.2.4.4: City East ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	68	74	68	74	68	74	70	76
2019	71	76	71	76	71	76	73	78
2020	72	78	72	78	72	78	74	80
2021	67	73	67	73	68	74	69	76
2022	66	72	66	72	67	73	69	75
2023	66	72	66	72	67	73	69	75
2024	64	71	65	72	66	73	68	74
2025	64	71	65	72	66	73	68	76
2026	63	70	64	71	66	73	68	75
2027	63	70	64	71	66	73	68	75

### 5.2.5 Civic Zone Substation Forecast

5.2.5.1 Seasonal average model

5.2.5.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, North Canberra regional population, state finance demand, lagged retail price and business energy efficiency. The model had an adjusted R-squared statistic of 96% and projections are displayed in Figure 5.2.5.1 – more detail in Jacobs report on the actual model.

5.2.5.1.2 Forecast trend and block load analysis

Figure 5.2.5.1: Civic ZSS seasonal average demand – Model Fit and Forecast
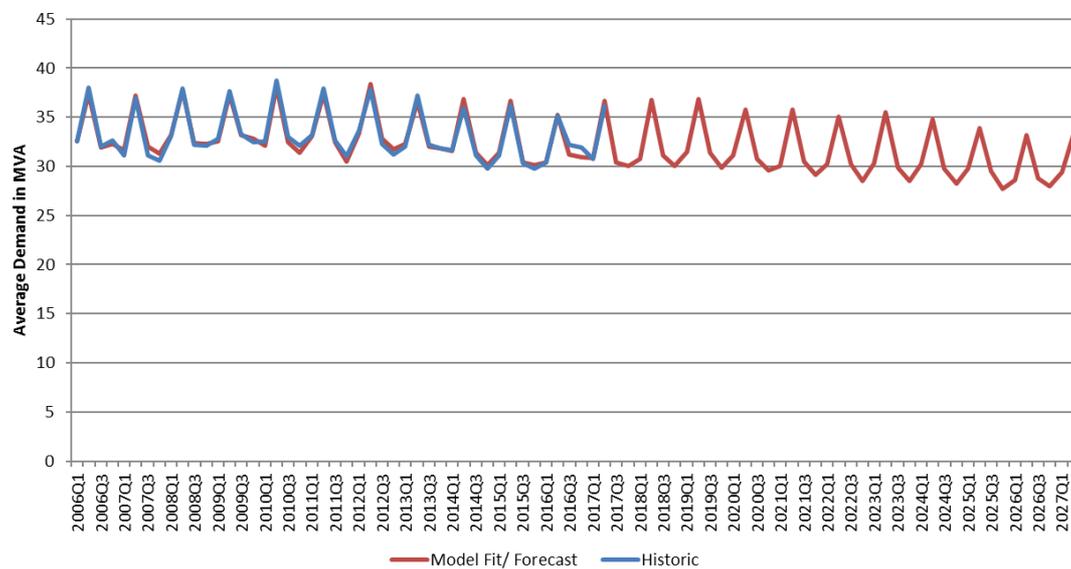
Block Load analysis and assumptions:

- Figure 5.2.5.1 demonstrates a clear downward trend over the next ten years. Therefore, block load adjustment is required if any;
- In order to avoid double accounting, the residential block loads should be excluded from block load adjustment since North Canberra regional population is a variable of model with a positive coefficient and the regional population is forecast to grow in next ten years;
- Civic ZSS will start supplying the new Whitlam estate from 2019/20 to 2021/22 financial year till reaching its maximum capacity;
- The new feeder from Civic ZSS will have a total capacity of 6 MVA, which means 6 MVA load will permanently be transferred from City East to Civic on 1 July 2020;
- More block load information can be found under Appendix 6.3.

5.2.5.2   Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.3.

5.2.5.3   Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.5.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.5.3: Stack Chart by structure change impact;
- Table 5.2.5.1 to 5.2.5.4: Actual or Forecast figures for Figure 5.2.5.2 and 5.2.5.3.

Key notes from Figure 5.2.5.2:

- Civic ZSS's maximum demand has been steady and below both continuous and emergency rating;
- With large capacity, Civic ZSS will play a key role in supplying load growth in the following areas:
  - Molonglo Valley developments (Whitlam new estate) prior to commissioning of Molonglo ZSS;
  - A new feeder to support Canberra City & Northbourne Avenue developments;
- See 5.2.5.1.2 for assumptions and time line of block load movements.

Figure 5.2.5.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the commercial nature of zone substation, the ZSS peak demand is forecast to occur around 3:00 PM in summer and 9:30 AM in winter. The battery storage impact is projected to be at its minimum level, because the system is on charging mode (charging from sun/solar panels) according to our assumed charge and discharge pattern shown in Figure 4.5.3.

Figure 5.2.5.2: Civic ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.5.2: Civic ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

![evoenergy logo]

Figure 5.2.5.3: POE Forecast breakdown by structure change technology – Vertical analysis

| Summer POE Forecasts | Winter POE Forecasts |

Civic ZSS 10-year summer demand forecast (50% POE)

Legend: Rooftop PV, Battery, EV, Operational Less EV

Civic ZSS 10-year winter demand forecast (50% POE)

Legend: Rooftop PV, Battery, EV, Operational Less EV

**Figure 5.2.5.3: POE Forecast breakdown by structure change technology – Vertical analysis**

Summer POE Forecasts

Winter POE Forecasts

Civic ZSS 10-year summer demand forecast (10% POE)

Civic ZSS 10-year winter demand forecast (10% POE)
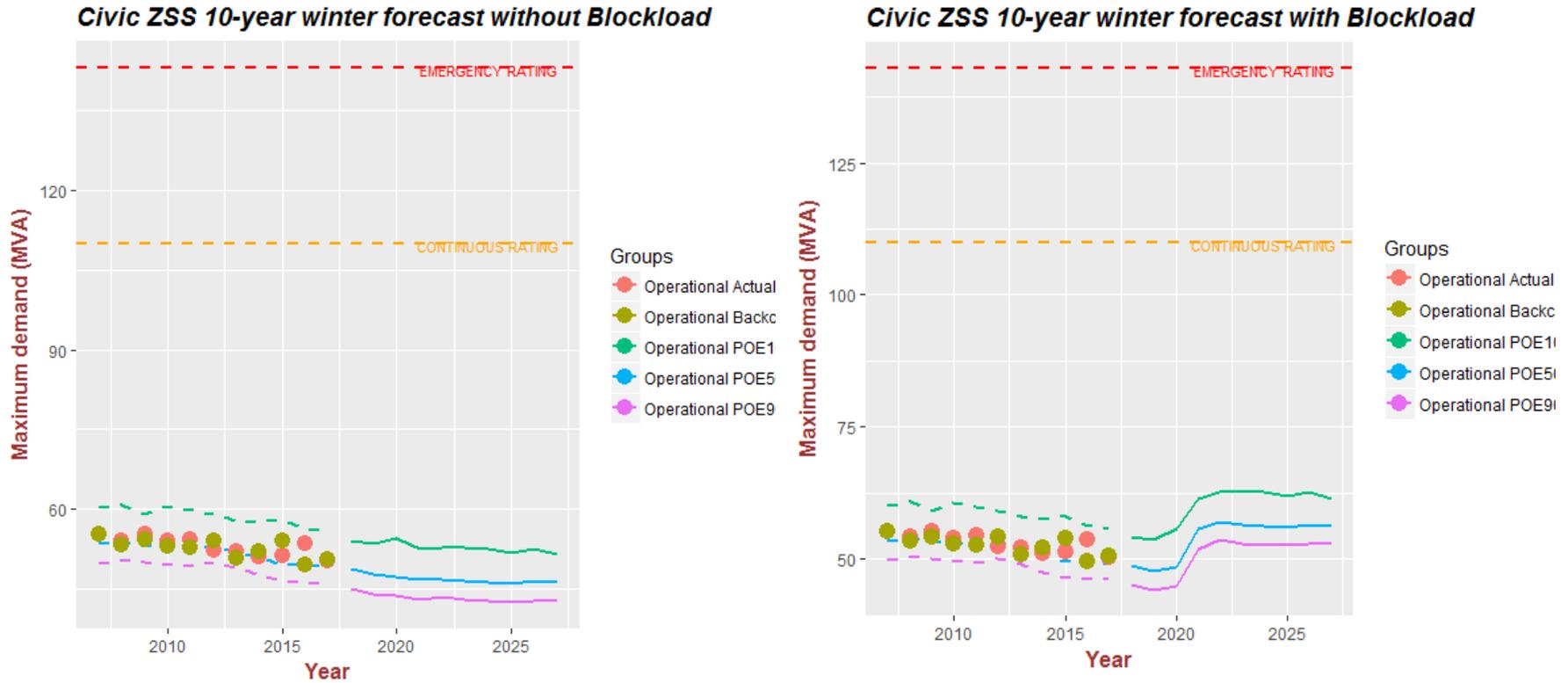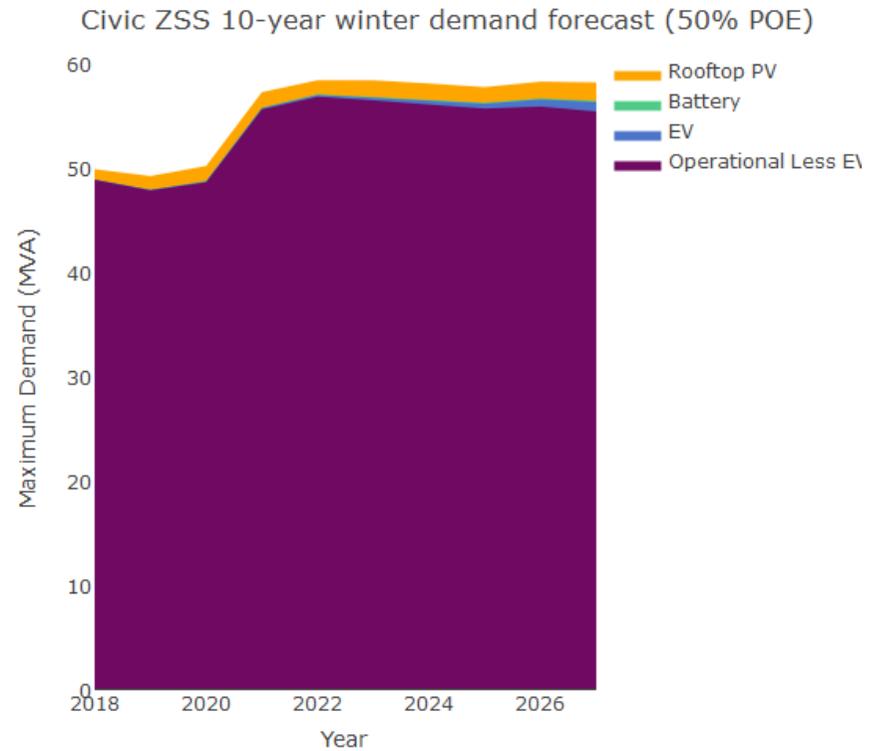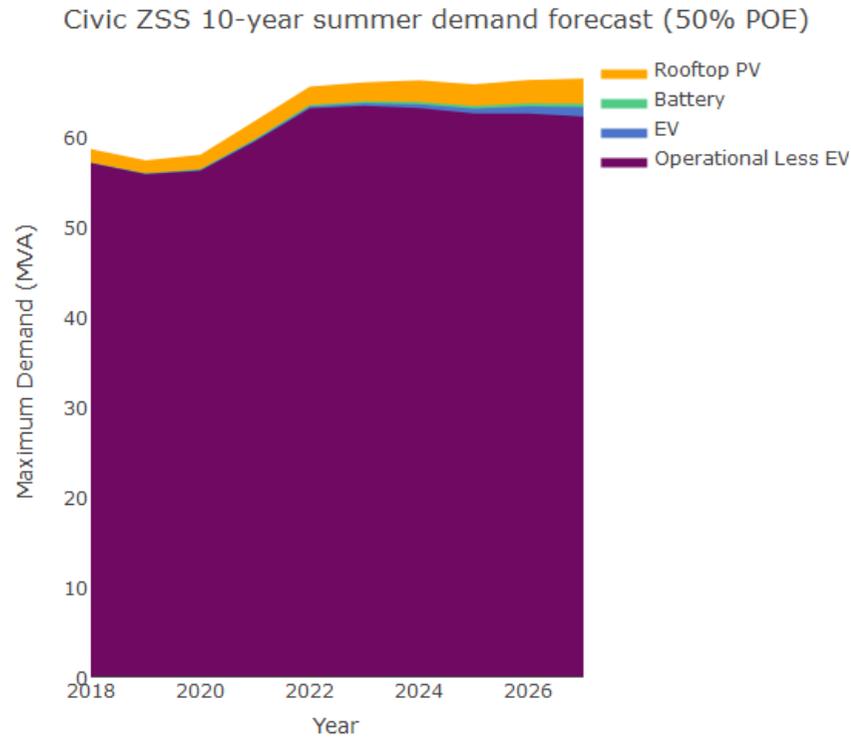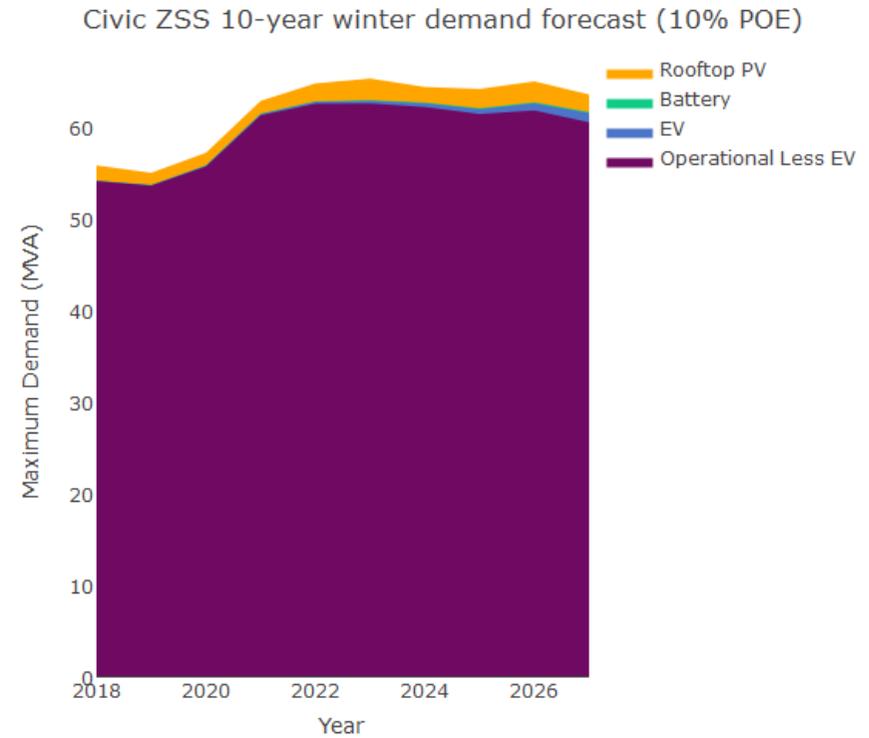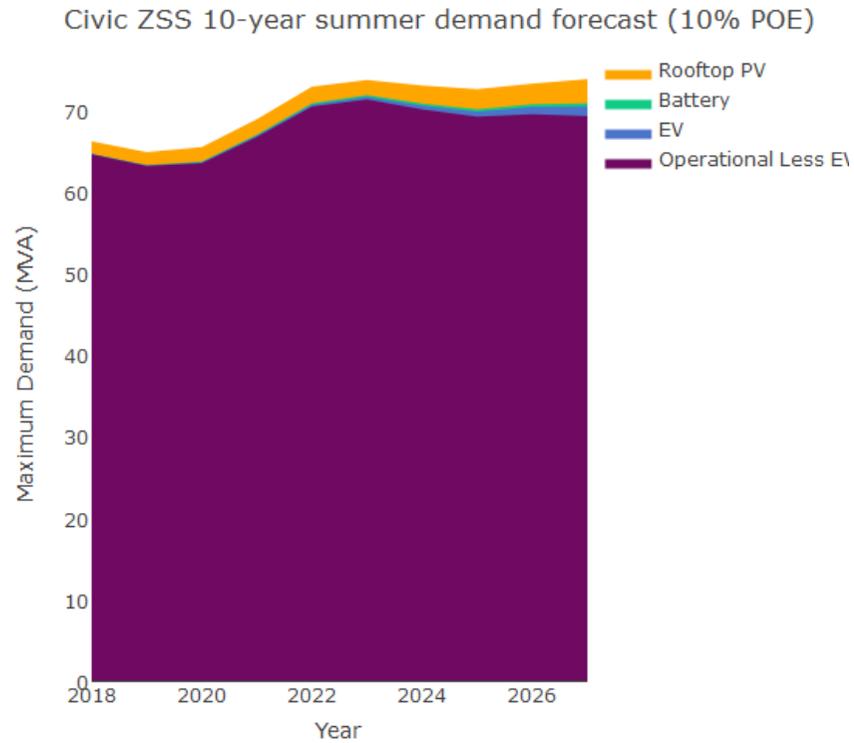
Table 5.2.5.1: Civic ZSS summer back-cast and weather correction in MVA

Year	Summer		Weather Correction		
	Actual	Fitted	POE90	POE50	POE10
2008	62	61	55	61	69
2009	56	55	56	62	70
2010	63	63	56	63	70
2011	60	63	55	62	70
2012	65	59	55	62	68
2013	52	47	54	61	67
2014	59	59	53	60	66
2015	51	50	52	58	64
2016	57	56	51	58	65
2017	60	61	52	58	65

Table 5.2.5.2: Civic ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	57	65	57	65	57	65	58	66
2019	56	63	56	63	56	63	57	65
2020	56	63	56	64	56	64	58	65
2021	59	67	59	67	60	67	62	69
2022	63	70	63	71	63	71	65	73
2023	63	71	64	72	64	72	66	74
2024	63	70	63	70	64	71	66	73
2025	62	69	63	70	63	70	66	72
2026	62	69	63	70	64	71	66	73
2027	62	69	63	70	63	71	66	74

Table 5.2.5.3: Civic ZSS winter back-cast and weather correction in MVA

Year	Winter Actual	Winter Fitted	Weather Correction POE90	Weather Correction POE50	Weather Correction POE10
2007	55	55	50	53	60
2008	54	53	50	54	61
2009	55	54	50	53	59
2010	54	53	50	53	61
2011	54	53	49	53	60
2012	52	54	50	53	59
2013	52	51	49	52	58
2014	51	52	48	51	58
2015	51	54	46	50	58
2016	54	50	46	49	56
2017	50	51	46	49	56

Table 5.2.5.4: Civic ZSS winter forecast breakdown in MVA

Winter Year	Operational Demand less EV POE50	Operational Demand less EV POE10	Plus EV (Operational Demand) POE50	Plus EV (Operational Demand) POE10	Plus Battery POE50	Plus Battery POE10	Plus Rooftop Solar (Underlying Demand) POE50	Plus Rooftop Solar (Underlying Demand) POE10
2018	49	54	49	54	49	54	50	56
2019	48	54	48	54	48	54	49	55
2020	49	56	49	56	49	56	50	57
2021	56	61	56	61	56	61	57	63
2022	57	63	57	63	57	63	58	65
2023	56	63	57	63	57	63	58	65
2024	56	62	56	63	56	63	58	64
2025	56	61	56	62	56	62	58	64
2026	56	62	56	63	57	63	58	65
2027	55	61	56	62	56	62	58	64

### 5.2.6 East Lake Zone Substation Forecast

5.2.6.1 Seasonal average model

5.2.6.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Fyshwick regional population and retail price. The model had an adjusted R-squared statistic of 78% and projections are displayed in Figure 5.2.6.1 – more detail in Jacobs report on the actual model.

5.2.6.1.2 Forecast trend and block load analysis

Figure 5.2.6.1: East Lake ZSS seasonal average demand – Model Fit and Forecast
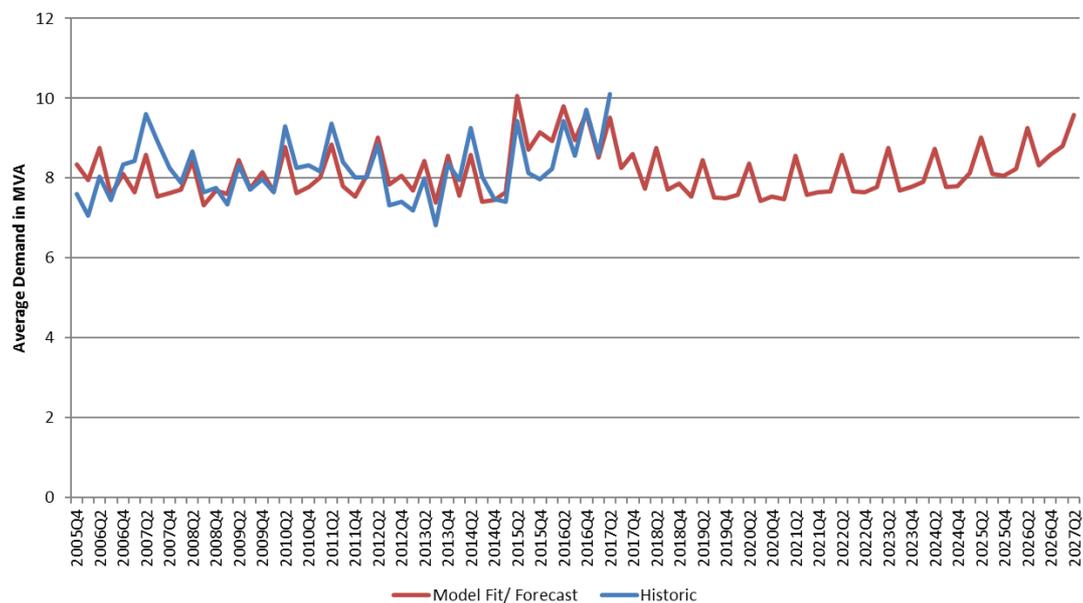
Block load analysis and assumptions:

- No clear upward trend is indicated in Figure 5.2.6.1. Therefore, block load adjustment is required if any;
- In order to avoid double accounting, the residential block loads should be excluded from block load adjustment since Fyshwick regional population is a variable of average demand model with a positive coefficient and a slow population grow is forecast by ACT government in next ten years;
- Fyshwick ZSS is planned to be decommissioned at the end of 2023/24 and all its load will be permanently transferred to East Lake ZSS;
- At the time of decommissioning, Fyshwick ZSS's summer and winter maximum demand is forecast to be 26.5 MVA and 22.5 MVA and then each will be treated as a block load and fully transferred to East Lake ZSS at the end of 2023/24;
- More block load information can be found under Appendix 6.3.

5.2.6.2 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.4.

5.2.6.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.6.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.6.3: Stack Chart by structure change impact;
- Table 5.2.6.1 to 5.2.6.4: Actual figures for Figure 5.2.6.2 and 5.2.6.3.

Key findings from Figure 5.2.6.2:

- Strong commercial and industrial load growth presented in Fyshwick-Pialligo and Russell- Kingston area due to customer demand;
- East Lake ZSS's normal cyclic rating (55 MVA) is forecast to be exceeded by 2024/25 financial year due to decommissioning of Fyshwick ZSS;
- East Lake ZSS' 2nd transformer is urgently required prior to Fyshwick ZSS' decommissioning to secure sustainable power supply to the whole Fyshwick area.
- New feeders are proposed to be installed from East Lake Zone Substation to the Kingston Foreshore and Russell areas in the 2019-24 Regulatory Control Period.

Figure 5.2.6.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the commercial nature of zone substation, the ZSS peak demand is forecast to occur around 12:30 PM in summer and 10:00 AM in winter. The battery storage impact is projected to be at its minimum level, because the system is on charging mode (charging from sun/solar panels) according to our assumed charge and discharge pattern shown in Figure 4.5.3.

Figure 5.2.6.2: East Lake ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.6.2: East Lake ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.6.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

East_Lake ZSS 10-year summer demand forecast (50% POE)

East Lake ZSS 10-year winter demand forecast (50% POE)
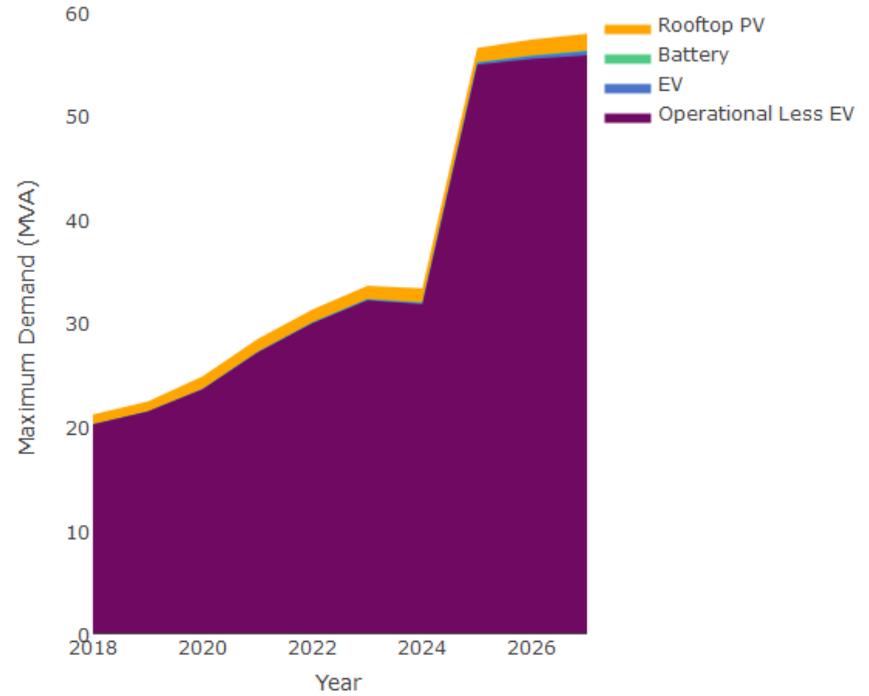
![evoenergy logo]

Figure 5.2.6.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

East_Lake ZSS 10-year summer demand forecast (10% POE)
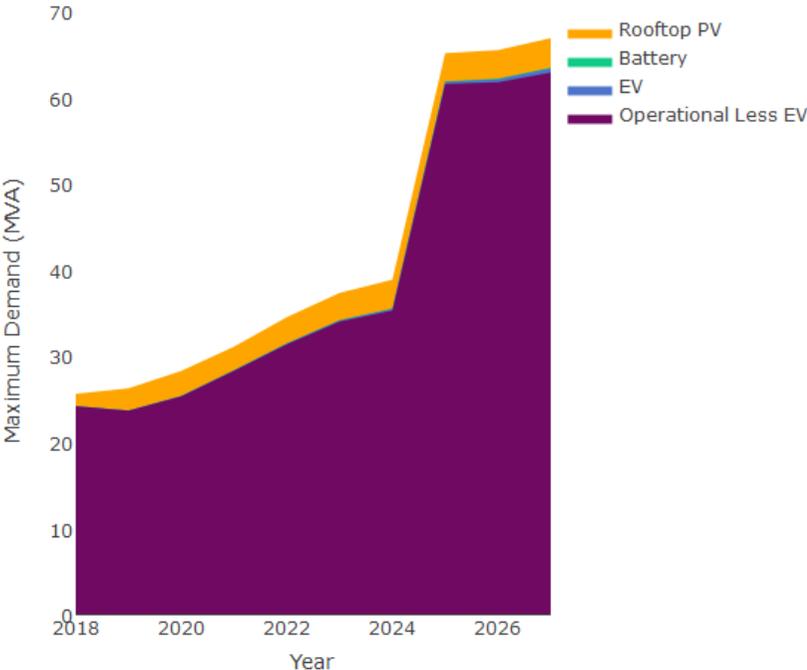
East Lake ZSS 10-year winter demand forecast (10% POE)
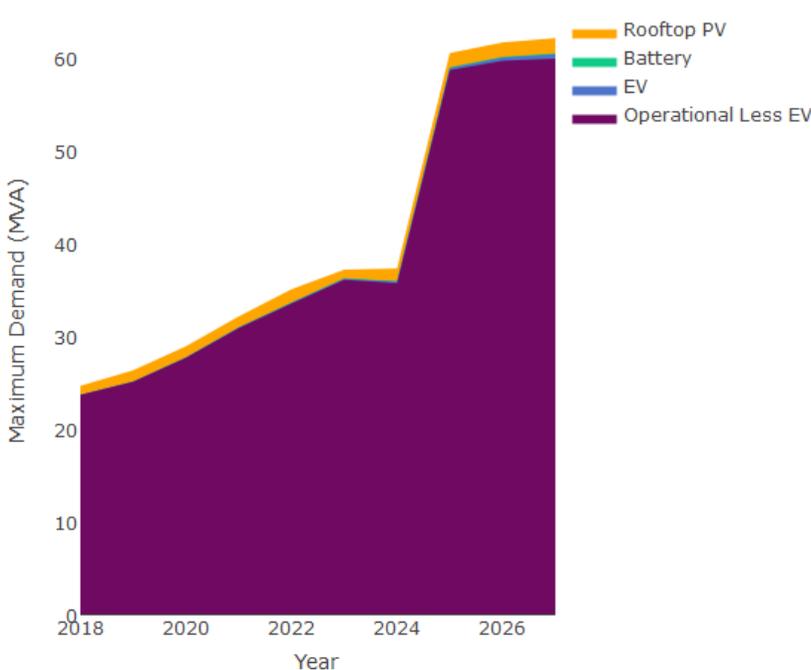
Table 5.2.6.1: East Lake ZSS summer back-cast and weather correction in MVA

Year	Summer		Weather Correction		
	Actual	Fitted	POE90	POE50	POE10
2015	16	16	15	18	22
2016	18	20	17	21	26
2017	19	22	16	21	24

Table 5.2.6.2: East Lake ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	20	24	20	24	20	24	21	26
2019	19	24	19	24	19	24	21	26
2020	21	25	21	25	21	25	24	28
2021	24	28	24	28	24	28	27	31
2022	27	31	27	31	27	31	30	34
2023	30	34	30	34	30	34	33	37
2024	31	35	31	35	31	35	34	39
2025	57	62	58	62	58	62	61	65
2026	58	62	58	62	58	62	61	66
2027	58	63	58	63	59	63	62	67

Table 5.2.6.3: East Lake ZSS winter back-cast and weather correction in MVA

Year	Winter		Weather Correction		
	Actual	**Fitted**	**POE90**	**POE50**	**POE10**
2014	19	16	15	18	21
2015	18	20	16	20	24
2016	18	19	17	20	24
2017	18	19	16	20	24

Table 5.2.6.4: East Lake ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**
2018	20	24	20	24	20	24	21	25
2019	21	25	21	25	21	25	22	26
2020	24	28	24	28	24	28	25	29
2021	27	31	27	31	27	31	28	32
2022	30	34	30	34	30	34	31	35
2023	32	36	32	36	32	36	34	37
2024	32	36	32	36	32	36	33	37
2025	55	59	55	59	55	59	56	60
2026	56	60	56	60	56	60	57	62
2027	56	60	57	61	57	61	58	62

### 5.2.7 Fyshwick Zone Substation Forecast

5.2.7.1 Seasonal average model

5.2.7.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather and state final demand. The model had an adjusted R-squared statistic of 90% and projections are displayed in Figure 5.2.7.1 – more detail in Jacobs report on the actual model.

5.2.7.1.2 Forecast trend and block load analysis

Figure 5.2.7.1: Fyshwick ZSS seasonal average demand – Model Fit and Forecast
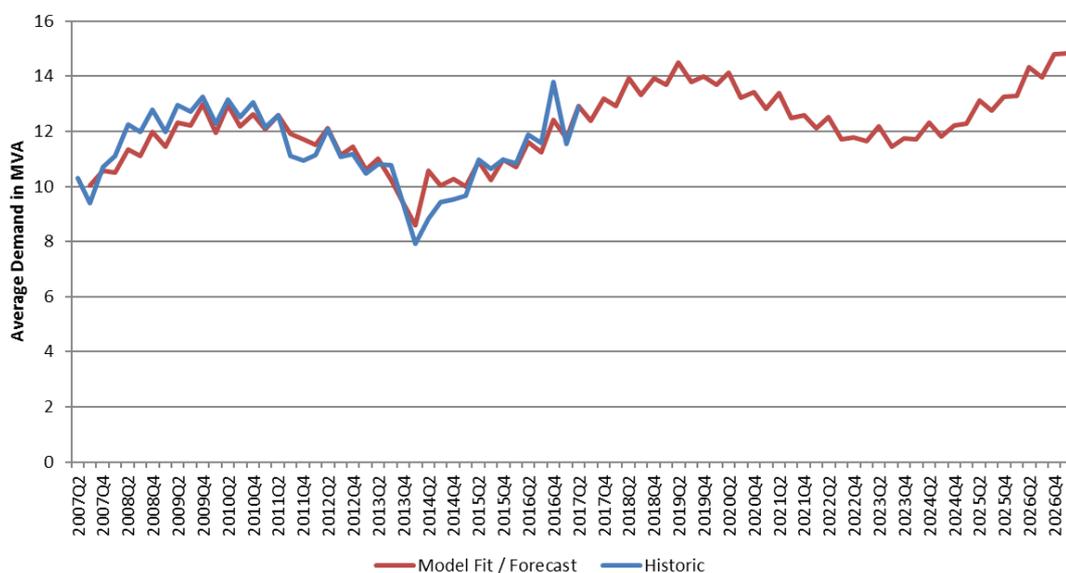
Block load analysis and assumption:

- Fyshwick ZSS is planned to be decommissioned at the end of 2023/24;
- At time of decommissioning, Fyshwick ZSS's maximum demand is around 26.5 MVA;
- Note that the following permanent load transfers have been made from Fyshwick ZSS: 1) 2.5 MVA load removed during 2009-10; 2) 2 MVA load removed during 2010-11; 3) 1 MVA load removed during 2011-12.

5.2.7.2 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.5.

5.2.7.3 Final summer and Winter Demand forecast

The final forecast results and historical load analysis are presented by following formats:

- Figure 5.2.7.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.7.3: Stack Chart by structure change impact;
- Table 5.2.7.1 to 5.2.7.4: Actual figures for Figure 5.2.7.2 and 5.2.7.3.

Key findings from Figure 6.21:

- See "Block Load Analysis" in section 5.2.7.1.4

Figure 5.2.7.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the commercial nature of zone substation, the ZSS peak demand is forecast to occur around 1:30 PM in summer and 10:30 AM in winter. The battery storage impact is projected to be at its minimum level, because the system is on charging mode (charging from sun/solar panels) according to our assumed charge and discharge pattern shown in Figure 4.5.3.

Figure 5.2.7.2: Fyshwick ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.7.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

Fyshwick ZSS 10-year summer demand forecast (50% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV

Fyshwick ZSS 10-year winter demand forecast (50% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV

![evoenergy logo]

Figure 5.2.7.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

Fyshwick ZSS 10-year summer demand forecast (10% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV

Fyshwick ZSS 10-year winter demand forecast (10% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV
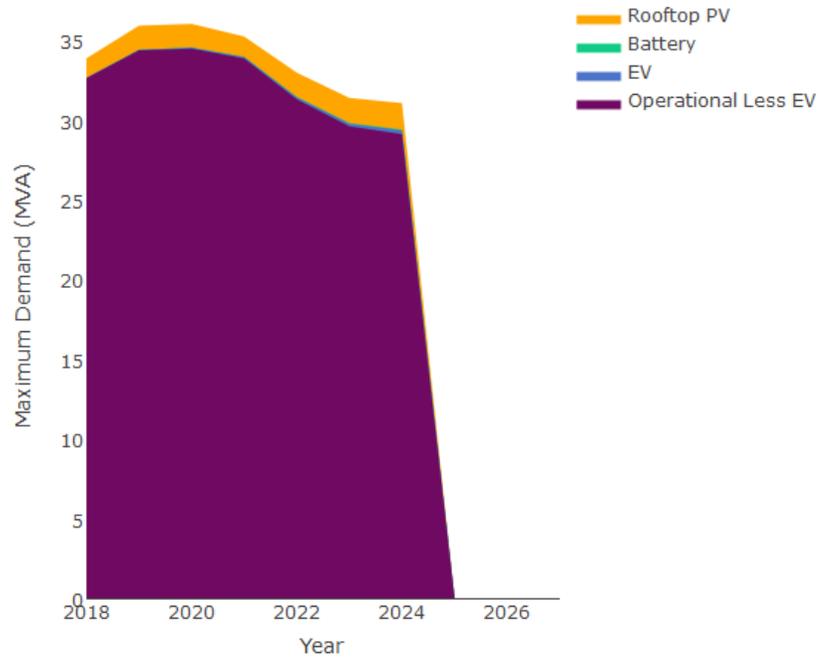
Table 5.2.7.1: Fyshwick ZSS summer back-cast and weather correction in MVA

	Summer		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2015	20	20	19	23	27
2016	24	23	20	24	28
2017	26	25	21	26	30

Table 5.2.7.2: Fyshwick ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	29	33	29	33	29	33	30	34
2019	30	34	30	34	30	34	31	36
2020	30	34	30	35	30	35	32	36
2021	29	34	29	34	29	34	31	35
2022	27	31	27	31	27	31	29	33
2023	25	30	25	30	25	30	27	31
2024	25	29	25	29	25	29	27	31
2025	0	0	0	0	0	0	0	0
2026	0	0	0	0	0	0	0	0
2027	0	0	0	0	0	0	0	0

Table 5.2.7.3: Fyshwick ZSS winter back-cast and weather correction in MVA

Year	Winter		Weather Correction		
	Actual	**Fitted**	**POE90**	**POE50**	**POE10**
2014	17	18	15	18	21
2015	19	19	15	18	22
2016	20	20	17	20	23
2017	22	21	19	22	25

Table 5.2.7.4: Fyshwick ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**
2018	23	27	23	27	23	27	24	28
2019	24	28	24	28	24	28	25	30
2020	24	28	24	28	24	28	25	30
2021	22	26	22	26	22	26	24	28
2022	20	24	21	24	21	24	22	26
2023	20	24	20	24	20	24	21	25
2024	20	24	20	24	20	24	22	26
2025	0	0	0	0	0	0	0	0
2026	0	0	0	0	0	0	0	0
2027	0	0	0	0	0	0	0	0

## 5.2.8   Gilmore Zone Substation Forecast

5.2.8.1   Seasonal average model

5.2.8.1.1   Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather and state final demand. The model had an adjusted R-squared statistic of 94% and projections are displayed in Figure 5.2.8.1 – more detail in Jacobs report on the actual model.

5.2.8.1.2   Forecast trend and block load analysis

Figure 5.2.8.1: Gilmore ZSS seasonal average demand – Model Fit and Forecast
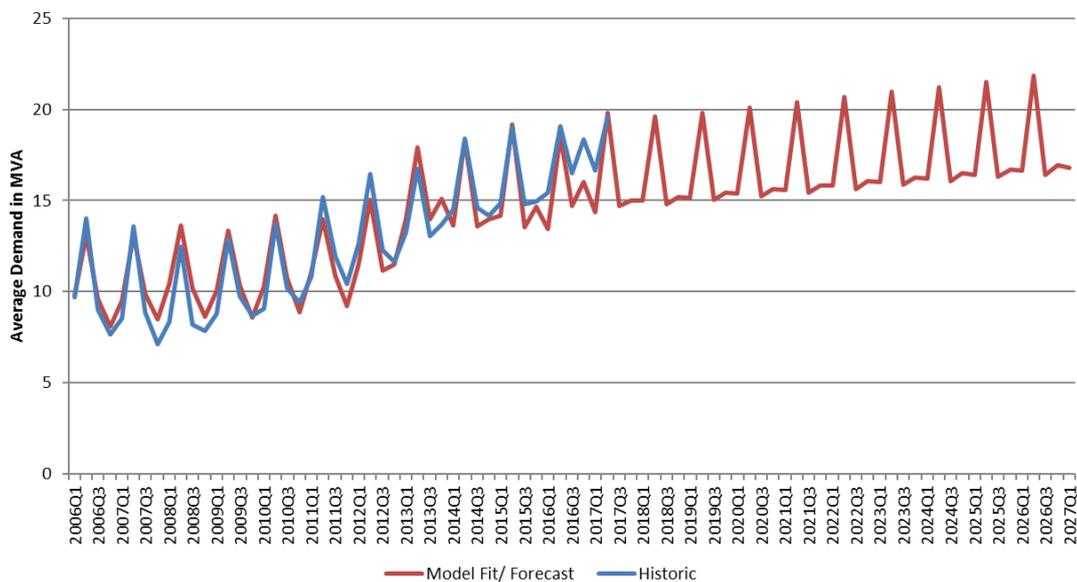
Block Load analysis and assumptions:

- Figure 5.2.8.1 demonstrates a clear upward trend over the next ten years. Therefore, further block load analysis is needed to determine whether any block load should be added;
- Tables 5.2.8.1 & 5.2.8.2 show that there is no significant load growth in first two years whereas Table 5.2.8.3 demonstrates very strong customer load demand in those two years. Therefore, Year 2018 and 2019's summer and winter POE forecast need to be block-load adjusted according to Table 5.2.8.3;
- More block load information can be found under Appendix 6.3.

Table 5.2.8.1: Gilmore ZSS 10-year summer demand forecast without any block loads (in MVA)

Summer	Year	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Operational Demand less EV	POE50	31	31	32	32	32	33	33	33	33	34
	POE10	39	39	40	41	41	42	41	42	43	43

Table 5.2.8.2: Gilmore ZSS 10-year winter demand forecast without any block loads (in MVA)

Winter	Year	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Operational Demand less EV	POE50	31	31	32	32	33	32	33	34	34	35
	POE10	36	36	38	38	39	39	39	41	41	41

Table 5.2.8.3: Gilmore ZSS 10-year cumulative block load forecast - Probability Adjusted (in MVA)

Season	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Summer	3.2	5.1	5.6	5.9	6.0	6.0	6.0	6.1	6.1	6.1
Winter	4.4	5.5	5.8	6.0	6.0	6.1	6.1	6.1	6.2	6.2

5.2.8.2   Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.6.

5.2.8.3   Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.8.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.8.3: Stack Chart by structure change impact;
- Table 5.2.8.4 to 5.2.8.7: Actual or Forecast figures for Figure 5.2.8.2 and 5.2.8.3.

Key notes from Figure 5.2.8.2 are:

- Industrial load growth has been consistent in Hume, which drives the growth of electricity demand at Gilmore ZSS;
- Figure 5.2.8.2 indicates that 10% POE forecast for both summer and winter is forecast to exceed the continuous rating approximately by 3 MVA by 2020;
- Gilmore ZSS is capable to meet all electricity demand in the surrounding area for the next ten years under the "N-1" standard.

Figure 5.2.8.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the residential and commercial mix nature of zone substation, the ZSS peak demand is forecast to occur around 5:30 PM in summer and 8:00 AM in winter. The battery storage impact is projected to be at its minimum in winter and at its maximum in summer based on our assumed charge and discharge pattern shown in Figure 4.5.3.

Figure 5.2.8.2: Gilmore ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.8.2: Gilmore ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.8.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

Gilmore ZSS 10-year summer demand forecast (50% POE)

Gilmore ZSS 10-year winter demand forecast (50% POE)

Figure 5.2.8.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Gilmore ZSS 10-year summer demand forecast (10% POE)

- Rooftop PV
- Battery
- EV
- Operational Less EV

Winter POE Forecasts

Gilmore ZSS 10-year winter demand forecast (10% POE)

- Rooftop PV
- Battery
- EV
- Operational Less EV
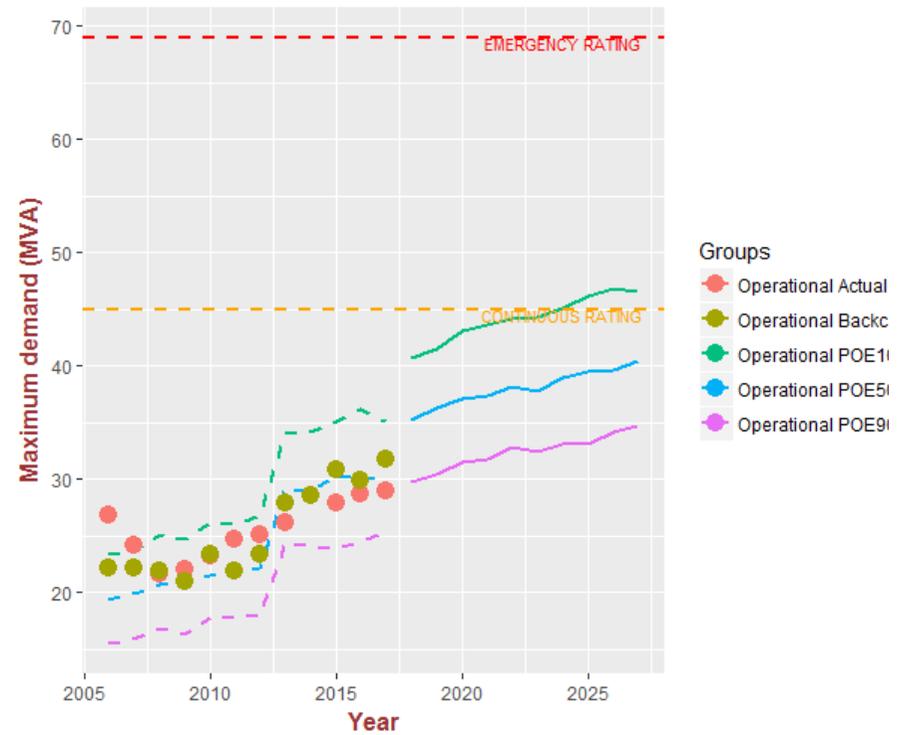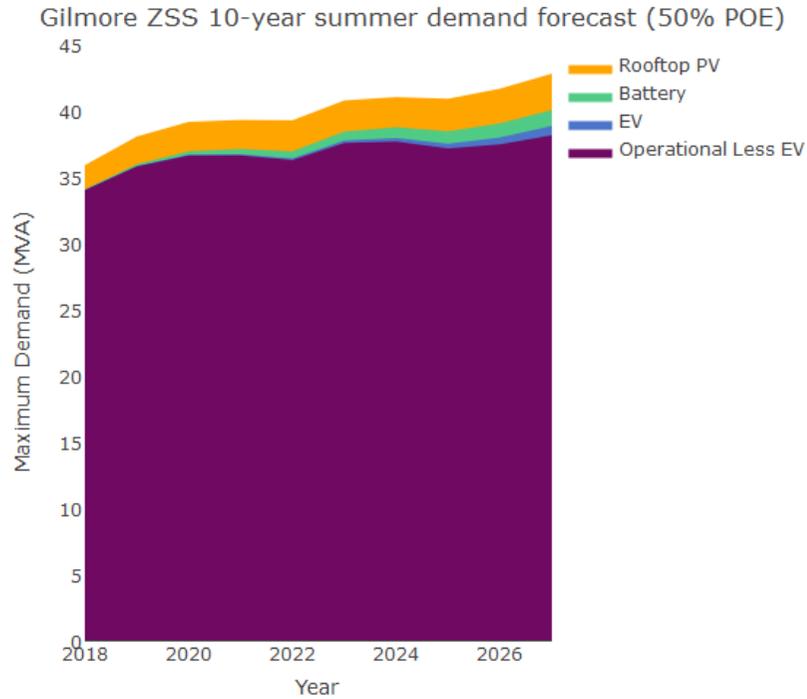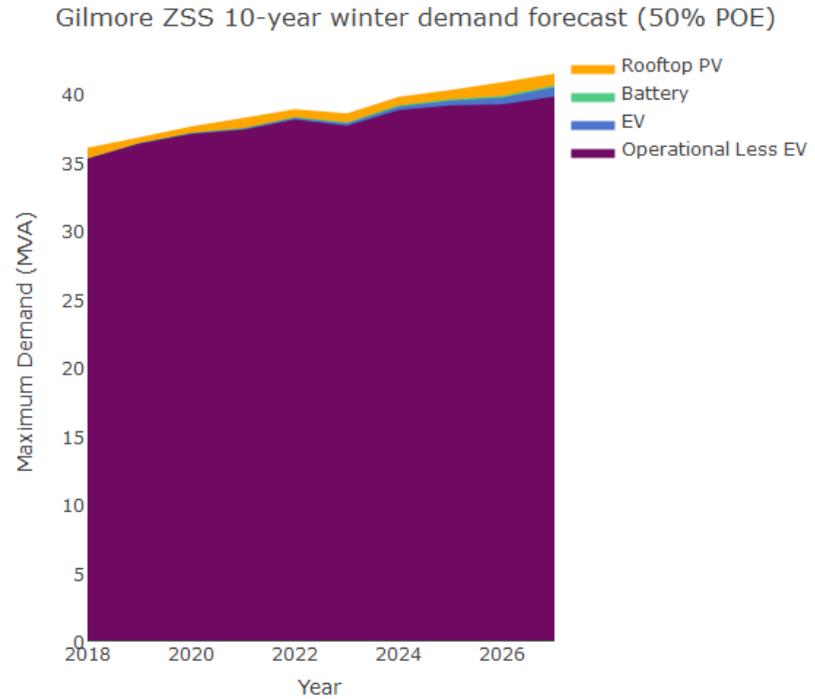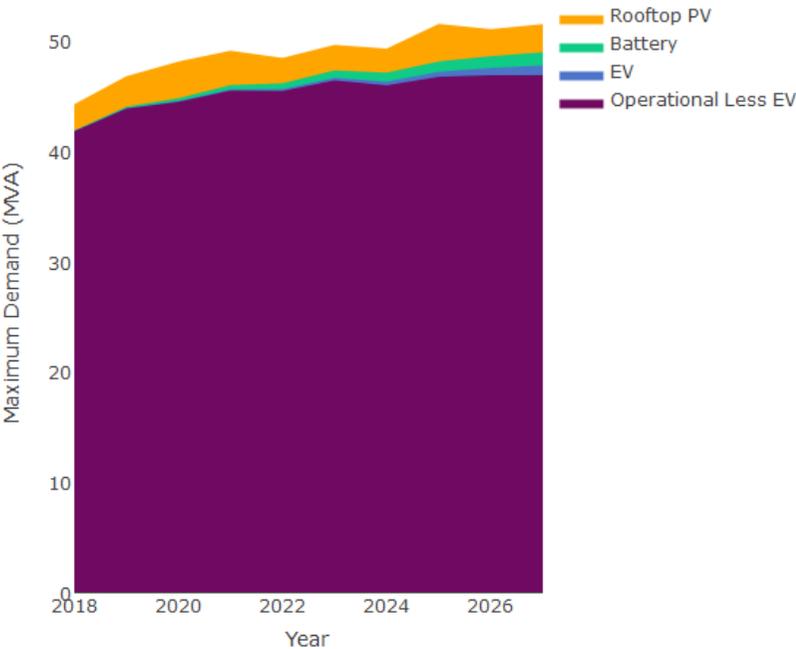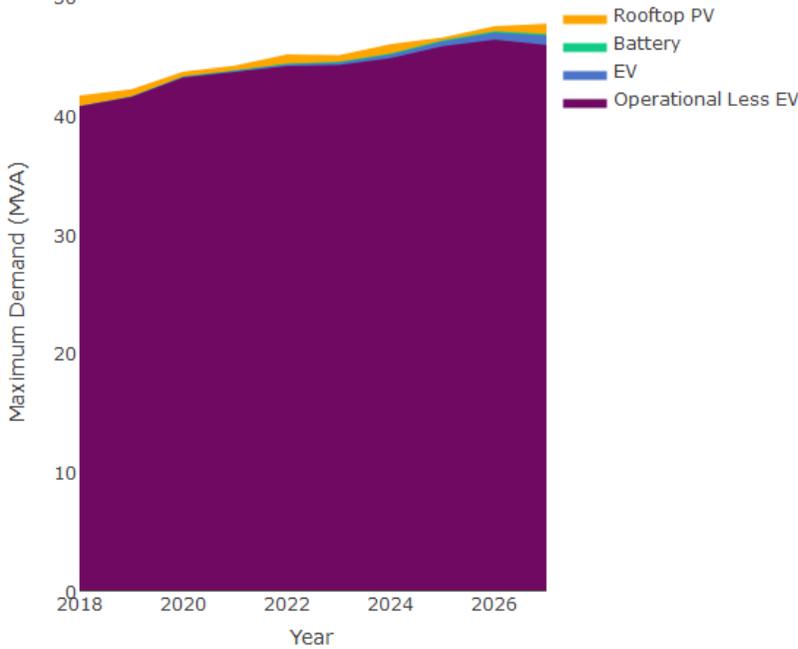
Table 5.2.8.4: Gilmore ZSS summer back-cast and weather correction in MVA

Year	Summer Actual	Summer Fitted	Weather Correction POE90	Weather Correction POE50	Weather Correction POE10
2006	17	16	12	16	21
2007	16	16	13	17	22
2008	15	15	15	19	25
2009	19	18	14	18	24
2010	20	18	13	18	23
2011	22	19	15	19	25
2012	19	15	16	22	27
2013	22	23	18	24	31
2014	26	31	25	31	40
2015	22	22	24	30	38
2016	26	28	25	32	40
2017	35	33	24	31	40

Table 5.2.8.5: Gilmore ZSS summer forecast break down in MVA

Year	Operational Demand less EV POE50	Operational Demand less EV POE10	Plus EV (Operational Demand) POE50	Plus EV (Operational Demand) POE10	Plus Battery POE50	Plus Battery POE10	Plus Rooftop Solar (Underlying Demand) POE50	Plus Rooftop Solar (Underlying Demand) POE10
2018	34	42	34	42	34	42	36	44
2019	36	44	36	44	36	44	38	47
2020	37	44	37	44	37	45	39	48
2021	37	45	37	46	37	46	39	49
2022	36	45	36	46	37	46	39	48
2023	38	46	38	47	38	47	41	50
2024	38	46	38	46	39	47	41	49
2025	37	47	38	47	38	48	41	51
2026	37	47	38	47	39	49	42	51
2027	38	47	39	48	40	49	43	51

Table 5.2.8.6: Gilmore ZSS winter back-cast and weather correction in MVA

	Winter		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2006	27	22	15	19	23
2007	24	22	16	20	24
2008	22	22	17	21	25
2009	22	21	16	21	25
2010	23	23	18	22	26
2011	25	22	18	22	26
2012	25	23	18	22	27
2013	26	28	24	29	34
2014	29	29	24	29	34
2015	28	31	24	30	35
2016	29	30	24	30	36
2017	29	32	25	30	35

Table 5.2.8.7: Gilmore ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	35	41	35	41	35	41	36	42
2019	36	41	36	41	36	41	37	42
2020	37	43	37	43	37	43	38	44
2021	37	44	37	44	37	44	38	44
2022	38	44	38	44	38	44	39	45
2023	38	44	38	44	38	44	39	45
2024	39	45	39	45	39	45	40	46
2025	39	46	39	46	40	46	40	46
2026	39	46	40	47	40	47	41	47
2027	40	46	40	47	41	47	41	48

5.2.9 Gold Creek Zone Substation Forecast

5.2.9.1 Seasonal average model

5.2.9.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Gungahlin regional population and retail price. The model had an adjusted R-squared statistic of 98% and projections are displayed in Figure 5.2.9.1 – more detail in Jacobs report on the actual model.

5.2.9.1.2 Forecast trend and block load analysis

Figure 5.2.9.1: Gold Creek ZSS seasonal average demand – Model Fit and Forecast
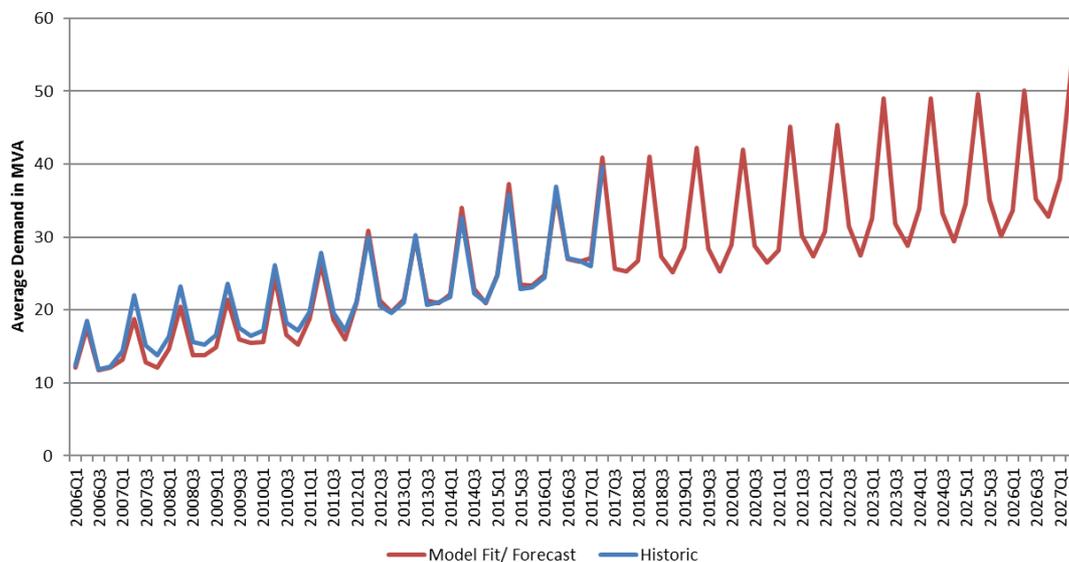
Block Load analysis and assumptions:

- Figure 5.2.9.1 demonstrates a clear upward trend over the next ten years. Therefore, further block load analysis is needed to determine whether any block loads should be added;
- In order to avoid double accounting, the residential block loads should be excluded from block load adjustment if any as Gungahlin regional population is a variable of average demand model with a positive coefficient and the regional population is forecast to grow rapidly due to more land lease in next ten year;
- Table 5.2.9.3 indicates there would be a total of 5.8 MVA additional commercial and industrial load for Gold Creek ZSS including 3 MVA Canberra Metro Redundant Peak Demand requested for TPS 1, which should be added on as the block load adjustment;
- More block load information can be found under Appendix 6.3.

Table 5.2.9.1: Gold Creek ZSS 10-year summer demand forecast without any block loads (in MVA)

Summer	Year	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Operational Demand less EV	POE50	60	62	63	65	66	67	68	69	72	72
	POE10	72	74	77	79	79	83	84	86	90	89

Table 5.2.9.2: Gold Creek ZSS 10-year summer demand forecast without any block loads (in MVA)

Summer	Year	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Operational Demand less EV	POE50	68	69	71	74	75	77	78	80	82	85
	POE10	76	77	80	83	84	87	89	91	93	97

Table 5.2.9.3: Gold Creek ZSS 10-year cumulative commercial & industrial block load forecast - Probability Adjusted (in MVA)

Season	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Summer	0.2	2.1	4.0	4.8	5.7	5.8	5.8	5.8	5.8	5.8
Winter	0.3	3.9	4.1	5.5	5.8	5.8	5.8	5.8	5.8	5.8

5.2.9.2 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.7.

5.2.9.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.9.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.9.3: Stack Chart by structure change impact;
- Table 5.2.9.4 to 5.2.9.7: Actual or Forecast figures for Figure 5.2.9.2 and 5.2.9.3.

Key notes from Figure 5.2.9.2 are:

- The winter 2 hour emergency rating is forecast to be exceeded by its 50% POE forecast by 2021;
- Winter maximum demand is hardly impacted or offset by rooftop PV as its peak time is always after daylight;
- A third 132/11 kV 30/55 mVA transformer is proposed to be installed at Gold Creek Zone Substation in the 2019-24 Regulatory Control Period.

Figure 5.2.9.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the predominant residential nature of zone substation, the ZSS peak demand is forecast to occur around 5:30 PM in summer and 7:00 PM in winter. The battery

storage impact is projected to be at its maximum in both summer and winter based on Figure 4.5.3. Roof top PV has zero impact on the winter demand than the summer demand as winter peak occurs after daylight.

Figure 5.2.9.2: Gilmore ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.9.2: Gilmore ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.9.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Gold Creek ZSS 10-year summer demand forecast (50% POE)

Winter POE Forecasts

Gold Creek ZSS 10-year winter demand forecast (50% POE)

![evoenergy logo]

Figure 5.2.9.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

Gold Creek ZSS 10-year summer demand forecast (10% POE)

Gold Creek ZSS 10-year winter demand forecast (10% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV
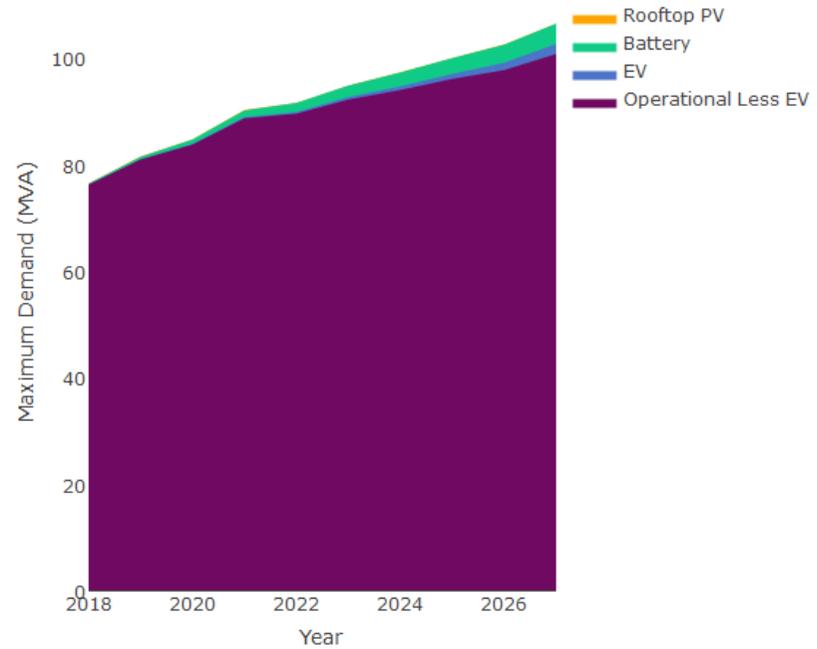
Table 5.2.9.4: Gold Creek ZSS summer back-cast and weather correction in MVA

	Summer		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	26	30	23	30	36
2008	28	26	27	34	41
2009	38	41	28	35	43
2010	37	40	30	37	45
2011	43	38	32	40	49
2012	36	30	35	43	53
2013	48	50	39	49	57
2014	53	52	40	50	61
2015	44	39	43	54	64
2016	58	57	43	54	66
2017	69	73	45	58	71

Table 5.2.9.5: Gold Creek ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	60	73	60	73	60	73	62	74
2019	64	76	64	76	65	76	66	77
2020	67	81	67	81	68	82	69	84
2021	70	84	70	84	71	85	72	87
2022	72	85	72	85	74	87	76	88
2023	72	88	72	89	75	91	76	92
2024	73	89	73	90	76	92	78	94
2025	74	91	74	92	77	95	79	97
2026	77	94	78	95	82	99	84	101
2027	76	93	78	95	81	99	84	101

Table 5.2.9.6: Gold Creek ZSS winter back-cast and weather correction in MVA

| Year | Winter | | Weather Correction | | |
	Actual	Fitted	POE90	POE50	POE10
2007	35	32	31	35	38
2008	36	36	34	38	43
2009	38	37	35	41	44
2010	42	42	38	42	48
2011	47	44	42	46	51
2012	48	50	46	51	57
2013	53	50	49	55	60
2014	56	54	52	57	64
2015	64	63	54	60	69
2016	66	58	56	62	70
2017	71	68	58	65	73

Table 5.2.9.7: Gold Creek ZSS winter forecast breakdown in MVA

| Winter | Operational Demand less EV | | Plus EV (Operational Demand) | | Plus Battery | | Plus Rooftop Solar (Underlying Demand) | |
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	68	76	68	76	68	76	68	76
2019	73	81	73	81	73	81	74	81
2020	75	84	75	84	76	85	76	85
2021	79	89	79	89	81	90	81	90
2022	80	89	80	90	82	91	82	91
2023	82	92	82	93	85	95	85	95
2024	84	94	84	95	87	97	87	97
2025	85	96	86	97	89	100	89	100
2026	87	98	88	99	91	102	92	102
2027	90	101	91	103	95	106	95	106

5.2.10 Latham Zone Substation Forecast

5.2.10.1 Seasonal average model

5.2.10.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Belconnen regional population, retail price and residential energy efficiency. The model had an adjusted R-squared statistic of 99% and projections are displayed in Figure 5.2.10.1 – more detail in Jacobs report on the actual model.

5.2.10.1.2 Forecast trend and block load analysis

Figure 5.2.10.1: Latham ZSS seasonal average demand – Model Fit and Forecast
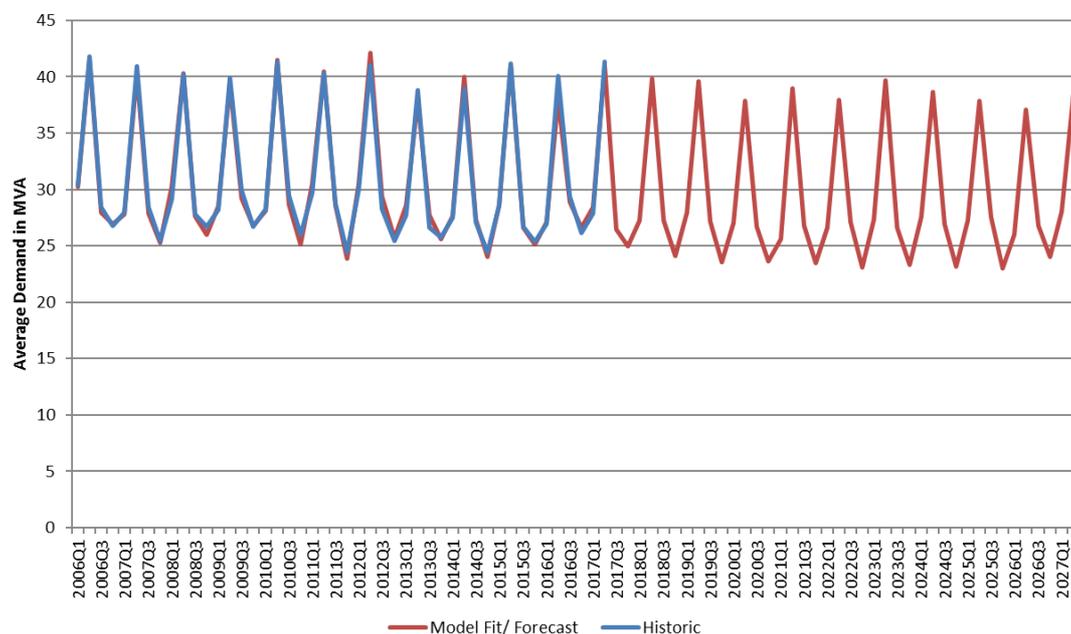
Block Load analysis and assumptions:

- No clear upward trend is indicated in Figure 5.2.10.1. Therefore, post model block load adjustment is required if any;
- Belconnen regional population is an explanatory variable of its average demand model. However, this proxy is not the best indicator to demonstrate the strong new subdivision development of the West Belconnen and Parkwood. Thus, new estate's block load should be included as part of Latham's demand forecast;
- Strathnairn Zone Substation is proposed to be constructed by Jun 2026 to supply the new Ginninderry Estate (Refer to section 5.2.2 for details). Therefore, a load drop is expected by the end of 2025/26 due to permanent load transfer from Latham ZSS to Strathairn ZSS;
- More block load information can be found under Appendix 6.3.

5.2.10.2 Half-hourly model: summer and winter

A total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.8.

5.2.10.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.10.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.10.3: Stack Chart by structure change impact;
- Table 5.2.10.1 to 5.2.10.4: Actual or Forecast figures for Figure 5.2.10.2 and 5.2.10.3.

Key notes from Figure 5.2.10.2:

- Both summer and winter POE forecast indicate that Latham ZSS still has sufficient spare capacity to meet the electricity demand of the area it supplies over the next ten years;
- Rooftop PV has little impact on Latham ZSS' winter maximum demand.

Figure 5.2.10.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the predominant residential nature of zone substation, the ZSS peak demand is forecast to occur around 5:30 PM in summer and 6:30 PM in winter. The battery storage impact is projected to be at its maximum in both summer and winter based on Figure 4.5.3. Roof top PV has zero impact on the winter demand than the summer demand as winter peak occurs after daylight.

Figure 5.2.10.2: Latham ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.10.2: Latham ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.10.3: POE Forecast breakdown by structure change technology – Vertical analysis

| Summer POE Forecasts | Winter POE Forecasts |

Latham ZSS 10-year summer demand forecast (50% POE)

Latham ZSS 10-year winter demand forecast (50% POE)

Figure 5.2.10.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

Latham ZSS 10-year summer demand forecast (10% POE)

Latham ZSS 10-year winter demand forecast (10% POE)

Legend: Rooftop PV, Battery, EV, Operational Less EV

Table 5.2.10.1: Latham ZSS summer back-cast and weather correction in MVA

Year	Summer		Weather Correction		
	Actual	**Fitted**	**POE90**	**POE50**	**POE10**
2006	49	57	48	55	62
2007	50	53	47	55	62
2008	46	46	47	55	62
2009	55	58	47	54	61
2010	54	56	46	54	62
2011	56	52	46	54	62
2012	45	41	45	54	61
2013	52	53	47	53	60
2014	55	53	45	52	60
2015	45	41	44	51	59
2016	53	53	45	53	61
2017	56	59	44	52	61

Table 5.2.10.2: Latham ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**
2018	52	59	52	59	52	60	53	60
2019	51	59	51	59	52	59	53	60
2020	52	59	52	59	53	60	54	61
2021	52	59	52	59	54	61	55	62
2022	53	60	53	60	55	62	56	63
2023	53	61	54	61	56	63	57	64
2024	54	60	54	61	57	63	58	65
2025	53	61	54	61	57	64	58	65
2026	55	62	56	63	59	66	60	67
2027	45	53	46	54	50	58	52	59

Table 5.2.10.3: Latham ZSS winter back-cast and weather correction in MVA

	Winter		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2006	73	72	67	72	77
2007	72	70	67	73	78
2008	69	69	67	72	77
2009	67	65	66	71	77
2010	71	71	67	71	77
2011	69	68	67	71	76
2012	66	70	67	71	76
2013	68	63	65	70	74
2014	68	68	65	70	75
2015	70	71	65	69	75
2016	74	65	64	69	74
2017	67	70	64	68	73

Table 5.2.10.4: Latham ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	68	73	68	73	68	73	68	73
2019	68	74	68	74	69	74	69	74
2020	69	74	69	74	70	75	70	75
2021	70	75	70	75	71	76	71	76
2022	69	75	69	75	71	77	71	77
2023	70	75	70	75	72	77	72	77
2024	70	75	71	76	73	78	73	79
2025	71	76	72	77	75	79	75	80
2026	63	68	64	70	68	73	68	73
2027	63	68	64	70	68	73	68	74

5.2.11 Telopea Park Zone Substation Forecast

5.2.11.1 Seasonal average model

5.2.11.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, South Canberra regional population and residential energy efficiency. The model had an adjusted R-squared statistic of 99% and projections are displayed in Figure 5.2.11.1 – more detail in Jacobs report on the actual model.

5.2.11.1.2 Forecast trend and block load analysis

Figure 5.2.11.1: Telopea Park ZSS seasonal average demand – Model Fit and Forecast
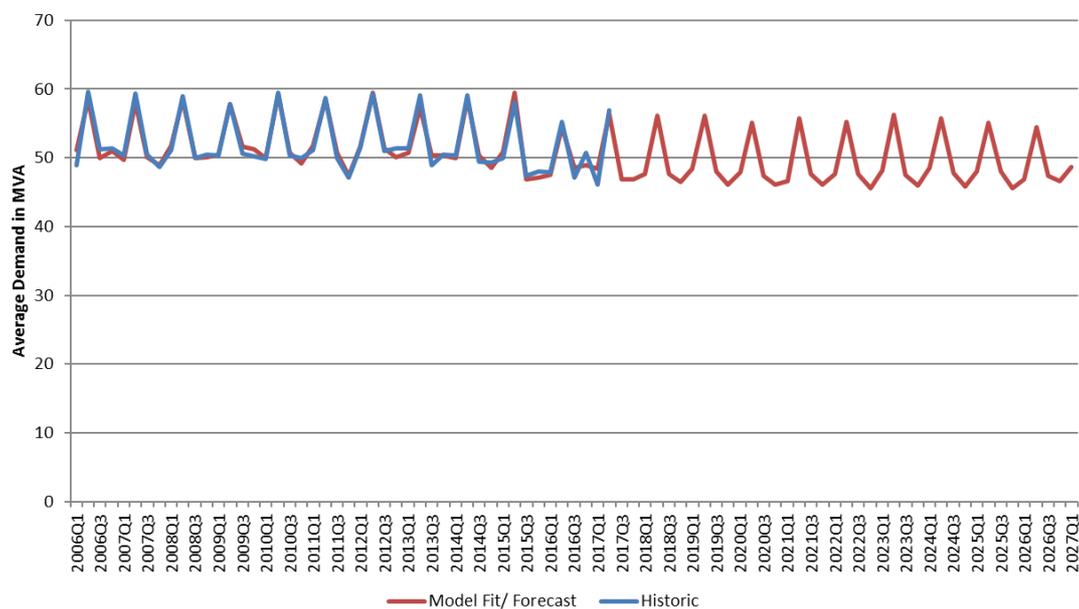
Block Load analysis and assumptions:

- No clear upward trend is indicated in Figure 5.2.11.1. Therefore, post model block load adjustment is required if any;
- South Canberra regional population is an explanatory variable of its average demand model with a positive coefficient. However, this proxy is too broad and large to reflect the strong development around Kingston Foreshore area. Thus, residential block load should be included as part of Telopea Park's demand forecast in this incident;
- More block load information can be found under Appendix 6.3.

5.2.11.2 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.9.

5.2.11.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.11.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.11.3: Stack Chart by structure change impact;
- Table 5.2.11.1 to 5.2.11.4: Actual or Forecast figures for Figure 5.2.11.2 and 5.2.11.3.

Key notes from Figure 5.2.11.2:

- Telopea Park ZSS is forecast to exceed its summer continuous rating by 2025, which implies that ZSS is slowly approaching its full capacity;

Figure 5.2.11.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the commercial nature of zone substation, the ZSS peak demand is forecast to occur around 3:00 PM in summer and 8:30 AM in winter. The battery storage impact is projected to be medium in summer and at its minimum in winter according to the assumed charge and discharge pattern shown in Figure 4.5.3.

Figure 5.2.11.2: Telopea Park ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis
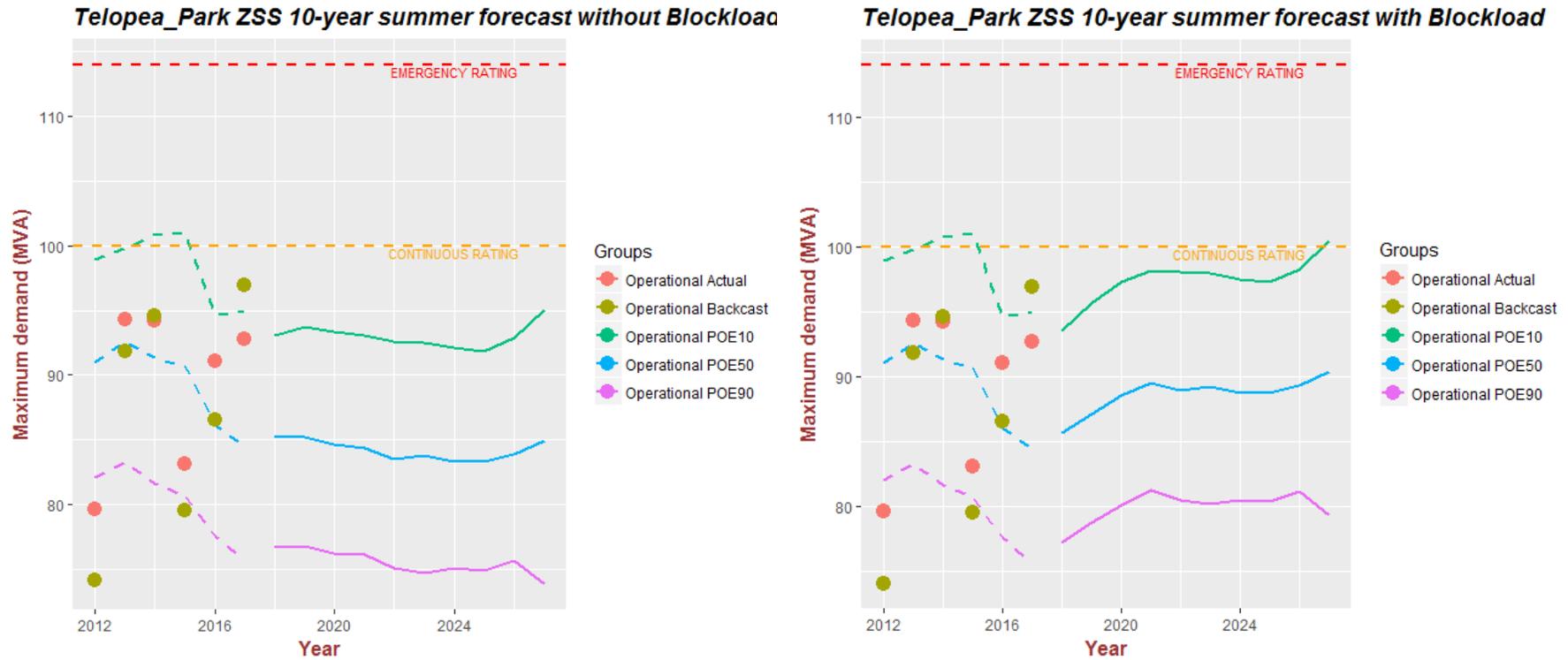
Figure 5.2.11.2: Telopea Park ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis
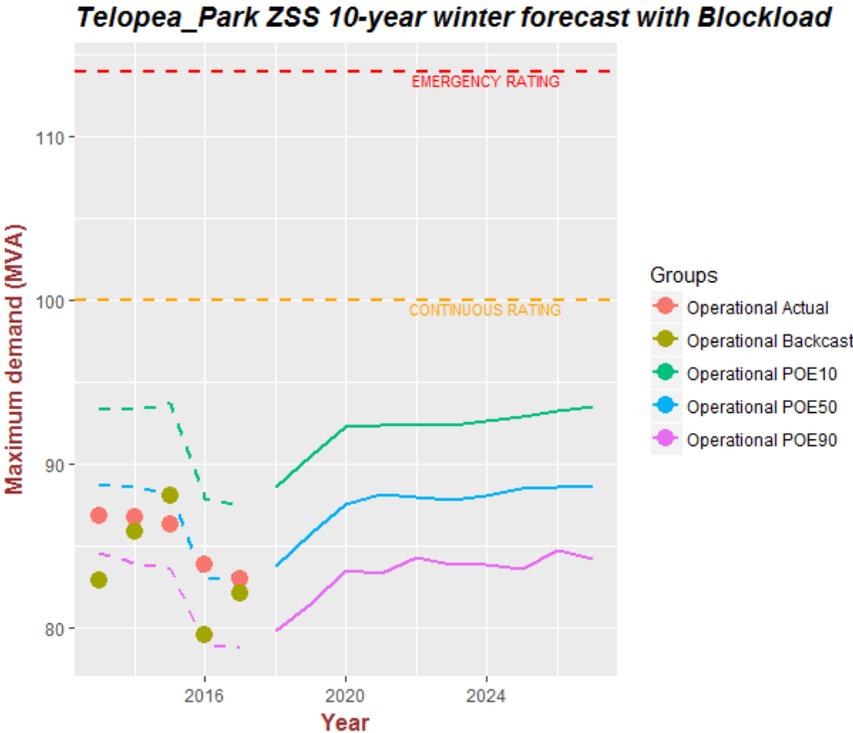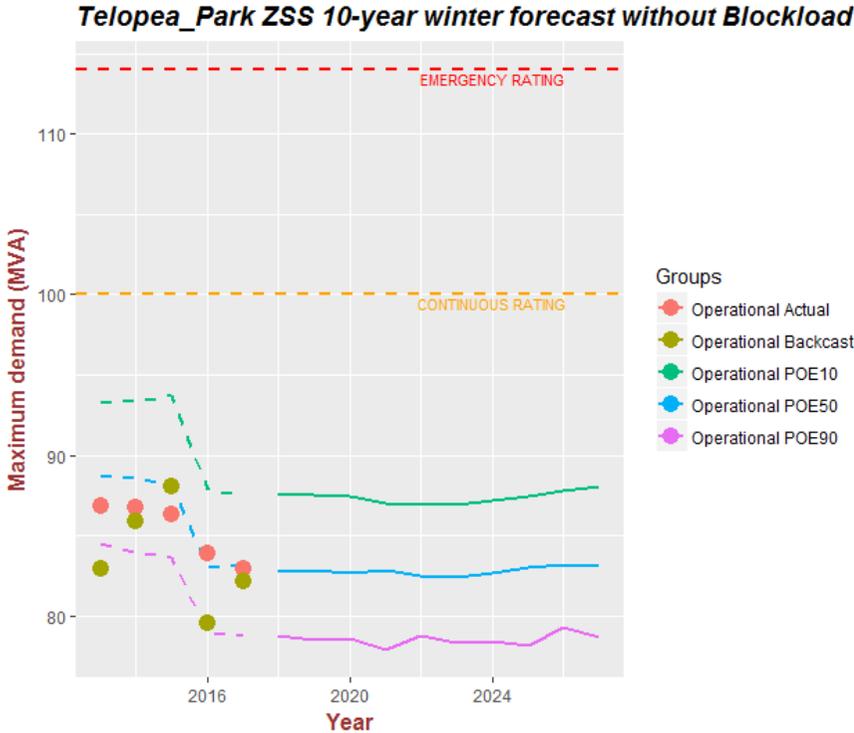
Figure 5.2.11.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Telopea_Park ZSS 10-year summer demand forecast (50% POE)

Winter POE Forecasts
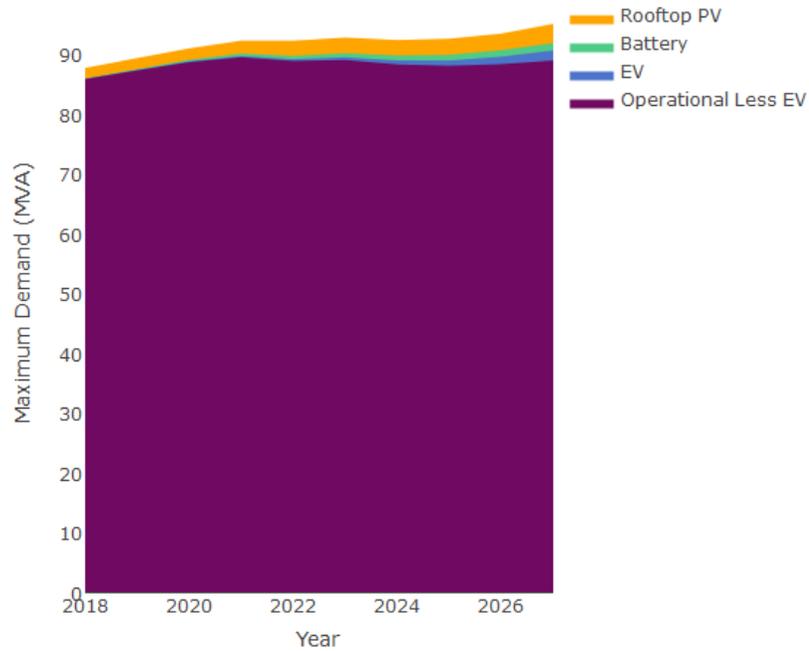
Telopea_Park ZSS 10-year winter demand forecast (50% POE)
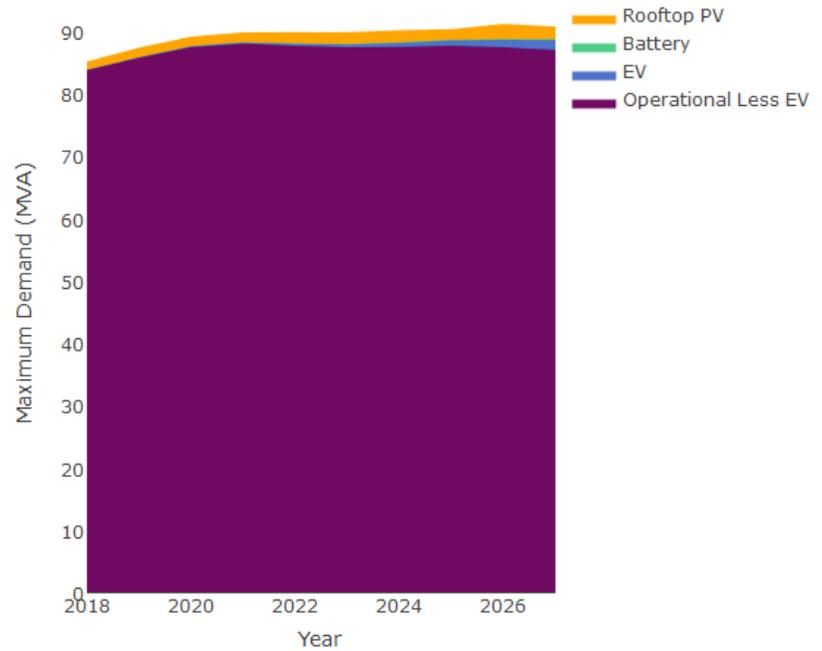
Figure 5.2.11.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Telopea_Park ZSS 10-year summer demand forecast (10% POE)

Winter POE Forecasts
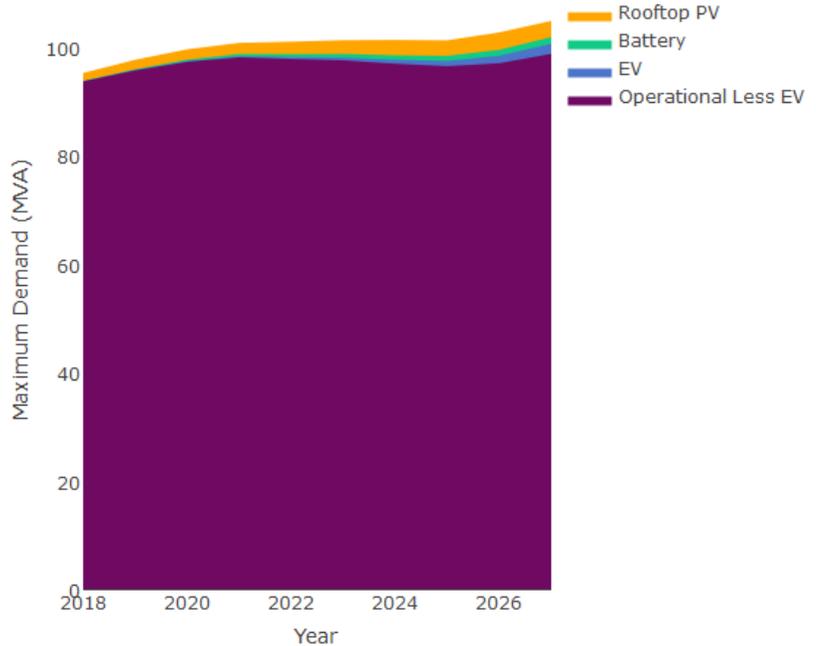
Telopea_Park ZSS 10-year winter demand forecast (10% POE)
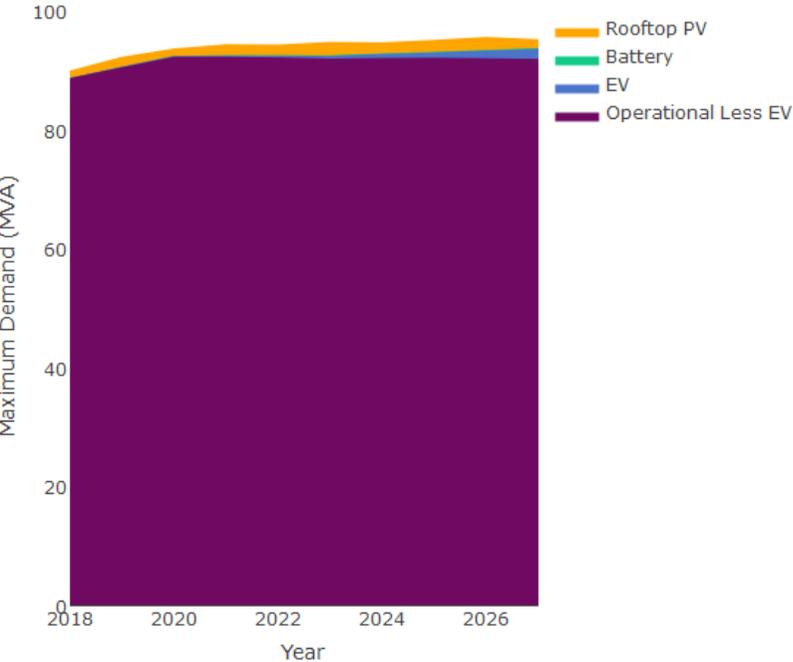
Table 5.2.11.1: Telopea Park ZSS summer back-cast and weather correction in MVA

	Summer		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2012	80	74	82	91	99
2013	94	92	83	93	100
2014	94	95	82	91	101
2015	83	80	81	91	101
2016	91	87	78	86	95
2017	93	97	76	84	95

Table 5.2.11.2: Telopea Park ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	86	94	86	94	86	94	88	95
2019	87	96	87	96	87	96	89	98
2020	88	97	89	97	89	98	91	99
2021	89	98	89	98	90	99	92	101
2022	89	98	89	98	90	99	92	101
2023	89	97	89	98	90	99	93	101
2024	88	97	89	98	90	98	92	101
2025	88	96	89	97	90	98	92	101
2026	88	97	89	98	90	99	93	103
2027	89	99	90	101	92	102	95	105

Table 5.2.11.3: Telopea Park ZSS winter back-cast and weather correction in MVA

	Winter		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2013	87	83	84	89	93
2014	87	86	84	89	93
2015	86	88	84	88	94
2016	84	80	79	83	88
2017	83	82	79	83	87

Table 5.2.11.4: Telopea Park ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	84	89	84	89	84	89	85	90
2019	86	90	86	90	86	90	87	92
2020	87	92	88	92	88	92	89	94
2021	88	92	88	92	88	92	90	94
2022	88	92	88	92	88	92	90	94
2023	87	92	88	92	88	92	90	95
2024	87	92	88	93	88	93	90	95
2025	88	92	88	93	89	93	90	95
2026	87	92	89	93	89	93	91	96
2027	87	92	89	93	89	94	91	95

### 5.2.12 Theodore Zone Substation Forecast

5.2.12.1 Seasonal average model

5.2.12.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Tuggeranong regional population and retail price. The model had an adjusted R-squared statistic of 98% and projections are displayed in Figure 5.2.12.1 – more detail in Jacobs report on the actual model.

5.2.12.1.2 Forecast trend and block load analysis

Figure 5.2.12.1: Theodore ZSS seasonal average demand – Model Fit and Forecast
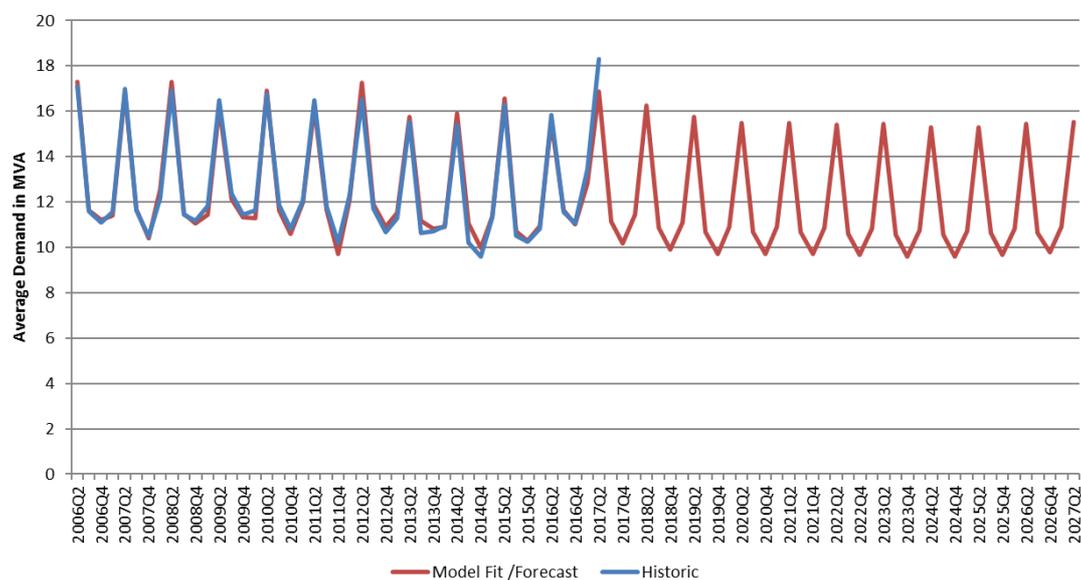
Block Load analysis and assumptions:

- No clear upward trend is indicated in Figure 5.2.12.1. Therefore, post model block load adjustment is required if any;
- No population growth is forecast for Theodore ZSS area as it is already a well-established suburb;
- No significant spot load is noted around Theodore ZSS area.

5.2.12.2 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.10.

5.2.12.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.12.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;

- Figure 5.2.12.3: Stack Chart by structure change impact;
- Table 5.2.12.1 to 5.2.12.4: Actual or Forecast figures for Figure 5.2.12.2 and 5.2.12.3.

Key notes from Figure 5.2.12.2 are:

- No net load growth is forecast over the next ten years for Theodore ZS;
- Theodore ZSS will have significant spare capacity available for any future developments and load transfers.

Figure 5.2.12.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the predominant residential nature of zone substation, the ZSS peak demand is forecast to occur around 6:00 PM in summer and 7:00 PM in winter. The battery storage impact is projected to be at its maximum in both summer and winter based on Figure 4.5.3. Roof top PV has less impact on the winter demand than the summer demand as winter peak occurs after daylight.

Figure 5.2.12.2: Theodore ZSS summer and winter demand forecast - Horizontal Analysis
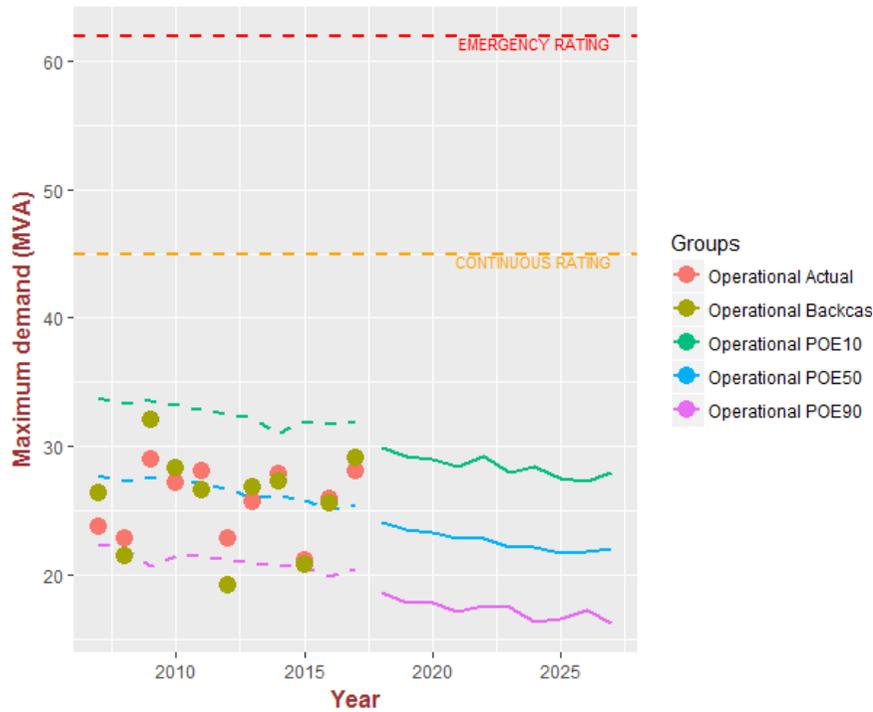
Figure 5.2.12.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Theodore ZSS 10-year summer demand forecast (50% POE)

Winter POE Forecasts

Theodore ZSS 10-year winter demand forecast (50% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV

Figure 5.2.12.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts

Theodore ZSS 10-year summer demand forecast (10% POE)

- Rooftop PV
- Battery
- EV
- Operational Less EV

Winter POE Forecasts

Theodore ZSS 10-year winter demand forecast (10% POE)

- Rooftop PV
- Battery
- EV
- Operational Less EV

EVO Energy Peak Demand Forecast for period: 2018-2027   EVO Energy
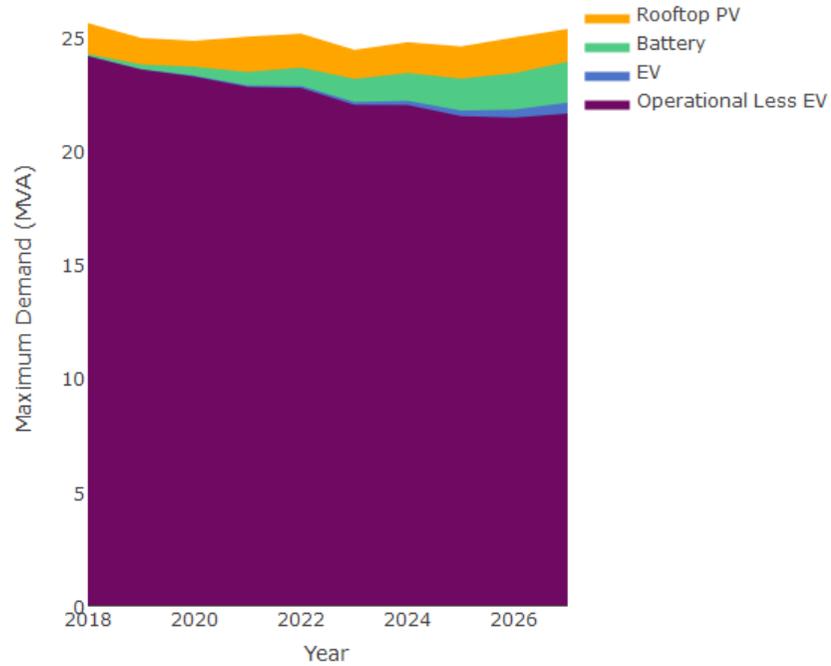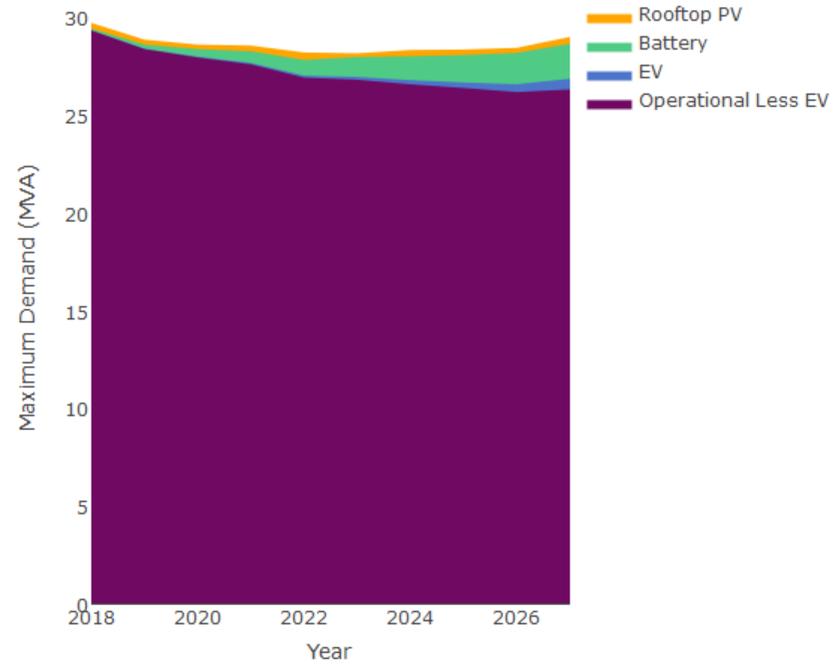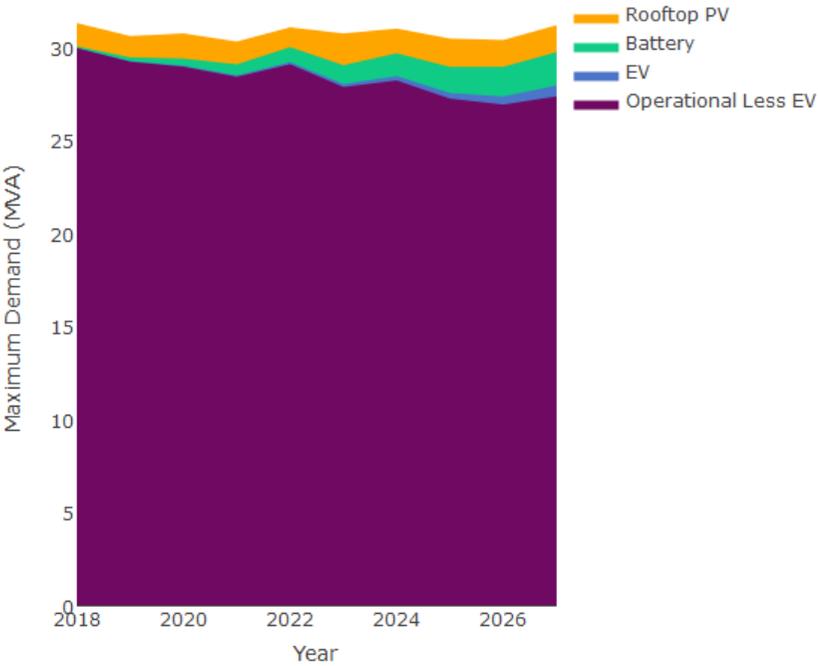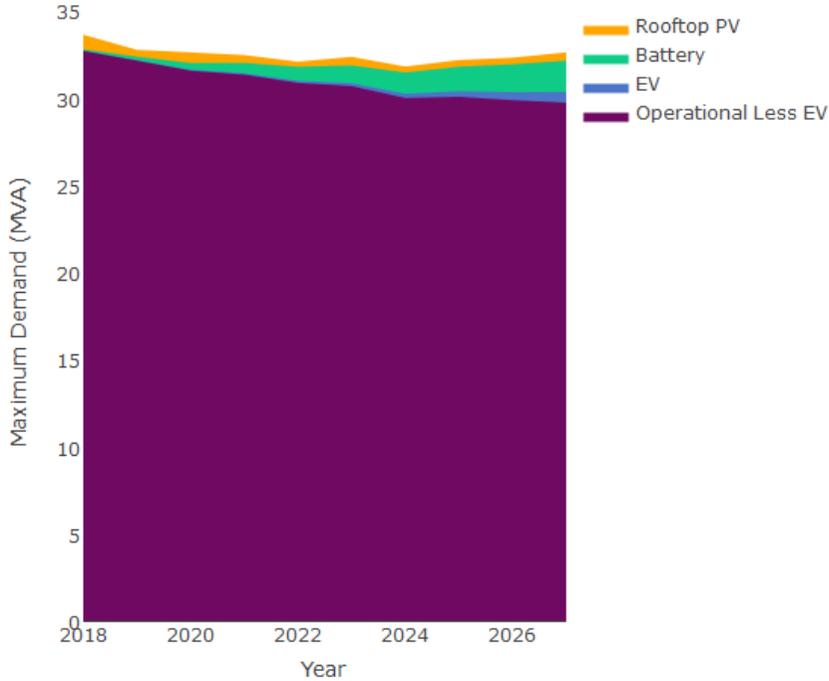
Table 5.2.12.1: Theodore ZSS summer back-cast and weather correction in MVA

|	Summer		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	24	26	22	28	34
2008	23	21	22	27	33
2009	29	32	21	27	34
2010	27	28	21	27	33
2011	28	27	21	27	33
2012	23	19	21	27	33
2013	26	27	21	26	32
2014	28	27	21	26	31
2015	21	21	21	26	32
2016	26	26	20	25	32
2017	28	29	20	25	32

Table 5.2.12.2: Theodore ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	24	30	24	30	24	30	26	31
2019	24	29	24	29	24	29	25	31
2020	23	29	23	29	24	29	25	31
2021	23	28	23	28	23	29	25	30
2022	23	29	23	29	24	30	25	31
2023	22	28	22	28	23	29	24	31
2024	22	28	22	28	23	30	25	31
2025	21	27	22	27	23	29	25	30
2026	21	27	22	27	23	29	25	30
2027	22	27	22	28	24	30	25	31

Table 5.2.12.3: Theodore ZSS winter back-cast and weather correction in MVA

	Winter		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2006	32	32	28	31	36
2007	32	31	28	31	35
2008	30	30	29	31	35
2009	29	28	28	31	34
2010	30	30	28	31	35
2011	29	28	27	30	34
2012	28	30	27	31	34
2013	29	28	27	31	34
2014	29	28	27	30	33
2015	30	31	26	29	33
2016	29	28	27	30	33
2017	32	30	26	29	33

Table 5.2.12.4: Theodore ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	29	33	29	33	29	33	30	34
2019	28	32	28	32	29	32	29	33
2020	28	32	28	32	28	32	29	33
2021	28	31	28	31	28	32	29	32
2022	27	31	27	31	28	32	28	32
2023	27	31	27	31	28	32	28	32
2024	27	30	27	30	28	31	28	32
2025	26	30	27	30	28	32	28	32
2026	26	30	27	30	28	32	28	32
2027	26	30	27	30	29	32	29	33

### 5.2.13 Wanniassa Zone Substation Forecast

5.2.13.1 Seasonal average model

5.2.13.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Tuggeranong regional population, residential energy efficiency and unemployment. The model had an adjusted R-squared statistic of 98% and projections are displayed in Figure 5.2.13.1 – more detail in Jacobs report on the actual model.

5.2.13.1.2 Forecast trend and block load analysis

Figure 5.2.13.1: Wanniassa ZSS seasonal average demand – Model Fit and Forecast
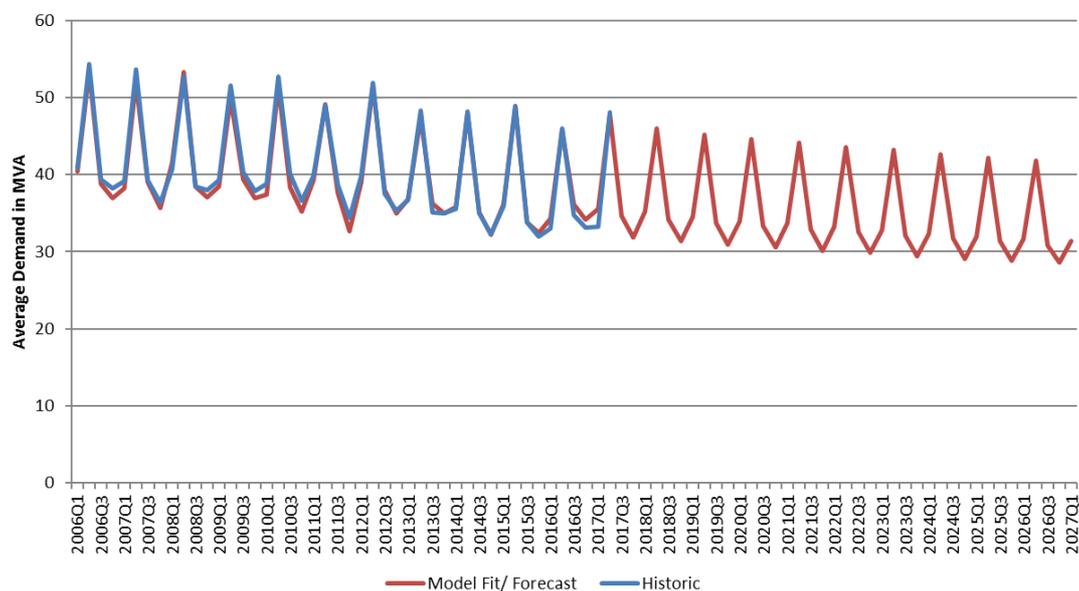
Block Load analysis and assumptions:

- A clear downward trend is shown in Figure 5.2.13.1. Therefore, post model block load adjustment is required if any;
- Tuggeranong regional population is an explanatory variable of its average demand model. However, this proxy is not the best indicator to reflect the strong residential and commercial development around Greenway area. Thus, residential block load should not be excluded from block load adjustment;
- More block load information can be found under Appendix 6.3.

5.2.13.2 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.11.

5.2.13.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.13.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.13.3: Stack Chart by structure change impact;
- Table 5.2.13.1 to 5.2.13.4: Actual or Forecast figures for Figure 5.2.13.2 and 5.2.13.3.

Key findings from Figure 5.2.13.2:

- The downward trend noticed from the average demand model could have been the result of rooftop solar PV, improvement of energy efficiency or both;
- Wanniassa ZSS should not have any constraint issue in next ten years as 10% POE forecast for both seasons is projected to be below the continuous rating.

Figure 5.2.13.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the predominant residential nature of zone substation, the ZSS peak demand is forecast to occur around 5:30 PM in summer and 7:00 PM in winter. The battery storage impact is projected to be at its maximum in both summer and winter based on Figure 4.5.3. Roof top PV has much less impact on the winter demand than the summer demand as winter peak is forecast occur after daylight.

Figure 5.2.13.2: Wanniassa ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis
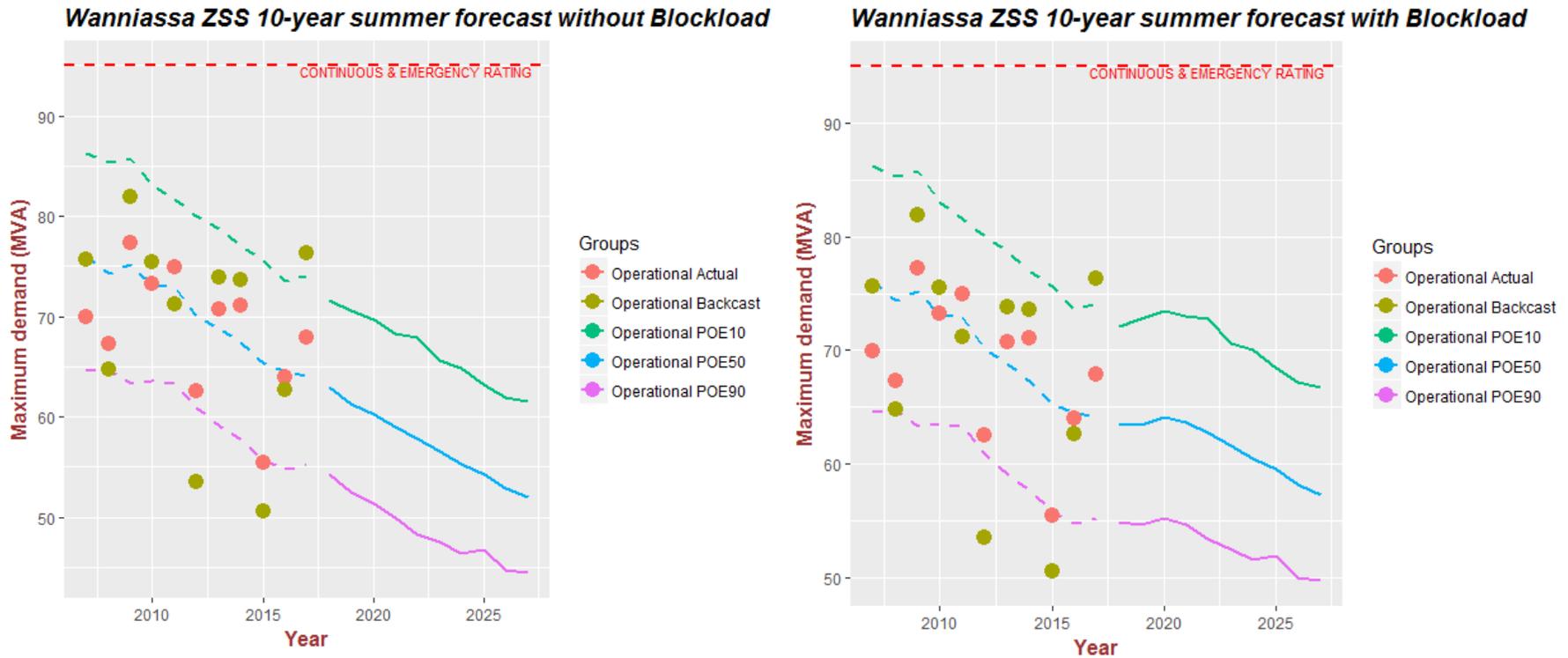
Figure 5.2.13.2: Wanniassa ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis
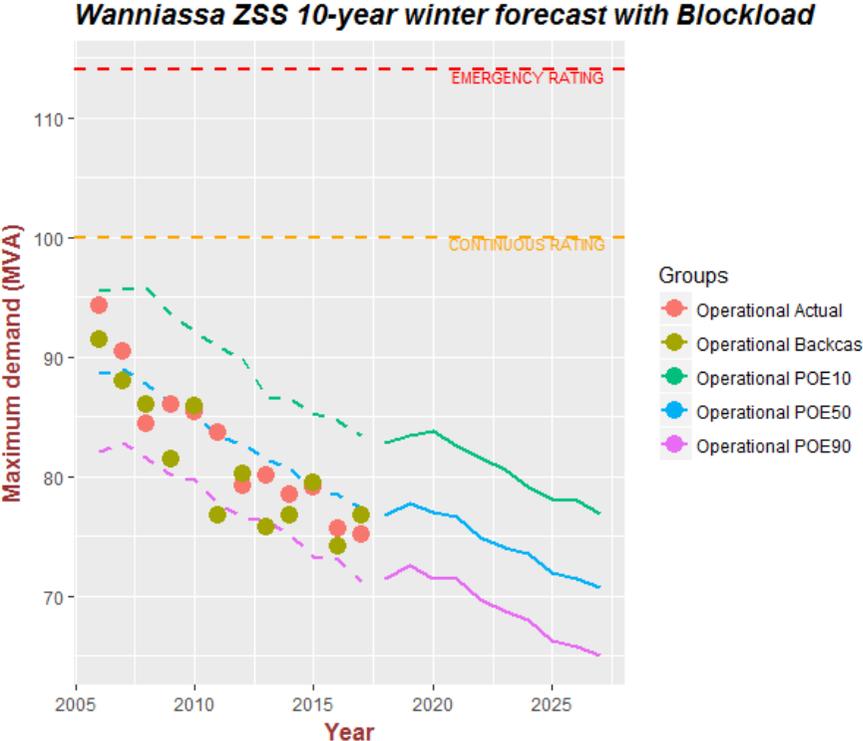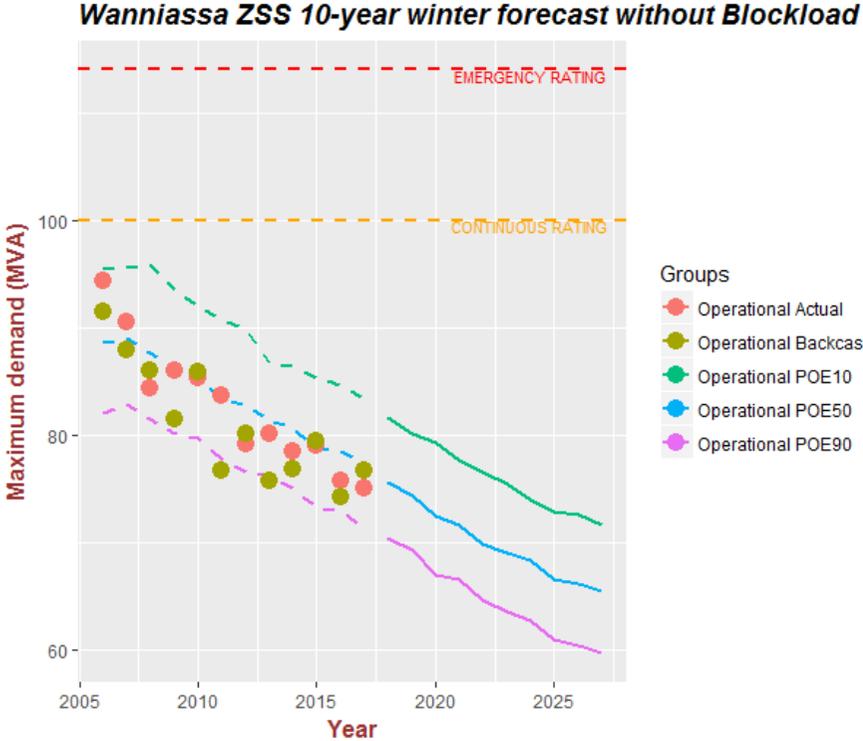
Figure 5.2.13.3: POE Forecast breakdown by structure change technology – Vertical analysis

| Summer POE Forecasts | Winter POE Forecasts |

Wanniassa ZSS 10-year summer demand forecast (50% POE)
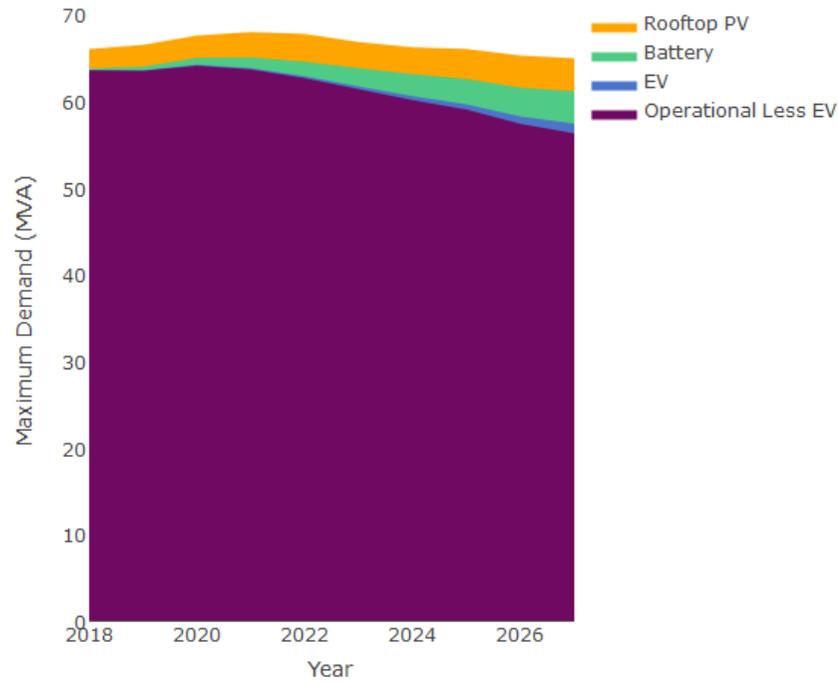
Wanniassa ZSS 10-year winter demand forecast (50% POE)
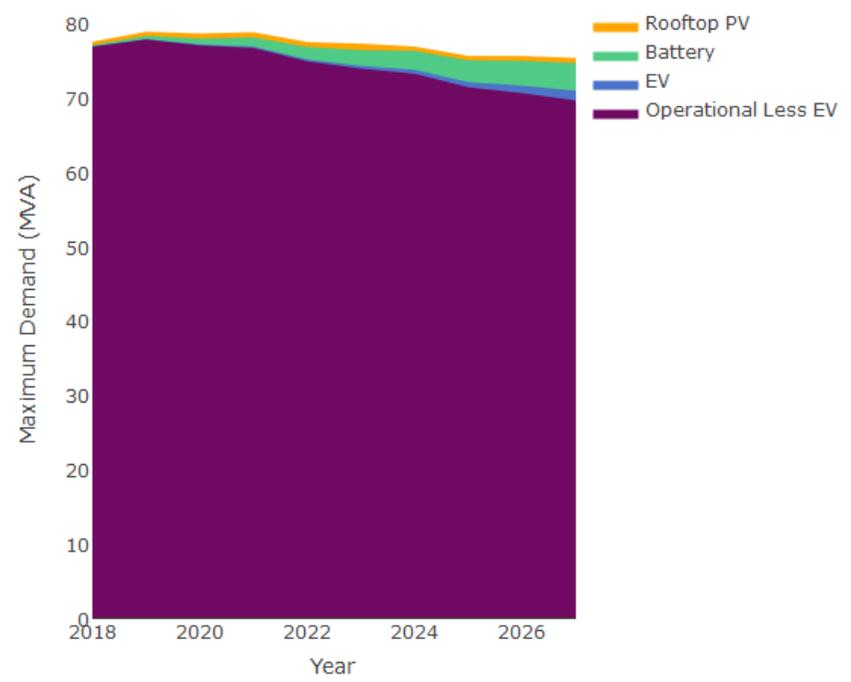
Figure 5.2.13.3: POE Forecast breakdown by structure change technology – Vertical analysis

| Summer POE Forecasts | Winter POE Forecasts |

Wanniassa ZSS 10-year summer demand forecast (10% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV

Y-axis: Maximum Demand (MVA)
X-axis: Year

Wanniassa ZSS 10-year winter demand forecast (10% POE)

Legend:
- Rooftop PV
- Battery
- EV
- Operational Less EV

Y-axis: Maximum Demand (MVA)
X-axis: Year
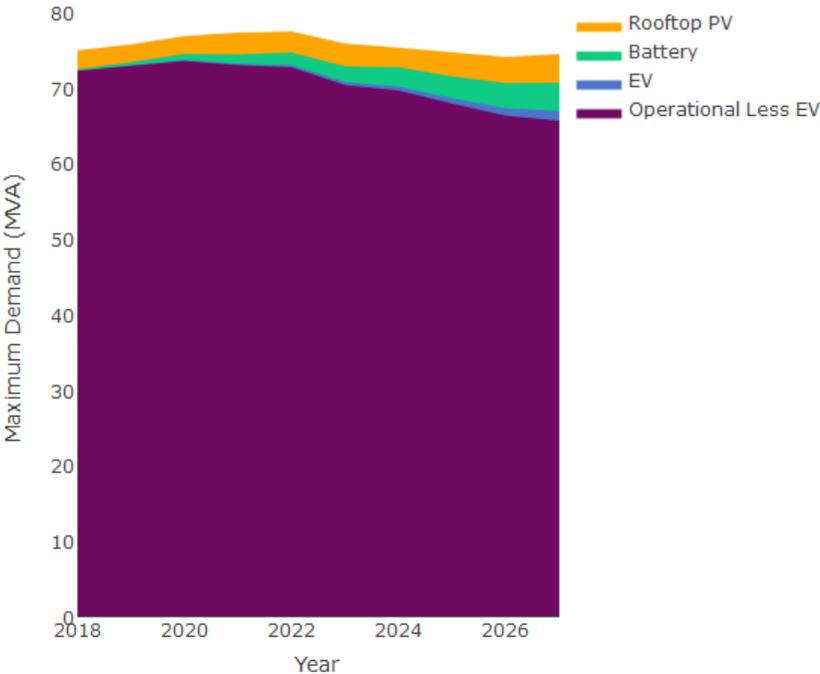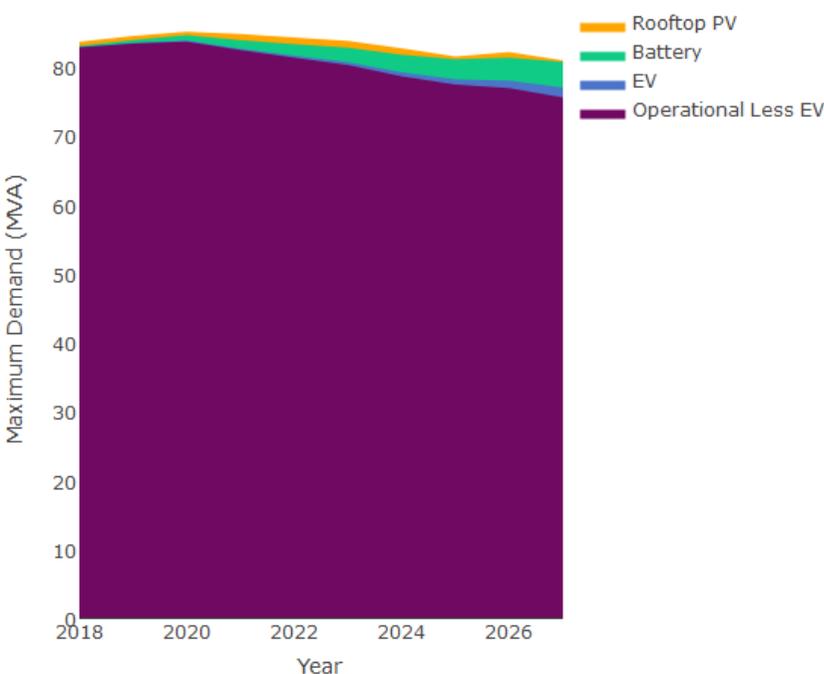
Table 5.2.13.1: Wanniassa ZSS summer back-cast and weather correction in MVA

Year	Summer		Weather Correction		
	Actual	**Fitted**	**POE90**	**POE50**	**POE10**
2007	70	76	65	76	86
2008	67	65	65	74	85
2009	77	82	63	75	86
2010	73	75	64	73	83
2011	75	71	63	73	82
2012	63	53	61	70	80
2013	71	74	59	69	79
2014	71	74	58	67	77
2015	55	51	56	65	76
2016	64	63	55	65	74
2017	68	76	55	64	74

Table 5.2.13.2: Wanniassa ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**
2018	63	72	63	72	64	72	66	75
2019	63	73	63	73	64	73	66	76
2020	64	73	64	74	65	74	67	77
2021	64	73	64	73	65	74	68	77
2022	63	73	63	73	64	75	68	77
2023	61	70	62	71	64	73	67	76
2024	60	69	60	70	63	73	66	75
2025	59	68	60	68	62	71	66	75
2026	57	66	58	67	61	70	65	74
2027	56	65	57	67	61	71	65	74

Table 5.2.13.3: Wanniassa ZSS winter back-cast and weather correction in MVA

| Year | Winter | | Weather Correction | | |
	Actual	Fitted	POE90	POE50	POE10
2006	94	91	82	89	96
2007	90	88	83	89	96
2008	84	86	82	88	96
2009	86	82	80	86	94
2010	85	86	80	85	92
2011	84	77	78	83	91
2012	79	80	77	83	90
2013	80	76	76	81	87
2014	79	77	75	81	86
2015	79	80	73	79	85
2016	76	74	73	78	85
2017	75	77	71	77	83

Table 5.2.13.4: Wanniassa ZSS winter forecast breakdown in MVA

| Winter | Operational Demand less EV | | Plus EV (Operational Demand) | | Plus Battery | | Plus Rooftop Solar (Underlying Demand) | |
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	77	83	77	83	77	83	77	84
2019	78	83	78	83	78	84	79	84
2020	77	84	77	84	78	85	78	85
2021	77	82	77	83	78	84	79	85
2022	75	81	75	82	77	83	77	84
2023	74	80	74	81	76	83	77	84
2024	73	79	74	79	76	82	77	83
2025	71	77	72	78	75	81	75	81
2026	70	77	71	78	75	81	75	82
2027	69	76	71	77	75	81	75	81

5.2.14 Woden Zone Substation Forecast

5.2.14.1 Seasonal average model

5.2.14.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Cotter regional population (Molonglo Valley), State final demand and business energy efficiency. The model had an adjusted R-squared statistic of 95% and projections are displayed in Figure 5.2.14.1 – more detail in Jacobs report on the actual model.

5.2.14.1.2 Forecast trend and block load analysis

Figure 5.2.14.1: Woden ZSS seasonal average demand – Model Fit and Forecast
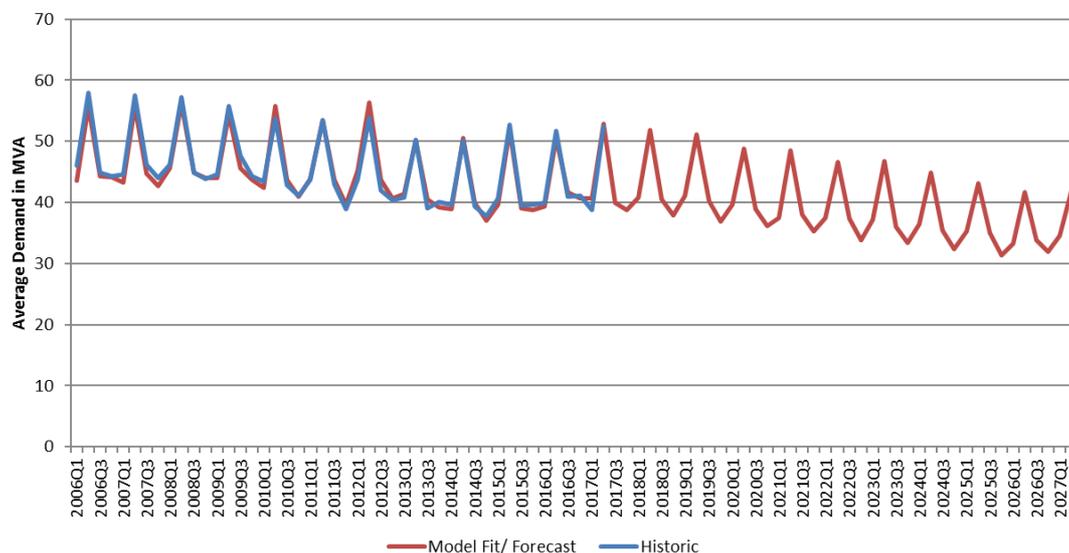
Block Load analysis and assumptions:

- A clear downward trend is shown in Figure 5.2.14.1. Therefore, post model block load adjustment is required if any;
- Cotter regional population is an explanatory variable of its average demand model, which is not the best proxy for Woden ZSS as it ignores the old Woden area including Weston Creek. Thus, the residential block load should not be excluded from block load adjustment;
- Other key assumptions are:
    1) Molonglo Mobile substation (MOSS) is planned to be commissioned at the end of 2021/22 and will start supplying Molonglo development such as Denman Prospect and Whitlam from June 2022 onwards;
    2) Black Mountain feeder from Civic will start supplying Whitlam area from 2019/20 to 2020/22 until reaching its maximum capacity;

3) A permanent single transformer Molonglo ZSS is planned to be commissioned by June 2027; and

4) After commission of Molonglo MOSS, no significant residential load growth is forecast from 2022/23 onwards as Woden/Weston Creek is a well-established area, but 300 kVA annual commercial load growth is assumed due to future redevelopment and expansion of regional shopping districts by ACT Government.

- More block load information can be found under Appendix 6.3.

5.2.14.2 Denman Prospect block load forecast

ACT government currently does not include Denman Prospect development in its annual published land release program. The government says it is currently working on release strategies for Denman Prospect Stages 2 and 3 on its website. So we have to collect all possible Intelligences from internal and external sources to create an appropriate land release plan for Denman Prospect estate:

1) The estate will ultimately provide for some 4,000 dwellings and is to be delivered in the following three stages:
   a) Stage 1 (approx. 2,000 dwellings)
   b) Stage 2 (approx. 1,200 dwellings)
   c) Stage 3 (approx. 1,000 dwellings);
2) The 1st Sale/Auction of Stage 1A was held in October 2015;
3) Stage 1A's 401 dwellings have not yet been fully sold as at 24th October 17;
4) Stage 1B's civil work has already begun back in February 2017 and the first 2 sub stages of the development is expected to be completed by early or mid-2018 (Stage 1B includes 600 detached dwellings and 1000 medium and high density apartments;
5) In June 2017, Capital Airport Group has been selected to develop the Stage 2 of Denman Prospect.

Key observations:

1) It takes developer approximately a fully year to develop a 400-dwellings sub stage including all civil works;

2) A full land sales cycle of one sub stage is approximately 2 to 3 years;

3) And each sub stage will only release 400 or less dwellings

Table 5.2.14.1 illustrates the assumed 10-year land release program for Denman Prospect estate.

Table 5.2.14.1: Assumed Denman Prospect land release program by dwellings

Financial Year	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Dwellings	100	400	400	400	400	300	300	300	300	250
Estimated Load (MVA)*	0.25	1.00	1.00	1.00	1.00	0.75	0.75	0.75	0.75	0.63

*2.5 kVA diversified peak demand is assumed for each individual dwelling.

Finally, Denman Prospect's block load need to be probability adjusted before added to the raw Woden forecast, because the Table 5.2.14.1 is not official land release program delivered from ACT government or the Capital Airport Group.

5.2.14.3 Half-hourly model: summer and winter

Total of 48 models were built to accommodate each half hour of the day. An example for each season can be found under Appendix 6.1.12.

5.2.14.4 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by following formats:

- Figure 5.2.14.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.14.3: Stack Chart by structure change impact;
- Table 5.2.14.1 to 5.2.14.4: Actual or Forecast figures for Figure 5.2.14.2 and 5.2.14.3.

Key findings from Figure 5.2.14.2:

- The downward trend noticed from average demand model could have been the result of rooftop solar PV, improvement of energy efficiency or combination of both. Business energy efficiency is also an explanatory variable of average demand model;

- The proposed new Molonglo ZSS will provide Woden ZSS with demand relief in the longer term after June 2022.

Figure 5.2.14.3 illustrates the vertical analysis of summer and winter POE forecast. Because of the residential and commercial mix nature of zone substation, the ZSS peak demand is forecast to occur around 4:00 PM in both summer and winter. The battery storage impact is projected to be at its maximum in both seasons based on Figure 4.5.3. The rooftop PV has much less impact on the winter demand than the summer demand due to the decline of generation efficiency in winter.

Figure 5.2.14.2: Woden ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.14.2: Woden ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

Figure 5.2.14.3: POE Forecast breakdown by structure change technology – Vertical analysis

| Summer POE Forecasts | Winter POE Forecasts |

Woden ZSS 10-year summer demand forecast (50% POE)

Woden ZSS 10-year winter demand forecast (50% POE)

Legend: Rooftop PV, Battery, EV, Operational Less EV

Figure 5.2.14.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	Winter POE Forecasts

Woden ZSS 10-year summer demand forecast (10% POE)

Woden ZSS 10-year winter demand forecast (10% POE)
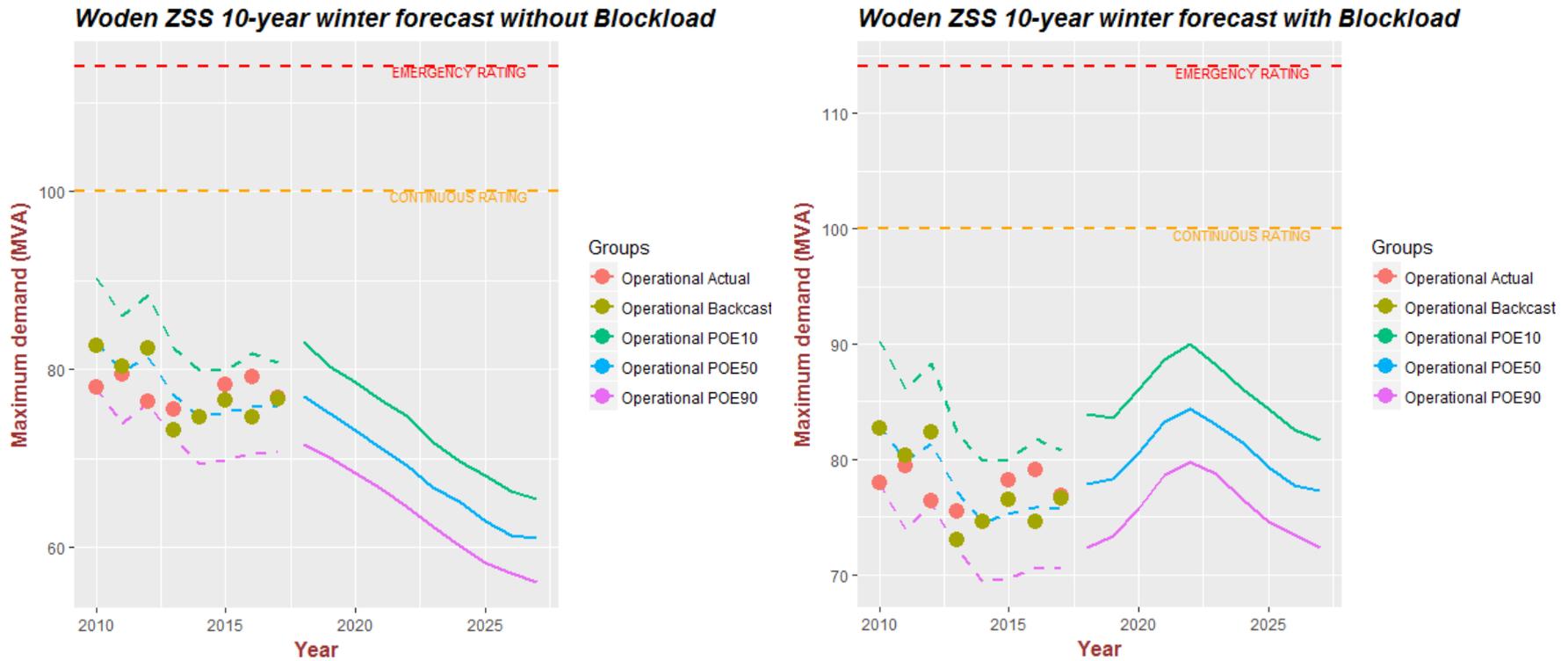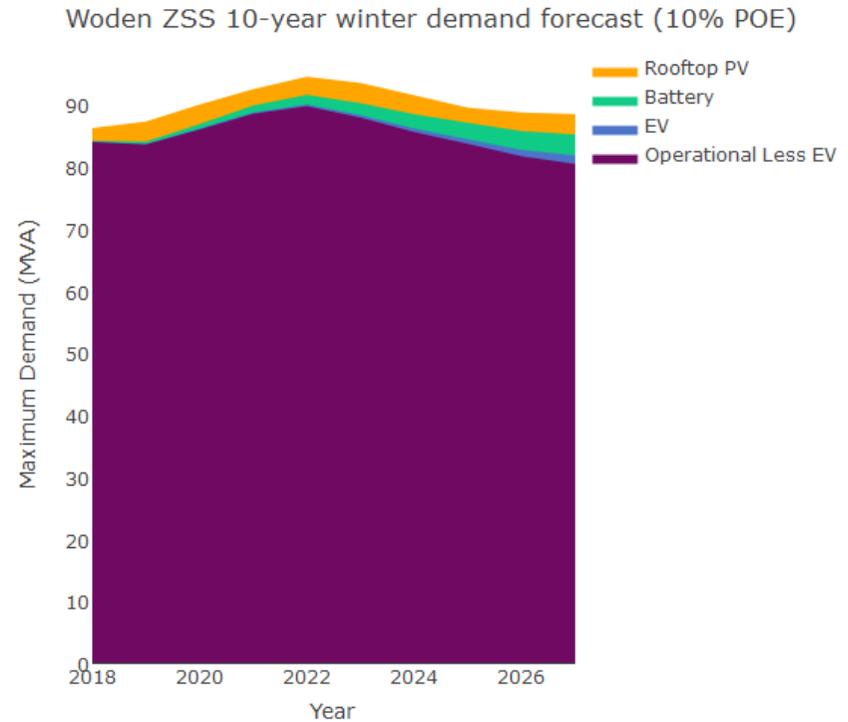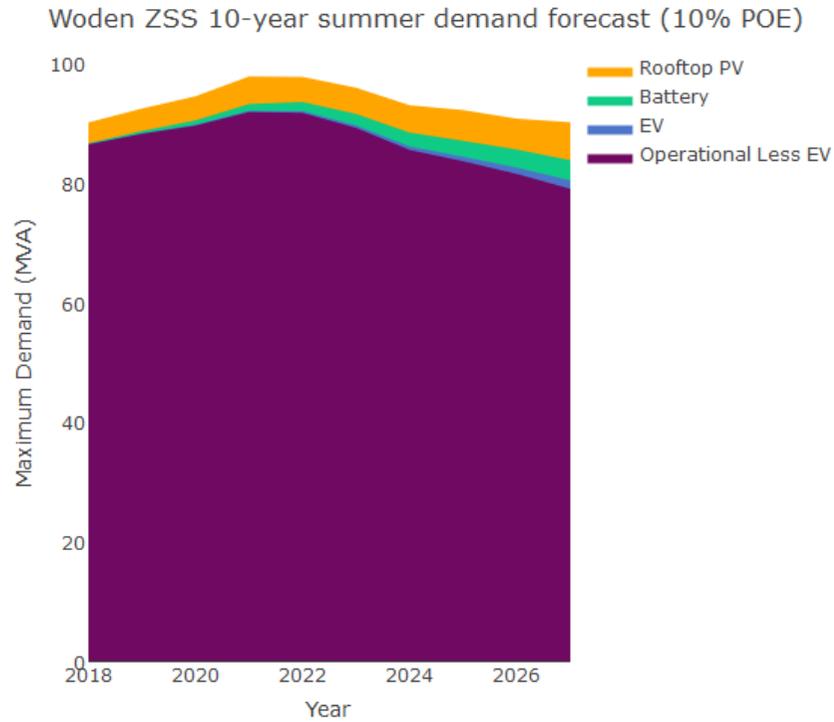
Table 5.2.14.2: Woden ZSS summer back-cast and weather correction in MVA

| Year | Summer | | Weather Correction | | |
	Actual	Fitted	POE90	POE50	POE10
2007	83	88	75	85	96
2008	81	77	73	87	99
2009	86	92	77	87	100
2010	84	88	73	84	95
2011	84	80	73	84	93
2012	65	61	72	83	94
2013	78	80	69	78	88
2014	78	79	65	74	85
2015	63	58	64	72	83
2016	78	76	66	76	85
2017	82	83	64	74	84

Table 5.2.14.3: Woden ZSS summer forecast break down in MVA

| Summer | Operational Demand less EV | | Plus EV (Operational Demand) | | Plus Battery | | Plus Rooftop Solar (Underlying Demand) | |
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	76	86	76	86	76	87	79	90
2019	78	88	78	88	79	89	82	92
2020	80	89	80	90	81	90	85	94
2021	82	92	82	92	83	93	87	98
2022	82	92	82	92	84	93	88	98
2023	79	89	80	89	82	91	86	96
2024	77	85	78	86	80	88	84	93
2025	75	84	75	84	78	87	84	92
2026	73	81	74	82	77	85	82	91
2027	71	79	72	80	76	84	82	90

Table 5.2.14.4: Woden ZSS winter back-cast and weather correction in MVA

	Winter		Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2010	78	83	78	83	90
2011	79	80	74	80	86
2012	76	82	76	81	88
2013	75	73	72	77	82
2014	75	75	69	75	80
2015	78	76	70	75	80
2016	79	75	71	76	82
2017	77	77	71	76	81

Table 5.2.14.5: Woden ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar (Underlying Demand)	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2018	78	84	78	84	78	84	81	86
2019	78	84	78	84	79	84	81	87
2020	80	86	81	86	81	87	84	90
2021	83	88	83	89	84	90	87	92
2022	84	90	84	90	86	91	88	94
2023	83	88	83	88	85	90	87	93
2024	81	86	82	86	84	88	86	91
2025	79	84	79	84	82	87	84	89
2026	77	82	78	83	81	86	83	89
2027	76	80	77	82	81	85	83	88

5.2.15 Tennent Zone Substation Forecast

Tennent ZSS was constructed at Angle Crossing in southern ACT to enable connection of the Williamsdale Solar Farm to ActewAGL's 132 kV transmission network. The solar farm has a maximum design output of 10.1 MW and is connected at 11 kV to the Tennent Zone Substation via underground cables. The zone substation comprises a single 11/132 kV 15 MVA step-up transformer and is connected via a tee-arrangement to the Williamsdale–Theodore 132 kV transmission line.

Loads previously supplied from the Angle Crossing mobile substation have been transferred to Tennent Zone Substation. Therefore, the maximum demand of Tennent Zone is forecast to be 3 MVA, which is the maximum capacity of the Icon Water High Lift Pumping Station (HLPS) that has been transferred to Tennent from the decommissioned Angle Crossing mobile substation.

5.2.16 Molonglo Mobile Substation (MOSS) Forecast

Molonglo MOSS is planned to be built by the end of 2021/22 and has been designed to supply the whole Molonglo Valley area which has an ultimate load forecast of approximately 40 MVA. According to the pervious assumption in section 5.2.14, it will take up all new loads from Molonglo Valley development from 2022/23 onwards. Table 5.2.16 shows the deterministic demand forecast for Molonglo MOSS by financial year.

Table 5.2.16: Molonglo ZSS 10-year demand forecast

Financial Year	Demand Forecast (in MVA)
2017/18	0.0
2018/19	0.0
2019/20	0.0
2020/21	0.0
2021/22	0.0
2022/23	1.3
2023/24	2.4
2024/25	3.2
2025/26	3.8
2026/27	4.1

6 Appendix

6.1 Half-hourly (HH) models

6.1.1 System HH Model

6.1.1.1 System summer HH model summary (Example: 16:30 model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.171842 -0.029539  0.002621  0.028598  0.257993
```

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.0227407	0.0470128	0.484	0.628692	
dayMon	0.0241730	0.0055234	4.377	1.33e-05	***
daySat	-0.2142001	0.0054992	-38.951	< 2e-16	***
daySun	-0.2325496	0.0055599	-41.826	< 2e-16	***
dayThu	0.0185125	0.0054862	3.374	0.000767	***
dayTue	0.0265221	0.0054897	4.831	1.56e-06	***
dayWed	0.0209041	0.0055141	3.791	0.000159	***
holidayDay before	0.0142723	0.0115934	1.231	0.218575	
holidayHoliday	-0.1701628	0.0105858	-16.075	< 2e-16	***
holidayNormal	0.0447114	0.0089735	4.983	7.35e-07	***
ns(timeofyear, 9)1	0.0730609	0.0111918	6.528	1.04e-10	***
ns(timeofyear, 9)2	0.1068641	0.0140467	7.608	6.27e-14	***
ns(timeofyear, 9)3	0.1031031	0.0135680	7.599	6.69e-14	***
ns(timeofyear, 9)4	0.0978988	0.0136725	7.160	1.53e-12	***
ns(timeofyear, 9)5	0.0888724	0.0134138	6.625	5.57e-11	***
ns(timeofyear, 9)6	0.0869067	0.0139645	6.223	7.07e-10	***
ns(timeofyear, 9)7	0.0358061	0.0108541	3.299	0.001004	**
ns(timeofyear, 9)8	0.0086518	0.0223297	0.387	0.698497	
ns(timeofyear, 9)9	-0.1674893	0.0101278	-16.538	< 2e-16	***
ns(temp, df = 2)1	0.2200887	0.0451799	4.871	1.28e-06	***
ns(temp, df = 2)2	0.1638736	0.0377542	4.341	1.56e-05	***
ns(dtemp, 3)1	-0.0294364	0.0133019	-2.213	0.027120	*
ns(dtemp, 3)2	-0.0211414	0.0457401	-0.462	0.644030	
ns(dtemp, 3)3	0.0586216	0.0285572	2.053	0.040346	*
ns(prevtemp2, df = 2)1	-0.0904995	0.1037146	-0.873	0.383094	
ns(prevtemp2, df = 2)2	0.0625470	0.0625414	1.000	0.317501	
ns(prevtemp3, df = 2)1	0.2530301	0.0999555	2.531	0.011508	*
ns(prevtemp3, df = 2)2	0.2416206	0.0613147	3.941	8.67e-05	***
ns(prevtemp6, df = 2)1	0.1579343	0.0496808	3.179	0.001522	**
ns(prevtemp6, df = 2)2	0.0362816	0.0433377	0.837	0.402684	
ns(day1temp, df = 2)1	0.0267309	0.0239453	1.116	0.264541	
ns(day1temp, df = 2)2	0.0352246	0.0225565	1.562	0.118686	
ns(prevdtemp3, 3)1	0.0143443	0.0131750	1.089	0.276520	
ns(prevdtemp3, 3)2	0.0223038	0.0456883	0.488	0.625531	
ns(prevdtemp3, 3)3	0.0761497	0.0341628	2.229	0.026027	*
ns(day1dtemp, 3)1	-0.0210832	0.0122098	-1.727	0.084514	.
ns(day1dtemp, 3)2	-0.0007157	0.0444316	-0.016	0.987152	
ns(day1dtemp, 3)3	0.0713891	0.0270968	2.635	0.008550	**
ns(day6dtemp, 3)1	0.0054705	0.0121807	0.449	0.653448	
ns(day6dtemp, 3)2	-0.0368347	0.0443919	-0.830	0.406867	

```
ns(day6dtemp, 3)3     -0.0094573  0.0269456   -0.351 0.725677
ns(lastmin, 3)1        0.0794639  0.0148688    5.344 1.12e-07 ***
ns(lastmin, 3)2        0.1352508  0.0461738    2.929 0.003474 **
ns(lastmin, 3)3        0.0575276  0.0300518    1.914 0.055861 .
                     Estimate Std. Error t value Pr(>|t|)

ns(lastmax, 3)1       -0.0347319  0.0173129   -2.006 0.045104 *
ns(lastmax, 3)2       -0.1365979  0.0471334   -2.898 0.003834 **
ns(lastmax, 3)3       -0.0920876  0.0324661   -2.836 0.004652 **
ns(avetemp, 3)1        0.0467562  0.0256947    1.820 0.069097 .
ns(avetemp, 3)2       -0.0233053  0.0656412   -0.355 0.722632
ns(avetemp, 3)3        0.0886696  0.0404726    2.191 0.028686 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04764 on 1030 degrees of freedom
Multiple R-squared:  0.9389,   Adjusted R-squared:  0.936
F-statistic: 322.9 on 49 and 1030 DF,  p-value: < 2.2e-16
```

6.1.1.2 System winter HH model summary (Example: 18:00 model)

```
Residuals:
     Min        1Q     Median        3Q        Max
-0.084484 -0.016553 -0.000836  0.015275  0.092843

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.4441341  0.0166763  26.633  < 2e-16 ***
dayMon                  0.0420886  0.0029153  14.437  < 2e-16 ***
daySat                 -0.0846280  0.0028642 -29.547  < 2e-16 ***
daySun                 -0.0691983  0.0029179 -23.715  < 2e-16 ***
dayThu                  0.0298826  0.0028637  10.435  < 2e-16 ***
dayTue                  0.0369077  0.0029292  12.600  < 2e-16 ***
dayWed                  0.0353494  0.0028578  12.369  < 2e-16 ***
holidayDay before      -0.0706873  0.0117617  -6.010 2.55e-09 ***
holidayHoliday         -0.0659071  0.0117681  -5.600 2.72e-08 ***
holidayNormal          -0.0089669  0.0087567  -1.024 0.306071
ns(timeofyear, 9)1      0.0227832  0.0062152   3.666 0.000259 ***
ns(timeofyear, 9)2      0.0112321  0.0078176   1.437 0.151079
ns(timeofyear, 9)3     -0.0383533  0.0072281  -5.306 1.36e-07 ***
ns(timeofyear, 9)4     -0.0148676  0.0073511  -2.023 0.043375 *
ns(timeofyear, 9)5     -0.0191348  0.0071338  -2.682 0.007426 **
ns(timeofyear, 9)6     -0.0628058  0.0070864  -8.863  < 2e-16 ***
ns(timeofyear, 9)7     -0.0651424  0.0057552 -11.319  < 2e-16 ***
ns(timeofyear, 9)8     -0.0975243  0.0120728  -8.078 1.78e-15 ***
ns(timeofyear, 9)9     -0.1050526  0.0056801 -18.495  < 2e-16 ***
ns(temp, df = 2)1       0.1293767  0.0323942   3.994 6.95e-05 ***
ns(temp, df = 2)2       0.2763433  0.0341184   8.100 1.51e-15 ***
ns(prevtemp1, df = 2)1  0.0587174  0.0641520   0.915 0.360250
ns(prevtemp1, df = 2)2 -0.3369363  0.0649626  -5.187 2.57e-07 ***
ns(prevtemp2, df = 2)1 -0.3157099  0.0623937  -5.060 4.94e-07 ***
ns(prevtemp2, df = 2)2 -0.0274226  0.0520095  -0.527 0.598123
ns(prevtemp4, df = 2)1 -0.2113779  0.0502354  -4.208 2.80e-05 ***
ns(prevtemp4, df = 2)2 -0.1312813  0.0378116  -3.472 0.000537 ***
ns(prevtemp6, df = 2)1 -0.1198513  0.0376002  -3.188 0.001477 **
```

```
ns(prevtemp6, df = 2)2  -0.0998328  0.0333760  -2.991 0.002844 **
ns(day1temp, df = 2)1   -0.0332334  0.0124270  -2.674 0.007604 **
ns(day1temp, df = 2)2    0.0160975  0.0129704   1.241 0.214846
ns(day2temp, df = 2)1   -0.0348172  0.0107454  -3.240 0.001232 **
ns(day2temp, df = 2)2   -0.0083018  0.0101221  -0.820 0.412307
ns(day3temp, df = 2)1   -0.0238147  0.0100362  -2.373 0.017828 *
ns(day3temp, df = 2)2   -0.0145504  0.0089100  -1.633 0.102760
ns(day6temp, df = 2)1   -0.0120256  0.0091837  -1.309 0.190666
ns(day6temp, df = 2)2   -0.0008874  0.0074835  -0.119 0.905633
ns(lastmin, 3)1          0.0073381  0.0095628   0.767 0.443037
ns(lastmin, 3)2         -0.0022832  0.0237908  -0.096 0.923561
                          Estimate Std. Error t value Pr(>|t|)

ns(lastmin, 3)3          0.0347021  0.0147302   2.356 0.018662 *
ns(lastmax, 3)1          0.0307898  0.0124193   2.479 0.013323 *
ns(lastmax, 3)2          0.0872133  0.0329852   2.644 0.008314 **
ns(lastmax, 3)3          0.0868217  0.0295337   2.940 0.003356 **
ns(avetemp, 3)1         -0.0632409  0.0125319  -5.046 5.30e-07 ***
ns(avetemp, 3)2         -0.1330487  0.0311622  -4.270 2.13e-05 ***
ns(avetemp, 3)3         -0.1284684  0.0202429  -6.346 3.26e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02524 on 1058 degrees of freedom
Multiple R-squared:  0.9339,  Adjusted R-squared:  0.9311
F-statistic: 332.4 on 45 and 1058 DF,  p-value: < 2.2e-16
```

6.1.2   Belconnen ZSS HH Model

6.1.2.1   Belconnen summer HH model summary (Example: 17:00 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.213721 -0.032244 -0.000626  0.032921  0.284660

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.060494   0.034405  -1.758 0.079022 .
dayMon                  0.012518   0.006645   1.884 0.059919 .
daySat                 -0.246137   0.006599 -37.298  < 2e-16 ***
daySun                 -0.273000   0.006710 -40.688  < 2e-16 ***
dayThu                  0.007626   0.006604   1.155 0.248489
dayTue                  0.011801   0.006583   1.793 0.073345 .
dayWed                  0.009196   0.006614   1.390 0.164732
holidayDay before       0.021433   0.013911   1.541 0.123712
holidayHoliday         -0.197166   0.012691 -15.536  < 2e-16 ***
holidayNormal           0.055671   0.010778   5.165 2.92e-07 ***
ns(timeofyear, 9)1      0.059670   0.013524   4.412 1.14e-05 ***
ns(timeofyear, 9)2      0.092625   0.016852   5.497 4.98e-08 ***
ns(timeofyear, 9)3      0.079386   0.016457   4.824 1.64e-06 ***
ns(timeofyear, 9)4      0.088875   0.016430   5.409 8.01e-08 ***
ns(timeofyear, 9)5      0.070903   0.016071   4.412 1.14e-05 ***
ns(timeofyear, 9)6      0.053089   0.016693   3.180 0.001519 **
ns(timeofyear, 9)7      0.049742   0.012995   3.828 0.000138 ***
ns(timeofyear, 9)8     -0.024401   0.026798  -0.911 0.362773
```

```
ns(timeofyear, 9)9      -0.164889   0.012273 -13.435  < 2e-16 ***
ns(temp, df = 2)1        0.040255   0.091986   0.438 0.661761
ns(temp, df = 2)2       -0.079190   0.045182  -1.753 0.079980 .
ns(prevtemp1, df = 2)1   0.291783   0.087688   3.328 0.000910 ***
ns(prevtemp1, df = 2)2   0.274628   0.055157   4.979 7.59e-07 ***
ns(prevtemp3, df = 2)1   0.069505   0.075716   0.918 0.358863
ns(prevtemp3, df = 2)2   0.232442   0.043398   5.356 1.07e-07 ***
ns(prevtemp6, df = 2)1   0.183000   0.053795   3.402 0.000697 ***
ns(prevtemp6, df = 2)2   0.112144   0.039478   2.841 0.004598 **
ns(day1temp, df = 2)1    0.010058   0.035689   0.282 0.778132
ns(day1temp, df = 2)2    0.021363   0.024387   0.876 0.381250
ns(day5temp, df = 2)1    0.029218   0.022356   1.307 0.191550
ns(day5temp, df = 2)2   -0.026821   0.009746  -2.752 0.006036 **
ns(lastmin, 3)1          0.079060   0.018926   4.177 3.22e-05 ***
ns(lastmin, 3)2          0.138514   0.059469   2.329 0.020059 *
ns(lastmin, 3)3          0.079493   0.041438   1.918 0.055365 .
ns(lastmax, 3)1         -0.005994   0.018999  -0.315 0.752455
ns(lastmax, 3)2         -0.083963   0.046681  -1.799 0.072389 .
ns(lastmax, 3)3         -0.043173   0.036893  -1.170 0.242197
ns(avetemp, 3)1          0.038017   0.031307   1.214 0.224926
ns(avetemp, 3)2         -0.035546   0.079055  -0.450 0.653080
ns(avetemp, 3)3          0.039199   0.048609   0.806 0.420210
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05495 on 950 degrees of freedom
Multiple R-squared:  0.929,    Adjusted R-squared:  0.9261
F-statistic: 318.7 on 39 and 950 DF,  p-value: < 2.2e-16
```

6.1.2.2 Belconnen winter HH model summary (Example: 18:30 PM model)

```
Residuals:
      Min       1Q    Median       3Q       Max
-0.075032 -0.019328 -0.002463  0.016874  0.087194

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          0.499562   0.014644  34.114  < 2e-16 ***
dayMon               0.032039   0.003325   9.637  < 2e-16 ***
daySat              -0.103844   0.003271 -31.744  < 2e-16 ***
daySun              -0.097199   0.003349 -29.026  < 2e-16 ***
dayThu               0.019135   0.003266   5.860 6.35e-09 ***
dayTue               0.024672   0.003320   7.432 2.34e-13 ***
dayWed               0.025939   0.003270   7.931 5.93e-15 ***
holidayDay before   -0.085941   0.011196  -7.676 3.98e-14 ***
holidayHoliday      -0.088220   0.011243  -7.847 1.12e-14 ***
holidayNormal       -0.014263   0.007218  -1.976 0.048426 *
ns(timeofyear, 9)1   0.012520   0.006954   1.800 0.072113 .
ns(timeofyear, 9)2   0.009744   0.008660   1.125 0.260755
ns(timeofyear, 9)3  -0.027863   0.008087  -3.445 0.000595 ***
ns(timeofyear, 9)4   0.014636   0.008188   1.787 0.074177 .
ns(timeofyear, 9)5   0.004427   0.007999   0.553 0.580062
ns(timeofyear, 9)6  -0.025922   0.008006  -3.238 0.001245 **
ns(timeofyear, 9)7  -0.029096   0.006663  -4.367 1.40e-05 ***
ns(timeofyear, 9)8  -0.077163   0.013467  -5.730 1.34e-08 ***
```

```
ns(timeofyear, 9)9      -0.067227   0.006245 -10.765  < 2e-16 ***
ns(temp, df = 2)1        0.012844   0.025240   0.509 0.610960
ns(temp, df = 2)2        0.067181   0.028061   2.394 0.016851 *
ns(prevtemp1, df = 2)1  -0.001773   0.035051  -0.051 0.959662
ns(prevtemp1, df = 2)2   0.011815   0.044232   0.267 0.789435
ns(prevtemp2, df = 2)1  -0.101343   0.036111  -2.806 0.005109 **
ns(prevtemp2, df = 2)2  -0.196634   0.044054  -4.464 9.01e-06 ***
ns(prevtemp4, df = 2)1  -0.179606   0.035869  -5.007 6.56e-07 ***
ns(prevtemp4, df = 2)2  -0.060538   0.033072  -1.830 0.067485 .
ns(prevtemp6, df = 2)1  -0.087012   0.027574  -3.156 0.001651 **
ns(prevtemp6, df = 2)2  -0.067236   0.024439  -2.751 0.006048 **
ns(day1temp, df = 2)1   -0.043055   0.012157  -3.542 0.000417 ***
ns(day1temp, df = 2)2    0.001445   0.011910   0.121 0.903427
ns(day2temp, df = 2)1   -0.044011   0.010277  -4.282 2.03e-05 ***
ns(day2temp, df = 2)2   -0.011226   0.009155  -1.226 0.220435
ns(day5temp, df = 2)1   -0.012193   0.010257  -1.189 0.234859
ns(day5temp, df = 2)2   -0.006764   0.009152  -0.739 0.460055
ns(day6temp, df = 2)1   -0.008512   0.010219  -0.833 0.405097
ns(day6temp, df = 2)2    0.008845   0.008973   0.986 0.324476
ns(avetemp, 3)1         -0.036739   0.005243  -7.008 4.53e-12 ***
ns(avetemp, 3)2         -0.094719   0.015291  -6.194 8.63e-10 ***
ns(avetemp, 3)3         -0.070125   0.010140  -6.916 8.43e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02752 on 972 degrees of freedom
Multiple R-squared:  0.9133,  Adjusted R-squared:  0.9098
F-statistic: 262.5 on 39 and 972 DF,  p-value: < 2.2e-16
```

6.1.3   City East ZSS HH Model

6.1.3.1   City East summer HH model summary (Example: 16:00 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.48113 -0.03717 -0.00003  0.03900  0.47753

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)             -0.0160605  0.0439184  -0.366 0.714686
dayMon                   0.0159482  0.0095670   1.667 0.095879 .
daySat                  -0.3241436  0.0095158 -34.064  < 2e-16 ***
daySun                  -0.3608196  0.0095886 -37.630  < 2e-16 ***
dayThu                   0.0076473  0.0094975   0.805 0.420928
dayTue                   0.0001788  0.0095029   0.019 0.984991
dayWed                   0.0026775  0.0094922   0.282 0.777956
holidayDay before       -0.0072030  0.0198283  -0.363 0.716495
holidayHoliday          -0.2719712  0.0180262 -15.088  < 2e-16 ***
holidayNormal            0.0318061  0.0154104   2.064 0.039323 *
ns(timeofyear, 9)1       0.0740695  0.0193264   3.833 0.000136 ***
ns(timeofyear, 9)2       0.1244593  0.0241333   5.157 3.11e-07 ***
ns(timeofyear, 9)3       0.0913189  0.0238074   3.836 0.000134 ***
ns(timeofyear, 9)4       0.1254618  0.0237280   5.288 1.57e-07 ***
ns(timeofyear, 9)5       0.0944952  0.0231317   4.085 4.82e-05 ***
ns(timeofyear, 9)6       0.1170197  0.0241568   4.844 1.51e-06 ***
```

```
ns(timeofyear, 9)7      0.0271531  0.0187362    1.449 0.147638
ns(timeofyear, 9)8      0.0050358  0.0385858    0.131 0.896195
ns(timeofyear, 9)9     -0.2028399  0.0176038  -11.523  < 2e-16 ***
ns(temp, df = 2)1       0.2294485  0.0746246    3.075 0.002174 **
ns(temp, df = 2)2       0.1847696  0.0500603    3.691 0.000237 ***
ns(prevtemp2, df = 2)1  0.2478218  0.0868919    2.852 0.004448 **
ns(prevtemp2, df = 2)2  0.1272496  0.0593998    2.142 0.032453 *
ns(day1temp, df = 2)1   0.0189979  0.0433789    0.438 0.661530
ns(day1temp, df = 2)2  -0.0101737  0.0349419   -0.291 0.770998
ns(day2temp, df = 2)1   0.0572081  0.0315460    1.813 0.070106 .
ns(day2temp, df = 2)2   0.0155858  0.0193219    0.807 0.420097
ns(day3temp, df = 2)1  -0.0096629  0.0294121   -0.329 0.742587
ns(day3temp, df = 2)2  -0.0057140  0.0170183   -0.336 0.737137
ns(day5temp, df = 2)1   0.0269058  0.0272252    0.988 0.323298
ns(day5temp, df = 2)2  -0.0203215  0.0139126   -1.461 0.144477
ns(lastmin, 3)1         0.0735874  0.0256276    2.871 0.004187 **
ns(lastmin, 3)2         0.0594089  0.0821815    0.723 0.469938
ns(lastmin, 3)3         0.0597722  0.0550547    1.086 0.277922
ns(lastmax, 3)1        -0.0448133  0.0264534   -1.694 0.090618 .
ns(lastmax, 3)2        -0.0279070  0.0668661   -0.417 0.676521
ns(lastmax, 3)3         0.0091478  0.0524572    0.174 0.861603
ns(avetemp, 3)1         0.0878912  0.0397583    2.211 0.027323 *
ns(avetemp, 3)2         0.0644527  0.1051244    0.613 0.539967
ns(avetemp, 3)3         0.1296658  0.0604908    2.144 0.032348 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07508 on 860 degrees of freedom
Multiple R-squared:  0.8866,   Adjusted R-squared:  0.8814
F-statistic: 172.3 on 39 and 860 DF,  p-value: < 2.2e-16
```

6.1.3.2   City East winter HH model summary (Example: 16:00 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.17546 -0.02849 -0.00008  0.02946  0.17672

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         0.372149   0.025772  14.440  < 2e-16 ***
dayMon              0.011931   0.005653   2.111  0.03507 *
daySat             -0.204884   0.005536 -37.012  < 2e-16 ***
daySun             -0.218637   0.005650 -38.695  < 2e-16 ***
dayThu              0.008847   0.005522   1.602  0.10946
dayTue              0.011829   0.005607   2.110  0.03515 *
dayWed              0.010764   0.005528   1.947  0.05180 .
holidayDay before  -0.043429   0.019048  -2.280  0.02283 *
holidayHoliday     -0.144733   0.018961  -7.633 5.45e-14 ***
holidayNormal       0.005703   0.012173   0.469  0.63951
ns(timeofyear, 9)1 -0.001114   0.011435  -0.097  0.92245
ns(timeofyear, 9)2 -0.003085   0.014422  -0.214  0.83065
ns(timeofyear, 9)3 -0.008072   0.013293  -0.607  0.54383
ns(timeofyear, 9)4 -0.014813   0.013720  -1.080  0.28056
ns(timeofyear, 9)5  0.002686   0.013138   0.204  0.83805
ns(timeofyear, 9)6 -0.042882   0.013327  -3.218  0.00134 **
```

```
ns(timeofyear, 9)7       -0.027012   0.011056  -2.443  0.01474 *
ns(timeofyear, 9)8       -0.052601   0.022516  -2.336  0.01969 *
ns(timeofyear, 9)9       -0.053374   0.010393  -5.135 3.40e-07 ***
ns(temp, df = 2)1        -0.042116   0.065154  -0.646  0.51817
ns(temp, df = 2)2        -0.056092   0.055761  -1.006  0.31470
ns(prevtemp1, df = 2)1   -0.162237   0.093425  -1.737  0.08278 .
ns(prevtemp1, df = 2)2   -0.054042   0.066463  -0.813  0.41635
ns(prevtemp2, df = 2)1   -0.141449   0.083700  -1.690  0.09136 .
ns(prevtemp2, df = 2)2   -0.073434   0.061492  -1.194  0.23269
ns(prevtemp4, df = 2)1   -0.096713   0.072501  -1.334  0.18253
ns(prevtemp4, df = 2)2    0.036913   0.044206   0.835  0.40391
ns(prevtemp6, df = 2)1    0.015543   0.049170   0.316  0.75199
ns(prevtemp6, df = 2)2   -0.011925   0.031169  -0.383  0.70210
ns(day1temp, df = 2)1    -0.005426   0.018300  -0.297  0.76689
ns(day1temp, df = 2)2     0.028339   0.015461   1.833  0.06713 .
ns(day2temp, df = 2)1    -0.007113   0.017393  -0.409  0.68266
ns(day2temp, df = 2)2    -0.008051   0.013794  -0.584  0.55961
ns(day6temp, df = 2)1    -0.051736   0.016550  -3.126  0.00182 **
ns(day6temp, df = 2)2    -0.009176   0.011876  -0.773  0.43990
ns(lastmin, 3)1          -0.004256   0.007314  -0.582  0.56079
ns(lastmin, 3)2          -0.042234   0.024992  -1.690  0.09137 .
ns(lastmin, 3)3          -0.022714   0.012047  -1.885  0.05967 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04666 on 974 degrees of freedom
Multiple R-squared:  0.8584,   Adjusted R-squared:  0.853
F-statistic: 159.6 on 37 and 974 DF,  p-value: < 2.2e-16
```

6.1.4   Civic ZSS HH Model

6.1.4.1   Civic summer HH model summary (Example: 16:00 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.23525 -0.03530  0.00051  0.03441  0.32030

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.055280   0.025604  -2.159 0.031124 *
dayMon                  0.024163   0.007079   3.413 0.000672 ***
daySat                 -0.390915   0.007038 -55.541  < 2e-16 ***
daySun                 -0.410451   0.007130 -57.564  < 2e-16 ***
dayThu                  0.020391   0.007017   2.906 0.003753 **
dayTue                  0.030270   0.007030   4.306 1.85e-05 ***
dayWed                  0.024125   0.007058   3.418 0.000660 ***
holidayDay before       0.031157   0.014788   2.107 0.035410 *
holidayHoliday         -0.245253   0.013447 -18.239  < 2e-16 ***
holidayNormal           0.062933   0.011433   5.505 4.87e-08 ***
ns(timeofyear, 9)1      0.113359   0.014278   7.939 6.26e-15 ***
ns(timeofyear, 9)2      0.153934   0.017992   8.556  < 2e-16 ***
ns(timeofyear, 9)3      0.142117   0.017334   8.199 8.69e-16 ***
ns(timeofyear, 9)4      0.174572   0.017507   9.972  < 2e-16 ***
ns(timeofyear, 9)5      0.137037   0.017099   8.014 3.56e-15 ***
ns(timeofyear, 9)6      0.130333   0.017840   7.306 6.24e-13 ***
```

```
ns(timeofyear, 9)7       0.072193   0.013824    5.222 2.21e-07 ***
ns(timeofyear, 9)8       0.029625   0.028595    1.036 0.300490
ns(timeofyear, 9)9      -0.247603   0.013003  -19.042  < 2e-16 ***
ns(temp, df = 2)1        0.207394   0.050662    4.094 4.64e-05 ***
ns(temp, df = 2)2        0.216335   0.034265    6.314 4.34e-10 ***
ns(prevtemp2, df = 2)1   0.047293   0.073048    0.647 0.517525
ns(prevtemp2, df = 2)2   0.028593   0.051202    0.558 0.576692
ns(prevtemp4, df = 2)1   0.183705   0.055211    3.327 0.000914 ***
ns(prevtemp4, df = 2)2   0.105884   0.047521    2.228 0.026125 *
ns(lastmin, 3)1          0.083579   0.015882    5.262 1.79e-07 ***
ns(lastmin, 3)2          0.141234   0.047788    2.955 0.003207 **
ns(lastmin, 3)3          0.082939   0.039090    2.122 0.034140 *
ns(avetemp, 3)1          0.028699   0.022512    1.275 0.202708
ns(avetemp, 3)2         -0.038633   0.060594   -0.638 0.523928
ns(avetemp, 3)3          0.064267   0.036585    1.757 0.079330 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05604 on 869 degrees of freedom
Multiple R-squared:  0.9486,   Adjusted R-squared:  0.9468
F-statistic: 534.5 on 30 and 869 DF,  p-value: < 2.2e-16
```

6.1.4.2 Civic winter HH model summary (Example: 16:00 PM model)

```
Residuals:
    Min       1Q   Median       3Q      Max
-0.08084 -0.01830 -0.00009  0.01680  0.20294

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.3433961  0.0175412  19.577  < 2e-16 ***
dayMon                  0.0163847  0.0035452   4.622 4.32e-06 ***
daySat                 -0.2877278  0.0034644 -83.052  < 2e-16 ***
daySun                 -0.3041702  0.0035503 -85.674  < 2e-16 ***
dayThu                  0.0179195  0.0034707   5.163 2.95e-07 ***
dayTue                  0.0163264  0.0035230   4.634 4.07e-06 ***
dayWed                  0.0184977  0.0034630   5.342 1.15e-07 ***
holidayDay before      -0.0257641  0.0119555  -2.155 0.031409 *
holidayHoliday         -0.2152057  0.0118796 -18.116  < 2e-16 ***
holidayNormal           0.0001023  0.0076498   0.013 0.989332
ns(timeofyear, 9)1      0.0058499  0.0072219   0.810 0.418128
ns(timeofyear, 9)2     -0.0183724  0.0091270  -2.013 0.044393 *
ns(timeofyear, 9)3     -0.0165351  0.0084809  -1.950 0.051503 .
ns(timeofyear, 9)4      0.0071974  0.0086731   0.830 0.406823
ns(timeofyear, 9)5      0.0176700  0.0083957   2.105 0.035579 *
ns(timeofyear, 9)6     -0.0110412  0.0084072  -1.313 0.189393
ns(timeofyear, 9)7     -0.0021811  0.0070234  -0.311 0.756211
ns(timeofyear, 9)8     -0.0210492  0.0142846  -1.474 0.140924
ns(timeofyear, 9)9     -0.0206264  0.0065460  -3.151 0.001677 **
ns(temp, df = 2)1      -0.0648047  0.0410853  -1.577 0.115049
ns(temp, df = 2)2      -0.0778440  0.0351708  -2.213 0.027109 *
ns(prevtemp1, df = 2)1 -0.1017617  0.0585554  -1.738 0.082552 .
ns(prevtemp1, df = 2)2 -0.0445229  0.0417851  -1.066 0.286906
ns(prevtemp2, df = 2)1 -0.1419639  0.0523084  -2.714 0.006766 **
ns(prevtemp2, df = 2)2 -0.0490674  0.0387202  -1.267 0.205378
```

```
ns(prevtemp4, df = 2)1  -0.1100425  0.0461335  -2.385 0.017256 *
ns(prevtemp4, df = 2)2  -0.0186342  0.0281263  -0.663 0.507797
ns(prevtemp6, df = 2)1   0.0710786  0.0334059   2.128 0.033612 *
ns(prevtemp6, df = 2)2   0.0262150  0.0205233   1.277 0.201792
ns(day2temp, df = 2)1   -0.0002907  0.0110847  -0.026 0.979082
ns(day2temp, df = 2)2    0.0085788  0.0093842   0.914 0.360851
ns(day3temp, df = 2)1   -0.0212350  0.0110031  -1.930 0.053911 .
ns(day3temp, df = 2)2   -0.0094220  0.0086470  -1.090 0.276150
ns(day6temp, df = 2)1   -0.0357473  0.0104201  -3.431 0.000628 ***
ns(day6temp, df = 2)2    0.0043159  0.0075352   0.573 0.566935
ns(lastmin, 3)1          0.0307432  0.0105396   2.917 0.003617 **
ns(lastmin, 3)2          0.0918028  0.0287369   3.195 0.001446 **
ns(lastmin, 3)3          0.0664912  0.0182402   3.645 0.000281 ***
ns(lastmax, 3)1          0.0138984  0.0085078   1.634 0.102668
ns(lastmax, 3)2          0.0354137  0.0227714   1.555 0.120230
ns(lastmax, 3)3          0.0675968  0.0207042   3.265 0.001133 **
ns(avetemp, 3)1         -0.0607248  0.0122156  -4.971 7.87e-07 ***
ns(avetemp, 3)2         -0.1416106  0.0300917  -4.706 2.89e-06 ***
ns(avetemp, 3)3         -0.1082466  0.0224463  -4.822 1.65e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02921 on 968 degrees of freedom
Multiple R-squared:  0.964,    Adjusted R-squared:  0.9624
F-statistic: 602.6 on 43 and 968 DF,  p-value: < 2.2e-16
```

6.1.5   East Lake ZSS HH Model

6.1.5.1   East Lake summer HH model summary (Example: 14:00 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.36632 -0.03966 -0.00252  0.04139  0.48920

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)            -1.302e-01  7.885e-02  -1.651  0.10013
dayMon                  5.095e-02  2.068e-02   2.464  0.01445 *
daySat                 -5.031e-01  2.075e-02 -24.243  < 2e-16 ***
daySun                 -6.131e-01  2.100e-02 -29.194  < 2e-16 ***
dayThu                  2.881e-02  2.085e-02   1.382  0.16825
dayTue                  4.598e-02  2.083e-02   2.208  0.02821 *
dayWed                  5.751e-02  2.105e-02   2.732  0.00677 **
holidayDay before      -4.591e-02  4.461e-02  -1.029  0.30443
holidayHoliday         -3.651e-01  3.887e-02  -9.395  < 2e-16 ***
holidayNormal           7.679e-02  3.481e-02   2.206  0.02833 *
ns(timeofyear, 9)1      2.235e-01  4.270e-02   5.235 3.63e-07 ***
ns(timeofyear, 9)2      2.269e-01  5.531e-02   4.103 5.61e-05 ***
ns(timeofyear, 9)3      2.306e-01  5.130e-02   4.496 1.08e-05 ***
ns(timeofyear, 9)4      2.383e-01  5.307e-02   4.492 1.10e-05 ***
ns(timeofyear, 9)5      2.396e-01  5.018e-02   4.774 3.15e-06 ***
ns(timeofyear, 9)6      2.288e-01  5.443e-02   4.203 3.72e-05 ***
ns(timeofyear, 9)7      1.194e-01  4.104e-02   2.911  0.00395 **
ns(timeofyear, 9)8      1.855e-01  8.674e-02   2.138  0.03352 *
ns(timeofyear, 9)9     -2.613e-01  4.073e-02  -6.416 7.50e-10 ***
```

```
ns(temp, df = 2)1          4.219e-01  1.797e-01   2.347  0.01975 *
ns(temp, df = 2)2          1.627e-02  1.299e-01   0.125  0.90047
ns(prevtemp2, df = 2)1     3.737e-01  2.241e-01   1.668  0.09668 .
ns(prevtemp2, df = 2)2     3.084e-01  1.587e-01   1.944  0.05307 .
ns(prevtemp6, df = 2)1    -2.320e-01  1.277e-01  -1.816  0.07057 .
ns(prevtemp6, df = 2)2    -2.778e-02  9.026e-02  -0.308  0.75850
ns(day1temp, df = 2)1      9.349e-02  6.401e-02   1.460  0.14547
ns(day1temp, df = 2)2      1.036e-01  4.887e-02   2.121  0.03499 *
ns(day5temp, df = 2)1      6.420e-02  5.510e-02   1.165  0.24513
ns(day5temp, df = 2)2     -8.535e-02  3.405e-02  -2.507  0.01286 *
ns(lastmin, 3)1           7.010e-02  3.132e-02   2.238  0.02614 *
ns(lastmin, 3)2           1.730e-01  1.069e-01   1.618  0.10690
ns(lastmin, 3)3          -5.337e-05  5.088e-02  -0.001  0.99916
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.08952 on 238 degrees of freedom
Multiple R-squared:  0.9394,  Adjusted R-squared:  0.9315
F-statistic:   119 on 31 and 238 DF,  p-value: < 2.2e-16
```

6.1.5.2 East Lake winter HH model summary (Example: 14:00 PM model)

```
Residuals:
      Min       1Q    Median       3Q       Max
-0.281736 -0.037645  0.001756  0.044238  0.173466

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.67512    0.05114  13.200  < 2e-16 ***
dayMon                  0.05286    0.01335   3.960  9.1e-05 ***
daySat                 -0.51738    0.01315 -39.360  < 2e-16 ***
daySun                 -0.65902    0.01343 -49.067  < 2e-16 ***
dayThu                  0.04174    0.01305   3.198 0.001511 **
dayTue                  0.04686    0.01330   3.523 0.000484 ***
dayWed                  0.04322    0.01316   3.283 0.001130 **
holidayDay before      -0.14019    0.04107  -3.413 0.000718 ***
holidayHoliday         -0.67603    0.04106 -16.464  < 2e-16 ***
holidayNormal          -0.01614    0.02183  -0.739 0.460146
ns(temp, df = 2)1      -0.24440    0.08202  -2.980 0.003088 **
ns(temp, df = 2)2      -0.15171    0.05621  -2.699 0.007298 **
ns(prevtemp3, df = 2)1 -0.16449    0.08442  -1.948 0.052183 .
ns(prevtemp3, df = 2)2 -0.04598    0.05935  -0.775 0.439043
ns(day2temp, df = 2)1   0.02191    0.04538   0.483 0.629428
ns(day2temp, df = 2)2  -0.07432    0.02617  -2.840 0.004776 **
ns(day6temp, df = 2)1  -0.05795    0.04656  -1.245 0.214137
ns(day6temp, df = 2)2  -0.07043    0.02282  -3.086 0.002189 **
ns(avetemp, 3)1        -0.01459    0.01759  -0.829 0.407463
ns(avetemp, 3)2        -0.14646    0.04440  -3.299 0.001072 **
ns(avetemp, 3)3        -0.07437    0.02696  -2.758 0.006116 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0665 on 347 degrees of freedom
Multiple R-squared:  0.9549,  Adjusted R-squared:  0.9523
F-statistic: 367.6 on 20 and 347 DF,  p-value: < 2.2e-16
```

6.1.6　Fyshwick ZSS HH Model

6.1.6.1　Fyshwick summer HH model summary (Example: 14:00 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.30011 -0.04026 -0.00254  0.03562  0.36887
```

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.17299	0.08657	-1.998	0.04684	*
dayMon	0.04922	0.01809	2.721	0.00699	**
daySat	-0.35607	0.01811	-19.660	< 2e-16	***
daySun	-0.39173	0.01822	-21.505	< 2e-16	***
dayThu	0.02432	0.01803	1.349	0.17862	
dayTue	0.03379	0.01796	1.882	0.06112	.
dayWed	0.03611	0.01829	1.975	0.04946	*
holidayDay before	-0.02543	0.03878	-0.656	0.51263	
holidayHoliday	-0.30605	0.03413	-8.967	< 2e-16	***
holidayNormal	0.05014	0.03026	1.657	0.09882	.
ns(timeofyear, 9)1	0.19624	0.03756	5.225	3.82e-07	***
ns(timeofyear, 9)2	0.15581	0.04804	3.243	0.00135	**
ns(timeofyear, 9)3	0.21345	0.04491	4.753	3.48e-06	***
ns(timeofyear, 9)4	0.18746	0.04600	4.075	6.28e-05	***
ns(timeofyear, 9)5	0.21194	0.04436	4.777	3.12e-06	***
ns(timeofyear, 9)6	0.15039	0.04710	3.193	0.00160	**
ns(timeofyear, 9)7	0.08606	0.03582	2.403	0.01704	*
ns(timeofyear, 9)8	0.13295	0.07466	1.781	0.07624	.
ns(timeofyear, 9)9	-0.20533	0.03584	-5.729	3.06e-08	***
ns(prevtemp1, df = 2)1	0.56627	0.06964	8.132	2.40e-14	***
ns(prevtemp1, df = 2)2	0.24471	0.05712	4.284	2.67e-05	***
ns(day3temp, df = 2)1	0.04056	0.05079	0.799	0.42529	
ns(day3temp, df = 2)2	-0.01982	0.03200	-0.619	0.53640	
ns(day5temp, df = 2)1	0.01813	0.04759	0.381	0.70362	
ns(day5temp, df = 2)2	-0.09216	0.03068	-3.004	0.00295	**
ns(lastmin, 3)1	0.11972	0.03948	3.033	0.00270	**
ns(lastmin, 3)2	0.26709	0.11796	2.264	0.02446	*
ns(lastmin, 3)3	0.02577	0.06168	0.418	0.67641	
ns(lastmax, 3)1	0.04393	0.05139	0.855	0.39352	
ns(lastmax, 3)2	0.12017	0.14116	0.851	0.39546	
ns(lastmax, 3)3	-0.03178	0.07253	-0.438	0.66169	
ns(avetemp, 3)1	0.01287	0.05893	0.218	0.82736	
ns(avetemp, 3)2	-0.06484	0.13111	-0.494	0.62141	
ns(avetemp, 3)3	0.11062	0.08923	1.240	0.21628	

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07795 on 236 degrees of freedom
Multiple R-squared:  0.9179,  Adjusted R-squared:  0.9064
F-statistic: 79.91 on 33 and 236 DF,  p-value: < 2.2e-16
```

6.1.6.2   Fyshwick winter HH model summary (Example: 16:00 PM model)

```
Residuals:
      Min       1Q    Median       3Q       Max
-0.158835 -0.034377 -0.001752  0.030448  0.210834

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.551982   0.035912  15.370  < 2e-16 ***
dayMon                  0.040615   0.010519   3.861 0.000134 ***
daySat                 -0.381857   0.010342 -36.922  < 2e-16 ***
daySun                 -0.441597   0.010471 -42.173  < 2e-16 ***
dayThu                  0.016736   0.010240   1.634 0.103076
dayTue                  0.029421   0.010386   2.833 0.004882 **
dayWed                  0.022853   0.010274   2.224 0.026756 *
holidayDay before      -0.044195   0.032231  -1.371 0.171196
holidayHoliday         -0.443327   0.032262 -13.742  < 2e-16 ***
holidayNormal          -0.003885   0.017128  -0.227 0.820693
ns(prevtemp1, df = 2)1 -0.264198   0.037574  -7.031 1.07e-11 ***
ns(prevtemp1, df = 2)2 -0.098578   0.022578  -4.366 1.66e-05 ***
ns(day1temp, df = 2)1  -0.039419   0.036116  -1.091 0.275813
ns(day1temp, df = 2)2  -0.055864   0.021400  -2.611 0.009426 **
ns(day5temp, df = 2)1  -0.064864   0.036670  -1.769 0.077782 .
ns(day5temp, df = 2)2  -0.010765   0.018653  -0.577 0.564242
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05238 on 352 degrees of freedom
Multiple R-squared:  0.9395,   Adjusted R-squared:  0.9369
F-statistic: 364.2 on 15 and 352 DF,  p-value: < 2.2e-16
```

6.1.7   Gilmore ZSS HH Model

6.1.7.1   Gilmore summer HH model summary (Example: 15:30 PM model)

```
Residuals:
     Min       1Q    Median       3Q      Max
-0.40704 -0.05417 -0.00092  0.05007  0.38996

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)          -0.19670    0.04025  -4.887 1.18e-06 ***
dayMon                0.03610    0.01095   3.295 0.001017 **
daySat               -0.09887    0.01089  -9.078  < 2e-16 ***
daySun               -0.09285    0.01100  -8.438  < 2e-16 ***
dayThu                0.02770    0.01087   2.549 0.010952 *
dayTue                0.03102    0.01094   2.835 0.004663 **
dayWed                0.03068    0.01095   2.801 0.005188 **
holidayDay before     0.02355    0.02293   1.027 0.304546
holidayHoliday       -0.08160    0.02093  -3.898 0.000103 ***
holidayNormal         0.02395    0.01780   1.346 0.178726
ns(timeofyear, 9)1    0.10353    0.02204   4.697 2.99e-06 ***
ns(timeofyear, 9)2    0.17930    0.02792   6.423 2.03e-10 ***
ns(timeofyear, 9)3    0.07169    0.02671   2.684 0.007397 **
```

```
ns(timeofyear, 9)4        0.12442    0.02720    4.574 5.35e-06 ***
ns(timeofyear, 9)5        0.09423    0.02647    3.559 0.000389 ***
ns(timeofyear, 9)6        0.09744    0.02758    3.534 0.000428 ***
ns(timeofyear, 9)7        0.06535    0.02128    3.070 0.002193 **
ns(timeofyear, 9)8        0.05177    0.04410    1.174 0.240704
ns(timeofyear, 9)9       -0.14510    0.01993   -7.279 6.57e-13 ***
ns(temp, df = 2)1        -0.16752    0.09123   -1.836 0.066615 .
ns(temp, df = 2)2         0.19892    0.05703    3.488 0.000506 ***
ns(prevtemp2, df = 2)1    0.45896    0.10924    4.202 2.88e-05 ***
ns(prevtemp2, df = 2)2    0.45550    0.07550    6.033 2.23e-09 ***
ns(prevtemp6, df = 2)1    0.41909    0.10337    4.054 5.40e-05 ***
ns(prevtemp6, df = 2)2    0.02447    0.05458    0.448 0.653956
ns(lastmax, 3)1         -0.02252    0.02687   -0.838 0.402173
ns(lastmax, 3)2         -0.19950    0.07606   -2.623 0.008848 **
ns(lastmax, 3)3         -0.20156    0.04112   -4.902 1.10e-06 ***
ns(avetemp, 3)1          0.10907    0.02854    3.821 0.000140 ***
ns(avetemp, 3)2          0.14677    0.07799    1.882 0.060133 .
ns(avetemp, 3)3          0.30651    0.04883    6.278 5.02e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09515 on 1049 degrees of freedom
Multiple R-squared:  0.7967,   Adjusted R-squared:  0.7909
F-statistic:   137 on 30 and 1049 DF,  p-value: < 2.2e-16
```

6.1.7.2   Gilmore winter HH model summary (Example: 17:00 PM model)

```
Residuals:
      Min       1Q    Median       3Q       Max
-0.255951 -0.043652 -0.000336  0.043075  0.313248

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)              0.223693   0.046662    4.794 1.87e-06 ***
dayMon                   0.052163   0.008827    5.910 4.61e-09 ***
daySat                  -0.033211   0.008614   -3.855 0.000123 ***
daySun                   0.005327   0.008815    0.604 0.545752
dayThu                   0.039022   0.008597    4.539 6.29e-06 ***
dayTue                   0.049231   0.008772    5.612 2.55e-08 ***
dayWed                   0.040430   0.008643    4.678 3.27e-06 ***
holidayDay before       -0.076915   0.029796   -2.581 0.009973 **
holidayHoliday          -0.023121   0.029858   -0.774 0.438884
holidayNormal           -0.011099   0.019323   -0.574 0.565815
ns(timeofyear, 9)1       0.042386   0.018076    2.345 0.019218 *
ns(timeofyear, 9)2       0.005330   0.022936    0.232 0.816278
ns(timeofyear, 9)3      -0.005348   0.021139   -0.253 0.800309
ns(timeofyear, 9)4       0.014033   0.021686    0.647 0.517695
ns(timeofyear, 9)5       0.009608   0.020798    0.462 0.644193
ns(timeofyear, 9)6      -0.056916   0.020970   -2.714 0.006753 **
ns(timeofyear, 9)7      -0.010753   0.017122   -0.628 0.530127
ns(timeofyear, 9)8      -0.059610   0.036016   -1.655 0.098201 .
ns(timeofyear, 9)9      -0.067024   0.016532   -4.054 5.40e-05 ***
ns(temp, df = 2)1        0.554486   0.134529    4.122 4.05e-05 ***
ns(temp, df = 2)2        0.104121   0.107398    0.969 0.332526
ns(prevtemp1, df = 2)1  -0.918014   0.159541   -5.754 1.14e-08 ***
```

```
ns(prevtemp1, df = 2)2  -0.282214   0.126385   -2.233 0.025758 *
ns(prevtemp3, df = 2)1  -0.502636   0.137541   -3.654 0.000270 ***
ns(prevtemp3, df = 2)2  -0.391190   0.088432   -4.424 1.07e-05 ***
ns(prevtemp6, df = 2)1   0.164197   0.101056    1.625 0.104499
ns(prevtemp6, df = 2)2   0.064843   0.056607    1.146 0.252258
ns(day3temp, df = 2)1    0.009554   0.029601    0.323 0.746953
ns(day3temp, df = 2)2   -0.037343   0.023293   -1.603 0.109195
ns(day5temp, df = 2)1    0.001752   0.029426    0.060 0.952520
ns(day5temp, df = 2)2   -0.028440   0.022280   -1.276 0.202066
ns(lastmin, 3)1          0.080865   0.026575    3.043 0.002401 **
ns(lastmin, 3)2          0.236673   0.070043    3.379 0.000754 ***
ns(lastmin, 3)3          0.185841   0.039237    4.736 2.47e-06 ***
ns(lastmax, 3)1          0.042195   0.027541    1.532 0.125800
ns(lastmax, 3)2          0.130191   0.073587    1.769 0.077145 .
ns(lastmax, 3)3          0.148457   0.065750    2.258 0.024154 *
ns(avetemp, 3)1         -0.166507   0.033495   -4.971 7.76e-07 ***
ns(avetemp, 3)2         -0.348862   0.088349   -3.949 8.38e-05 ***
ns(avetemp, 3)3         -0.240923   0.054448   -4.425 1.06e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0761 on 1064 degrees of freedom
Multiple R-squared:  0.6695,   Adjusted R-squared:  0.6574
F-statistic: 55.27 on 39 and 1064 DF,  p-value: < 2.2e-16
```

6.1.8 Gold Creek ZSS HH Model

6.1.8.1 Gold Creek summer HH model summary (Example: 18:00 PM model)

```
Residuals:
     Min       1Q    Median       3Q       Max
-0.32166 -0.04889 -0.00014  0.04723  0.34216

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)              0.014673   0.051218    0.286 0.774575
dayMon                   0.055395   0.009194    6.025 2.42e-09 ***
daySat                  -0.029372   0.009138   -3.214 0.001351 **
daySun                   0.026273   0.009330    2.816 0.004965 **
dayThu                   0.031560   0.009170    3.442 0.000604 ***
dayTue                   0.037510   0.009126    4.110 4.29e-05 ***
dayWed                   0.041809   0.009152    4.568 5.56e-06 ***
holidayDay before       -0.029918   0.019216   -1.557 0.119825
holidayHoliday          -0.111160   0.017509   -6.349 3.36e-10 ***
holidayNormal            0.025686   0.014867    1.728 0.084358 .
ns(timeofyear, 9)1       0.072001   0.018780    3.834 0.000134 ***
ns(timeofyear, 9)2       0.117590   0.023351    5.036 5.70e-07 ***
ns(timeofyear, 9)3       0.108187   0.022775    4.750 2.35e-06 ***
ns(timeofyear, 9)4       0.133121   0.022779    5.844 7.00e-09 ***
ns(timeofyear, 9)5       0.052603   0.022257    2.363 0.018307 *
ns(timeofyear, 9)6       0.027597   0.023138    1.193 0.233291
ns(timeofyear, 9)7       0.015467   0.018023    0.858 0.390998
ns(timeofyear, 9)8       0.015383   0.037276    0.413 0.679932
ns(timeofyear, 9)9      -0.136710   0.016998   -8.043 2.61e-15 ***
ns(temp, df = 2)1       -0.132348   0.152469   -0.868 0.385596
```

```
ns(temp, df = 2)2        -0.014823   0.062709   -0.236 0.813186
ns(prevtemp1, df = 2)1    0.120929   0.181448    0.666 0.505275
ns(prevtemp1, df = 2)2    0.103884   0.098045    1.060 0.289613
ns(prevtemp2, df = 2)1    0.164313   0.160333    1.025 0.305708
ns(prevtemp2, df = 2)2    0.252625   0.083597    3.022 0.002579 **
ns(prevtemp4, df = 2)1    0.140085   0.092137    1.520 0.128744
ns(prevtemp4, df = 2)2    0.287952   0.059224    4.862 1.36e-06 ***
ns(prevtemp6, df = 2)1    0.132495   0.082532    1.605 0.108744
ns(prevtemp6, df = 2)2    0.234629   0.057771    4.061 5.28e-05 ***
ns(day1temp, df = 2)1     0.029597   0.051141    0.579 0.562900
ns(day1temp, df = 2)2    -0.101507   0.030984   -3.276 0.001090 **
ns(day5temp, df = 2)1     0.010610   0.033107    0.320 0.748674
ns(day5temp, df = 2)2    -0.053320   0.013468   -3.959 8.09e-05 ***
ns(lastmin, 3)1          0.114933   0.026405    4.353 1.49e-05 ***
ns(lastmin, 3)2          0.155925   0.081367    1.916 0.055625 .
ns(lastmin, 3)3          0.057762   0.049369    1.170 0.242297
ns(lastmax, 3)1          0.064792   0.027631    2.345 0.019239 *
ns(lastmax, 3)2         -0.107532   0.072016   -1.493 0.135723
ns(lastmax, 3)3         -0.038414   0.056310   -0.682 0.495293
ns(avetemp, 3)1          0.064297   0.045207    1.422 0.155275
ns(avetemp, 3)2         -0.087443   0.112226   -0.779 0.436074
ns(avetemp, 3)3          0.151741   0.069817    2.173 0.029996 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07599 on 948 degrees of freedom
Multiple R-squared:  0.8994,  Adjusted R-squared:  0.8951
F-statistic: 206.8 on 41 and 948 DF,  p-value: < 2.2e-16
```

6.1.8.2   Gold Creek winter HH model summary (Example: 17:00 PM model)

6.1.9   Latham ZSS HH Model

6.1.9.1   Latham summer HH model summary (Example: 17:00 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.237833 -0.042385 -0.002103  0.046710  0.306005

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)           -0.0203583  0.0409588   -0.497 0.619263
dayMon                 0.0333880  0.0076890    4.342 1.55e-05 ***
daySat                 0.0019756  0.0076336    0.259 0.795836
daySun                 0.0310501  0.0077654    3.999 6.83e-05 ***
dayThu                 0.0198129  0.0076416    2.593 0.009654 **
dayTue                 0.0261973  0.0076411    3.428 0.000631 ***
dayWed                 0.0225747  0.0076702    2.943 0.003321 **
holidayDay before      0.0067734  0.0160811    0.421 0.673695
holidayHoliday        -0.0483608  0.0147329   -3.283 0.001063 **
holidayNormal          0.0314806  0.0125143    2.516 0.012034 *
ns(timeofyear, 9)1     0.0309190  0.0156154    1.980 0.047965 *
ns(timeofyear, 9)2     0.0736156  0.0196045    3.755 0.000183 ***
ns(timeofyear, 9)3     0.0541293  0.0189507    2.856 0.004371 **
```

```
ns(timeofyear, 9)4         0.0282673  0.0190678   1.482 0.138520
ns(timeofyear, 9)5         0.0267215  0.0185681   1.439 0.150421
ns(timeofyear, 9)6         0.0113065  0.0193865   0.583 0.559874
ns(timeofyear, 9)7         0.0137732  0.0149825   0.919 0.358160
ns(timeofyear, 9)8        -0.0165560  0.0310687  -0.533 0.594229
ns(timeofyear, 9)9        -0.0795267  0.0140914  -5.644 2.15e-08 ***
ns(temp, df = 2)1         -0.2112802  0.1082621  -1.952 0.051259 .
ns(temp, df = 2)2         -0.0344437  0.0517621  -0.665 0.505928
ns(prevtemp1, df = 2)1     0.2198913  0.1194853   1.840 0.066007 .
ns(prevtemp1, df = 2)2     0.1237292  0.0794280   1.558 0.119597
ns(prevtemp2, df = 2)1     0.2770936  0.1098554   2.522 0.011806 *
ns(prevtemp2, df = 2)2     0.3182854  0.0733738   4.338 1.58e-05 ***
ns(prevtemp3, df = 2)1    -0.1546146  0.1078112  -1.434 0.151839
ns(prevtemp3, df = 2)2     0.1130775  0.0603039   1.875 0.061056 .
ns(prevtemp6, df = 2)1     0.3705818  0.0613005   6.045 2.08e-09 ***
ns(prevtemp6, df = 2)2     0.2420200  0.0440202   5.498 4.84e-08 ***
ns(day1temp, df = 2)1      0.0532915  0.0413252   1.290 0.197490
ns(day1temp, df = 2)2      0.0598394  0.0278306   2.150 0.031776 *
ns(day5temp, df = 2)1      0.0242096  0.0276025   0.877 0.380647
ns(day5temp, df = 2)2     -0.0072463  0.0131166  -0.552 0.580759
ns(day6temp, df = 2)1      0.0049442  0.0277106   0.178 0.858425
ns(day6temp, df = 2)2     -0.0424507  0.0130728  -3.247 0.001203 **
ns(lastmin, 3)1           0.1134646  0.0216828   5.233 2.02e-07 ***
ns(lastmin, 3)2           0.1951402  0.0693064   2.816 0.004961 **
ns(lastmin, 3)3           0.0855175  0.0477015   1.793 0.073303 .
ns(lastmax, 3)1           0.0005872  0.0227266   0.026 0.979390
ns(lastmax, 3)2          -0.2657499  0.0582820  -4.560 5.73e-06 ***
ns(lastmax, 3)3          -0.1636899  0.0430230  -3.805 0.000150 ***
ns(avetemp, 3)1           0.0232299  0.0360896   0.644 0.519931
ns(avetemp, 3)2          -0.1146186  0.0923659  -1.241 0.214916
ns(avetemp, 3)3           0.0228708  0.0553272   0.413 0.679419
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06642 on 1036 degrees of freedom
Multiple R-squared:  0.8853,   Adjusted R-squared:  0.8805
F-statistic: 185.9 on 43 and 1036 DF,  p-value: < 2.2e-16
```

6.1.9.2 Latham winter HH model summary (Example: 18:00 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.259072 -0.025517 -0.001336  0.022159  0.254407

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         0.447204   0.020622  21.686  < 2e-16 ***
dayMon              0.054916   0.004662  11.780  < 2e-16 ***
daySat              0.057062   0.004571  12.484  < 2e-16 ***
daySun              0.106541   0.004675  22.791  < 2e-16 ***
dayThu              0.033080   0.004566   7.245 8.25e-13 ***
dayTue              0.044533   0.004649   9.579  < 2e-16 ***
dayWed              0.041517   0.004559   9.106  < 2e-16 ***
holidayDay before  -0.121494   0.015814  -7.683 3.51e-14 ***
holidayHoliday      0.044421   0.015801   2.811 0.005026 **
holidayNormal      -0.035545   0.010259  -3.465 0.000552 ***
```

```
ns(timeofyear, 9)1        0.027145   0.009158    2.964 0.003105 **
ns(timeofyear, 9)2        0.026990   0.011647    2.317 0.020674 *
ns(timeofyear, 9)3       -0.021138   0.010531   -2.007 0.044968 *
ns(timeofyear, 9)4       -0.021450   0.011102   -1.932 0.053614 .
ns(timeofyear, 9)5       -0.022947   0.010584   -2.168 0.030378 *
ns(timeofyear, 9)6       -0.074754   0.010832   -6.901 8.83e-12 ***
ns(timeofyear, 9)7       -0.093765   0.009019  -10.396  < 2e-16 ***
ns(timeofyear, 9)8       -0.137712   0.018353   -7.504 1.30e-13 ***
ns(timeofyear, 9)9       -0.138235   0.008749  -15.801  < 2e-16 ***
ns(temp, df = 2)1         0.141365   0.033782    4.185 3.09e-05 ***
ns(temp, df = 2)2         0.266513   0.041504    6.421 2.03e-10 ***
ns(prevtemp1, df = 2)1   -0.115149   0.051906   -2.218 0.026736 *
ns(prevtemp1, df = 2)2   -0.397185   0.061852   -6.422 2.03e-10 ***
ns(prevtemp3, df = 2)1   -0.404586   0.048624   -8.321 2.65e-16 ***
ns(prevtemp3, df = 2)2   -0.180113   0.041672   -4.322 1.69e-05 ***
ns(prevtemp6, df = 2)1   -0.200238   0.043140   -4.642 3.89e-06 ***
ns(prevtemp6, df = 2)2   -0.180765   0.038316   -4.718 2.70e-06 ***
ns(lastmin, 3)1           0.027468   0.013923    1.973 0.048774 *
ns(lastmin, 3)2           0.097999   0.037685    2.600 0.009438 **
ns(lastmin, 3)3           0.105435   0.024074    4.380 1.31e-05 ***
ns(lastmax, 3)1           0.028096   0.016531    1.700 0.089502 .
ns(lastmax, 3)2           0.044171   0.043162    1.023 0.306366
ns(lastmax, 3)3           0.077997   0.037342    2.089 0.036970 *
ns(avetemp, 3)1          -0.108060   0.016590   -6.514 1.13e-10 ***
ns(avetemp, 3)2          -0.228411   0.043138   -5.295 1.45e-07 ***
ns(avetemp, 3)3          -0.200955   0.029264   -6.867 1.11e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04033 on 1068 degrees of freedom
Multiple R-squared:  0.894,    Adjusted R-squared:  0.8905
F-statistic: 257.4 on 35 and 1068 DF,  p-value: < 2.2e-16
```

6.1.10 Telopea Park ZSS HH Model

6.1.10.1 Telopea Park summer HH model summary (Example: 15:00 PM model)

```
Residuals:
    Min       1Q   Median       3Q      Max
-0.17549 -0.03306 -0.00151  0.03078  0.33499

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)         -0.033418   0.042412   -0.788 0.431102
dayMon               0.017672   0.009149    1.932 0.053967 .
daySat              -0.369200   0.009085  -40.639  < 2e-16 ***
daySun              -0.377784   0.009164  -41.225  < 2e-16 ***
dayThu               0.009511   0.009025    1.054 0.292437
dayTue               0.017409   0.009076    1.918 0.055666 .
dayWed               0.013629   0.009164    1.487 0.137547
holidayDay before    0.033021   0.019353    1.706 0.088575 .
holidayHoliday      -0.213041   0.017346  -12.282  < 2e-16 ***
holidayNormal        0.060255   0.014996    4.018 6.76e-05 ***
ns(timeofyear, 9)1   0.132160   0.018734    7.054 5.71e-12 ***
ns(timeofyear, 9)2   0.102463   0.023535    4.354 1.62e-05 ***
```

```
ns(timeofyear, 9)3       0.164093   0.022325    7.350 7.98e-13 ***
ns(timeofyear, 9)4       0.123026   0.022783    5.400 1.03e-07 ***
ns(timeofyear, 9)5       0.139053   0.022127    6.284 7.10e-10 ***
ns(timeofyear, 9)6       0.097117   0.023583    4.118 4.46e-05 ***
ns(timeofyear, 9)7       0.072458   0.017844    4.061 5.67e-05 ***
ns(timeofyear, 9)8      -0.007498   0.037226   -0.201 0.840444
ns(timeofyear, 9)9      -0.244121   0.016843  -14.494  < 2e-16 ***
ns(temp, df = 2)1        0.059566   0.080761    0.738 0.461125
ns(temp, df = 2)2        0.127441   0.052684    2.419 0.015916 *
ns(prevtemp2, df = 2)1   0.291861   0.088069    3.314 0.000986 ***
ns(prevtemp2, df = 2)2   0.146280   0.069131    2.116 0.034832 *
ns(prevtemp6, df = 2)1   0.054002   0.089702    0.602 0.547434
ns(prevtemp6, df = 2)2   0.029033   0.046136    0.629 0.529440
ns(day6temp, df = 2)1   -0.045455   0.031854   -1.427 0.154195
ns(day6temp, df = 2)2   -0.028640   0.012763   -2.244 0.025268 *
ns(lastmin, 3)1          0.081501   0.020469    3.982 7.84e-05 ***
ns(lastmin, 3)2          0.162858   0.064009    2.544 0.011245 *
ns(lastmin, 3)3          0.085654   0.031626    2.708 0.006992 **
ns(avetemp, 3)1          0.033644   0.026366    1.276 0.202536
ns(avetemp, 3)2          0.008864   0.069524    0.127 0.898600
ns(avetemp, 3)3          0.103378   0.041842    2.471 0.013813 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05564 on 507 degrees of freedom
Multiple R-squared:  0.9427,   Adjusted R-squared:  0.9391
F-statistic: 260.6 on 32 and 507 DF,  p-value: < 2.2e-16
```

6.1.10.2 Telopea Park winter HH model summary (Example: 15:00 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.16811 -0.03005 -0.00442  0.02672  0.20839

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)            0.366565   0.028850  12.706  < 2e-16 ***
dayMon                 0.015449   0.008283   1.865  0.06283 .
daySat                -0.263296   0.008091 -32.542  < 2e-16 ***
daySun                -0.261115   0.008273 -31.563  < 2e-16 ***
dayThu                 0.012220   0.008051   1.518  0.12976
dayTue                 0.015846   0.008164   1.941  0.05291 .
dayWed                 0.011393   0.008071   1.412  0.15879
holidayDay before     -0.047727   0.025790  -1.851  0.06490 .
holidayHoliday        -0.207486   0.025832  -8.032  8.9e-15 ***
holidayNormal          0.011158   0.014315   0.779  0.43614
ns(temp, df = 2)1     -0.049309   0.095485  -0.516  0.60583
ns(temp, df = 2)2     -0.142784   0.055465  -2.574  0.01037 *
ns(prevtemp1, df = 2)1 -0.335652   0.112131  -2.993  0.00291 **
ns(prevtemp1, df = 2)2 -0.026027   0.063150  -0.412  0.68043
ns(prevtemp6, df = 2)1 -0.075209   0.038189  -1.969  0.04953 *
ns(prevtemp6, df = 2)2 -0.020241   0.029145  -0.695  0.48773
ns(day2temp, df = 2)1   0.003084   0.026833   0.115  0.90854
ns(day2temp, df = 2)2  -0.017159   0.015127  -1.134  0.25729
ns(avetemp, 3)1        -0.033388   0.011777  -2.835  0.00479 **
ns(avetemp, 3)2        -0.048021   0.031803  -1.510  0.13177
```

```
ns(avetemp, 3)3          -0.004695   0.019850  -0.237  0.81315
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04583 on 439 degrees of freedom
Multiple R-squared:  0.9006,   Adjusted R-squared:  0.8961
F-statistic: 198.9 on 20 and 439 DF,  p-value: < 2.2e-16
```

6.1.11 Theodore ZSS HH Model

6.1.11.1 Theodore summer HH model summary (Example: 17:00 PM model)

```
Residuals:
     Min        1Q   Median       3Q       Max
-0.57145 -0.04612 -0.00109  0.04834  0.22073

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              -0.054681   0.050648  -1.080 0.280585
dayMon                    0.049785   0.009070   5.489 5.19e-08 ***
daySat                    0.056988   0.009019   6.318 4.06e-10 ***
daySun                    0.114405   0.009119  12.545  < 2e-16 ***
dayThu                    0.019740   0.008988   2.196 0.028326 *
dayTue                    0.029523   0.009006   3.278 0.001083 **
dayWed                    0.036486   0.009020   4.045 5.66e-05 ***
holidayDay before         0.010341   0.018908   0.547 0.584551
holidayHoliday           -0.022132   0.017208  -1.286 0.198706
holidayNormal             0.016326   0.014629   1.116 0.264691
ns(timeofyear, 9)1        0.022066   0.018584   1.187 0.235381
ns(timeofyear, 9)2        0.061083   0.022986   2.657 0.008007 **
ns(timeofyear, 9)3        0.055695   0.022688   2.455 0.014274 *
ns(timeofyear, 9)4        0.019125   0.022501   0.850 0.395556
ns(timeofyear, 9)5        0.001467   0.022014   0.067 0.946885
ns(timeofyear, 9)6       -0.015176   0.022946  -0.661 0.508528
ns(timeofyear, 9)7        0.005473   0.017790   0.308 0.758424
ns(timeofyear, 9)8       -0.001214   0.036685  -0.033 0.973608
ns(timeofyear, 9)9       -0.077128   0.016776  -4.598 4.85e-06 ***
ns(temp, df = 2)1        -0.272586   0.132079  -2.064 0.039309 *
ns(temp, df = 2)2        -0.067441   0.068337  -0.987 0.323951
ns(prevtemp1, df = 2)1    0.078251   0.143768   0.544 0.586372
ns(prevtemp1, df = 2)2    0.260396   0.108229   2.406 0.016320 *
ns(prevtemp2, df = 2)1    0.386618   0.125369   3.084 0.002103 **
ns(prevtemp2, df = 2)2    0.372567   0.093217   3.997 6.92e-05 ***
ns(prevtemp4, df = 2)1    0.044433   0.115321   0.385 0.700107
ns(prevtemp4, df = 2)2    0.194261   0.073567   2.641 0.008412 **
ns(prevtemp6, df = 2)1    0.289136   0.094477   3.060 0.002273 **
ns(prevtemp6, df = 2)2    0.201204   0.059688   3.371 0.000780 ***
ns(day1temp, df = 2)1    -0.026817   0.052085  -0.515 0.606759
ns(day1temp, df = 2)2    -0.051368   0.035679  -1.440 0.150277
ns(day5temp, df = 2)1     0.045417   0.035376   1.284 0.199516
ns(day5temp, df = 2)2    -0.005440   0.016278  -0.334 0.738327
ns(day6temp, df = 2)1    -0.014824   0.035235  -0.421 0.674054
ns(day6temp, df = 2)2    -0.040118   0.016327  -2.457 0.014184 *
ns(lastmin, 3)1           0.076835   0.022489   3.417 0.000661 ***
ns(lastmin, 3)2           0.209798   0.069214   3.031 0.002502 **
```

```
ns(lastmin, 3)3          0.117888   0.038465    3.065 0.002240 **
ns(lastmax, 3)1          0.044729   0.025907    1.727 0.084583 .
ns(lastmax, 3)2         -0.209373   0.063411   -3.302 0.000996 ***
ns(lastmax, 3)3         -0.151015   0.053206   -2.838 0.004632 **
ns(avetemp, 3)1          0.125014   0.039327    3.179 0.001527 **
ns(avetemp, 3)2          0.046043   0.100579    0.458 0.647213
ns(avetemp, 3)3          0.130809   0.062815    2.082 0.037571 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07489 on 946 degrees of freedom
Multiple R-squared:  0.9053,   Adjusted R-squared:  0.901
F-statistic: 210.4 on 43 and 946 DF,  p-value: < 2.2e-16
```

6.1.11.2 Theodore winter HH model summary (Example: 18:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.47136 -0.02075  0.00648  0.02946  0.10714

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.523943   0.027128  19.314  < 2e-16 ***
dayMon                  0.106703   0.006078  17.556  < 2e-16 ***
daySat                  0.064336   0.005956  10.802  < 2e-16 ***
daySun                  0.142011   0.006052  23.463  < 2e-16 ***
dayThu                  0.059589   0.005936  10.039  < 2e-16 ***
dayTue                  0.085159   0.006063  14.045  < 2e-16 ***
dayWed                  0.076240   0.005927  12.864  < 2e-16 ***
holidayDay before      -0.126529   0.020447  -6.188 8.66e-10 ***
holidayHoliday          0.037911   0.020516   1.848 0.064891 .
holidayNormal          -0.024205   0.013293  -1.821 0.068908 .
ns(timeofyear, 9)1      0.033368   0.011954   2.791 0.005343 **
ns(timeofyear, 9)2      0.042155   0.015232   2.767 0.005747 **
ns(timeofyear, 9)3     -0.022826   0.013642  -1.673 0.094582 .
ns(timeofyear, 9)4      0.020554   0.014448   1.423 0.155148
ns(timeofyear, 9)5     -0.002868   0.013774  -0.208 0.835115
ns(timeofyear, 9)6     -0.043423   0.014027  -3.096 0.002014 **
ns(timeofyear, 9)7     -0.072988   0.011632  -6.275 5.08e-10 ***
ns(timeofyear, 9)8     -0.118604   0.023831  -4.977 7.53e-07 ***
ns(timeofyear, 9)9     -0.145047   0.011424 -12.696  < 2e-16 ***
ns(temp, df = 2)1       0.019697   0.087091   0.226 0.821119
ns(temp, df = 2)2       0.085491   0.063794   1.340 0.180489
ns(prevtemp1, df = 2)1  0.035756   0.112181   0.319 0.749993
ns(prevtemp1, df = 2)2 -0.004178   0.084269  -0.050 0.960467
ns(prevtemp3, df = 2)1 -0.270934   0.072352  -3.745 0.000190 ***
ns(prevtemp3, df = 2)2 -0.234722   0.056854  -4.129 3.94e-05 ***
ns(prevtemp6, df = 2)1 -0.239336   0.063343  -3.778 0.000167 ***
ns(prevtemp6, df = 2)2 -0.219317   0.041694  -5.260 1.74e-07 ***
ns(day1temp, df = 2)1  -0.023842   0.028928  -0.824 0.410020
ns(day1temp, df = 2)2   0.010413   0.020105   0.518 0.604609
ns(lastmin, 3)1         0.035935   0.018904   1.901 0.057582 .
ns(lastmin, 3)2         0.040125   0.046948   0.855 0.392929
ns(lastmin, 3)3         0.068501   0.026185   2.616 0.009022 **
ns(avetemp, 3)1        -0.105338   0.025464  -4.137 3.80e-05 ***
ns(avetemp, 3)2        -0.191937   0.063983  -3.000 0.002764 **
```

```
ns(avetemp, 3)3          -0.174068   0.037175  -4.682 3.20e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05239 on 1069 degrees of freedom
Multiple R-squared:  0.8208,   Adjusted R-squared:  0.8151
F-statistic:   144 on 34 and 1069 DF,  p-value: < 2.2e-16
```

6.1.12 Wanniassa ZSS HH Model

6.1.12.1 Wanniassa summer HH model summary (Example: 17:00 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.17822 -0.03388  0.00189  0.03471  0.17215

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)           -0.056429   0.033842  -1.667 0.095755 .
dayMon                 0.021648   0.006179   3.504 0.000480 ***
daySat                -0.120610   0.006145 -19.627  < 2e-16 ***
daySun                -0.130335   0.006212 -20.982  < 2e-16 ***
dayThu                 0.013576   0.006118   2.219 0.026711 *
dayTue                 0.018646   0.006134   3.040 0.002431 **
dayWed                 0.016584   0.006145   2.699 0.007081 **
holidayDay before     -0.002063   0.012874  -0.160 0.872707
holidayHoliday        -0.142451   0.011709 -12.166  < 2e-16 ***
holidayNormal          0.027574   0.009961   2.768 0.005747 **
ns(timeofyear, 9)1     0.042541   0.012586   3.380 0.000755 ***
ns(timeofyear, 9)2     0.082916   0.015646   5.300 1.44e-07 ***
ns(timeofyear, 9)3     0.076838   0.015380   4.996 6.96e-07 ***
ns(timeofyear, 9)4     0.061141   0.015331   3.988 7.17e-05 ***
ns(timeofyear, 9)5     0.054991   0.014998   3.667 0.000259 ***
ns(timeofyear, 9)6     0.047565   0.015633   3.043 0.002411 **
ns(timeofyear, 9)7     0.042279   0.012114   3.490 0.000505 ***
ns(timeofyear, 9)8     0.005635   0.024986   0.226 0.821633
ns(timeofyear, 9)9    -0.113398   0.011426  -9.924  < 2e-16 ***
ns(temp, df = 2)1     -0.065793   0.089822  -0.732 0.464054
ns(temp, df = 2)2     -0.039443   0.046546  -0.847 0.396977
ns(prevtemp1, df = 2)1 0.112744   0.097894   1.152 0.249738
ns(prevtemp1, df = 2)2 0.119210   0.073722   1.617 0.106207
ns(prevtemp2, df = 2)1 0.236135   0.085264   2.769 0.005725 **
ns(prevtemp2, df = 2)2 0.383202   0.063499   6.035 2.28e-09 ***
ns(prevtemp4, df = 2)1 0.117875   0.078510   1.501 0.133586
ns(prevtemp4, df = 2)2 0.122393   0.050065   2.445 0.014679 *
ns(prevtemp6, df = 2)1 0.161794   0.064328   2.515 0.012063 *
ns(prevtemp6, df = 2)2 0.103094   0.040621   2.538 0.011310 *
ns(day1temp, df = 2)1 -0.007354   0.035481  -0.207 0.835847
ns(day1temp, df = 2)2 -0.009840   0.024303  -0.405 0.685655
ns(day5temp, df = 2)1  0.030987   0.022618   1.370 0.171014
ns(day5temp, df = 2)2 -0.024929   0.009152  -2.724 0.006568 **
ns(lastmin, 3)1        0.079479   0.015310   5.191 2.56e-07 ***
ns(lastmin, 3)2        0.168446   0.047090   3.577 0.000365 ***
ns(lastmin, 3)3        0.062912   0.026160   2.405 0.016367 *
ns(lastmax, 3)1        0.009081   0.017650   0.514 0.607036
```

```
ns(lastmax, 3)2          -0.109520   0.043193  -2.536 0.011384 *
ns(lastmax, 3)3          -0.095038   0.036247  -2.622 0.008883 **
ns(avetemp, 3)1           0.070344   0.026788   2.626 0.008781 **
ns(avetemp, 3)2          -0.038853   0.068494  -0.567 0.570676
ns(avetemp, 3)3           0.117474   0.042778   2.746 0.006144 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05103 on 948 degrees of freedom
Multiple R-squared:  0.93,    Adjusted R-squared:  0.927
F-statistic: 307.2 on 41 and 948 DF,  p-value: < 2.2e-16
```

6.1.12.2 Wanniassa winter HH model summary (Example: 18:00 PM model)

```
Residuals:
     Min        1Q    Median        3Q       Max
-0.189813 -0.021952 -0.000532  0.020263  0.145529

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.5067904  0.0214474  23.629  < 2e-16 ***
dayMon                    0.0428444  0.0039100  10.958  < 2e-16 ***
daySat                   -0.0201190  0.0038251  -5.260 1.74e-07 ***
daySun                   -0.0005811  0.0039237  -0.148 0.882290
dayThu                    0.0284758  0.0038131   7.468 1.70e-13 ***
dayTue                    0.0349882  0.0038893   8.996  < 2e-16 ***
dayWed                    0.0326867  0.0038285   8.538  < 2e-16 ***
holidayDay before        -0.0941194  0.0131904  -7.135 1.78e-12 ***
holidayHoliday           -0.0323084  0.0132160  -2.445 0.014662 *
holidayNormal            -0.0277859  0.0085621  -3.245 0.001210 **
ns(timeofyear, 9)1        0.0297427  0.0078121   3.807 0.000149 ***
ns(timeofyear, 9)2        0.0327322  0.0099660   3.284 0.001055 **
ns(timeofyear, 9)3       -0.0394442  0.0090011  -4.382 1.29e-05 ***
ns(timeofyear, 9)4       -0.0107377  0.0093856  -1.144 0.252856
ns(timeofyear, 9)5       -0.0209287  0.0090336  -2.317 0.020707 *
ns(timeofyear, 9)6       -0.0768053  0.0090955  -8.444  < 2e-16 ***
ns(timeofyear, 9)7       -0.0859487  0.0075390 -11.400  < 2e-16 ***
ns(timeofyear, 9)8       -0.1133945  0.0155427  -7.296 5.81e-13 ***
ns(timeofyear, 9)9       -0.1398402  0.0075011 -18.643  < 2e-16 ***
ns(temp, df = 2)1         0.1348894  0.0533599   2.528 0.011618 *
ns(temp, df = 2)2         0.2706032  0.0392559   6.893 9.33e-12 ***
ns(prevtemp1, df = 2)1    0.0625660  0.0878221   0.712 0.476363
ns(prevtemp1, df = 2)2   -0.2941676  0.0700334  -4.200 2.89e-05 ***
ns(prevtemp2, df = 2)1   -0.3406658  0.0773862  -4.402 1.18e-05 ***
ns(prevtemp2, df = 2)2   -0.0994173  0.0587066  -1.693 0.090661 .
ns(prevtemp4, df = 2)1   -0.2610493  0.0570951  -4.572 5.39e-06 ***
ns(prevtemp4, df = 2)2   -0.1234581  0.0434990  -2.838 0.004623 **
ns(prevtemp6, df = 2)1   -0.1621550  0.0459384  -3.530 0.000434 ***
ns(prevtemp6, df = 2)2   -0.1584471  0.0377157  -4.201 2.88e-05 ***
ns(day1temp, df = 2)1    -0.0345544  0.0181285  -1.906 0.056910 .
ns(day1temp, df = 2)2     0.0189228  0.0158698   1.192 0.233380
ns(day2temp, df = 2)1    -0.0675445  0.0154658  -4.367 1.38e-05 ***
ns(day2temp, df = 2)2    -0.0155684  0.0113627  -1.370 0.170935
ns(lastmin, 3)1           0.0289740  0.0123717   2.342 0.019367 *
ns(lastmin, 3)2           0.0453352  0.0314168   1.443 0.149309
ns(lastmin, 3)3           0.0778277  0.0175583   4.433 1.03e-05 ***
```

```
ns(lastmax, 3)1           0.0567017  0.0173320    3.271 0.001104 **
ns(lastmax, 3)2           0.1153715  0.0474939    2.429 0.015298 *
ns(lastmax, 3)3           0.0847160  0.0383559    2.209 0.027410 *
ns(avetemp, 3)1          -0.1096066  0.0164227   -6.674 4.00e-11 ***
ns(avetemp, 3)2          -0.2191755  0.0423466   -5.176 2.71e-07 ***
ns(avetemp, 3)3          -0.2066570  0.0246833   -8.372  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03369 on 1062 degrees of freedom
Multiple R-squared:  0.9074,   Adjusted R-squared:  0.9038
F-statistic: 253.8 on 41 and 1062 DF,  p-value: < 2.2e-16
```

6.1.13 Woden ZSS HH Model

6.1.13.1 Woden summer HH model summary (Example: 16:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.220960 -0.035468  0.002798  0.035722  0.212089

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)              0.058193   0.048956    1.189 0.234867
dayMon                   0.023178   0.006680    3.470 0.000544 ***
daySat                  -0.199180   0.006666  -29.880  < 2e-16 ***
daySun                  -0.229056   0.006747  -33.947  < 2e-16 ***
dayThu                   0.016838   0.006663    2.527 0.011662 *
dayTue                   0.025096   0.006667    3.764 0.000178 ***
dayWed                   0.021204   0.006675    3.177 0.001538 **
holidayDay before        0.029915   0.014008    2.136 0.032972 *
holidayHoliday          -0.142837   0.012815  -11.146  < 2e-16 ***
holidayNormal            0.052844   0.010845    4.872 1.29e-06 ***
ns(timeofyear, 9)1       0.075474   0.013528    5.579 3.15e-08 ***
ns(timeofyear, 9)2       0.092397   0.016969    5.445 6.61e-08 ***
ns(timeofyear, 9)3       0.101699   0.016497    6.165 1.04e-09 ***
ns(timeofyear, 9)4       0.067251   0.016578    4.057 5.39e-05 ***
ns(timeofyear, 9)5       0.074276   0.016135    4.603 4.73e-06 ***
ns(timeofyear, 9)6       0.068140   0.016857    4.042 5.73e-05 ***
ns(timeofyear, 9)7       0.052291   0.013148    3.977 7.51e-05 ***
ns(timeofyear, 9)8       0.028645   0.026998    1.061 0.288963
ns(timeofyear, 9)9      -0.154771   0.012308  -12.575  < 2e-16 ***
ns(temp, df = 2)1        0.182368   0.057266    3.185 0.001497 **
ns(temp, df = 2)2        0.168766   0.045154    3.738 0.000197 ***
ns(dtemp, 3)1           -0.029529   0.016428   -1.797 0.072579 .
ns(dtemp, 3)2           -0.008665   0.054314   -0.160 0.873278
ns(dtemp, 3)3            0.083659   0.033313    2.511 0.012194 *
ns(prevtemp2, df = 2)1   0.145457   0.101809    1.429 0.153413
ns(prevtemp2, df = 2)2   0.205929   0.061776    3.333 0.000891 ***
ns(prevtemp4, df = 2)1   0.145893   0.089187    1.636 0.102212
ns(prevtemp4, df = 2)2   0.176936   0.061951    2.856 0.004383 **
ns(prevtemp6, df = 2)1   0.044196   0.064387    0.686 0.492616
ns(prevtemp6, df = 2)2  -0.058884   0.053986   -1.091 0.275674
ns(day1temp, df = 2)1    0.003366   0.028074    0.120 0.904598
ns(day1temp, df = 2)2    0.035505   0.026398    1.345 0.178955
```

```
ns(prevdtemp2, 3)1        0.013698   0.017497    0.783 0.433868
ns(prevdtemp2, 3)2       -0.088296   0.064369   -1.372 0.170477
ns(prevdtemp2, 3)3       -0.007304   0.034392   -0.212 0.831852
ns(day1dtemp, 3)1        -0.015699   0.014513   -1.082 0.279645
ns(day1dtemp, 3)2         0.024197   0.051832    0.467 0.640729
ns(day1dtemp, 3)3         0.085954   0.031510    2.728 0.006493 **
ns(lastmax, 3)1          -0.060307   0.018758   -3.215 0.001348 **
ns(lastmax, 3)2          -0.193164   0.045714   -4.225 2.62e-05 ***
ns(lastmax, 3)3          -0.126674   0.038405   -3.298 0.001009 **
ns(avetemp, 3)1           0.162277   0.018049    8.991  < 2e-16 ***
ns(avetemp, 3)2           0.186033   0.049543    3.755 0.000184 ***
ns(avetemp, 3)3           0.205311   0.031128    6.596 7.03e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05533 on 946 degrees of freedom
Multiple R-squared:  0.9203,   Adjusted R-squared:  0.9167
F-statistic: 254.1 on 43 and 946 DF,  p-value: < 2.2e-16
```

6.1.13.2 Woden winter HH model summary (Example: 18:00 PM model)

```
Residuals:
      Min       1Q   Median       3Q      Max
-0.088734 -0.021376 -0.001126  0.017545  0.227598

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.373926   0.026696  14.007  < 2e-16 ***
dayMon                    0.039282   0.004938   7.956 7.22e-15 ***
daySat                   -0.082304   0.004817 -17.087  < 2e-16 ***
daySun                   -0.074055   0.004969 -14.902  < 2e-16 ***
dayThu                    0.024737   0.004824   5.128 3.80e-07 ***
dayTue                    0.031104   0.004876   6.379 3.24e-10 ***
dayWed                    0.027994   0.004806   5.825 8.73e-09 ***
holidayDay before        -0.092977   0.016402  -5.669 2.11e-08 ***
holidayHoliday           -0.076083   0.016232  -4.687 3.33e-06 ***
holidayNormal            -0.036175   0.009947  -3.637 0.000297 ***
ns(timeofyear, 9)1        0.022437   0.009636   2.329 0.020170 *
ns(timeofyear, 9)2        0.022083   0.012645   1.746 0.081175 .
ns(timeofyear, 9)3       -0.033640   0.011086  -3.035 0.002499 **
ns(timeofyear, 9)4       -0.015112   0.011691  -1.293 0.196581
ns(timeofyear, 9)5       -0.009880   0.011244  -0.879 0.379876
ns(timeofyear, 9)6       -0.078473   0.011388  -6.891 1.24e-11 ***
ns(timeofyear, 9)7       -0.033036   0.009584  -3.447 0.000601 ***
ns(timeofyear, 9)8       -0.102097   0.019313  -5.287 1.67e-07 ***
ns(timeofyear, 9)9       -0.118537   0.009092 -13.037  < 2e-16 ***
ns(temp, df = 2)1         0.130523   0.045550   2.866 0.004289 **
ns(temp, df = 2)2         0.145498   0.034428   4.226 2.69e-05 ***
ns(prevtemp1, df = 2)1   -0.131526   0.057926  -2.271 0.023475 *
ns(prevtemp1, df = 2)2   -0.169885   0.045851  -3.705 0.000228 ***
ns(prevtemp4, df = 2)1   -0.254497   0.053433  -4.763 2.32e-06 ***
ns(prevtemp4, df = 2)2   -0.124656   0.047792  -2.608 0.009294 **
ns(prevtemp6, df = 2)1   -0.082625   0.052528  -1.573 0.116176
ns(prevtemp6, df = 2)2   -0.070052   0.047579  -1.472 0.141380
ns(prevdtemp6, 3)1       -0.014743   0.009191  -1.604 0.109167
ns(prevdtemp6, 3)2        0.038733   0.037784   1.025 0.305668
```

```
ns(prevdtemp6, 3)3     0.013519   0.014473    0.934 0.350574
ns(lastmin, 3)1        0.032410   0.014875    2.179 0.029675 *
ns(lastmin, 3)2        0.070417   0.039155    1.798 0.072545 .
ns(lastmin, 3)3        0.090164   0.024147    3.734 0.000204 ***
ns(lastmax, 3)1        0.013350   0.016975    0.786 0.431894
ns(lastmax, 3)2        0.023382   0.045251    0.517 0.605519
ns(lastmax, 3)3        0.023922   0.042804    0.559 0.576433
ns(avetemp, 3)1       -0.088800   0.016825   -5.278 1.75e-07 ***
ns(avetemp, 3)2       -0.208176   0.042069   -4.948 9.39e-07 ***
ns(avetemp, 3)3       -0.185777   0.030089   -6.174 1.13e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03462 on 697 degrees of freedom
Multiple R-squared:  0.8805,   Adjusted R-squared:  0.874
F-statistic: 135.1 on 38 and 697 DF,  p-value: < 2.2e-16
```

6.2 Data sources of seasonal average demand input variables

The explanatory variables used in the modelling, along with their sources of historical/forecast data, are listed in the table below.

Key Driver	Frequency	Source of historical information	Source of future forecast
Temperature	Half-hourly	Purchased from BOM*	Double seasonal bootstrap simulation
CDDs/HDDs	Seasonal**	BOM	Double seasonal bootstrap simulation and 90th, 50th, 10th percentile of its simulation result
Electricity Price***	Quarterly	Jacobs	Jacobs
Gross State Product (GSP)	Annual	ABS 5220.0 Table 1 - Released	Jacobs Forecast
State Final Demand (SFD)	Quarterly	ABS 5206.0 Table 33 – Released	Jacobs Forecast
Consumer Price Index (CPI)	Monthly	ABS 6401.0 Table 5 – Released	Jacobs Forecast
Population	Quarterly	ABS 3101.0 Table 4 – Released	ACT government forecast
Employment	Monthly	ABS 6202.0 Table 11 – Released	Jacobs Forecast
Wage Price Index (WPI)	Monthly	ABS 6345.0 Table 2 – Released	Jacobs Forecast
Energy Efficiency	Quarterly	Jacobs	Jacobs Forecast

* Bureau of Meteorology

** Seasonal: half-yearly, quarterly, monthly, or every 4 month. It can be customised by MEFM user.

*** It includes average price, usage charge and supply charge. Average price is calculated based on average annual energy consumption of 7,000 kWh per household.

6.3 Block Loads Data

All block data were sourced from internal Project Justification Reports and ACT Government 2017/18-2020/21 Indicative Land Release Program as at 30th September 2017.

Table 6.3: Block load data by zone substation

Zone Substation	Project Name	Load Type	Data Centre*	Probability**	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23	2023-24	2024-25	2025-26	2026-27
Belconnen	B8,9 S48 - Supply to Mixed Development	Mix Use	No	Yes	0.5									
	B1 S3 - Supply to Student Accommodation [UC]	Residential	No	Yes	0.7									
	B34,37 S52 - Supply to Mixed Development	Mix Use	No	Yes	1.5									
	Lawson Stg FY17/18	Residential	No	No	1.5									
	B1 S1 - Supply to Calvary Hospital	Commercial	No	No		1.4								
	B1 S3 - Supply to UC Hospital	Commercial	No	No		1.4								
	Lawson Stg FY18/19	Residential	No	No		1.5								
	B2 S200 - High Rise Complex	Residential	No	Yes			2.2	6.3						
	Supply upgrade to Metronode Data Centre	Industrial	Yes	No	0.1	2.0	0.7	0.7	0.3	0.6	0.4	0.6	0.3	0.3
City East	B7 S18 – 92 Northbourne Ave, mixed-use development	Mix Use	No	Yes	0.8	0.5								
	B13 S7 – Lowanna St, mixed-use development	Mix Use	No	Yes	0.7									
	Canberra Metro TPS4	Industrial	No	Yes		2.6								
	B3 S33 – Challis St, mixed-use development	Mix Use	No	Yes			0.5	0.5						
	B2 S33 – Northbourne Ave / Challis St, Mix use	Mix Use	No	Yes			1.0	1.0	0.7					
	20000972 - B21 S30 - Mixed Development	Mix Use	No	Yes		0.5	0.5	0.5						
City East/Civic	B21, S 63 – London Circuit, commercial development	Commercial	No	Yes	0.5	0.5	1.0	1.5	1.5	1.5				
	B4 S19 – London Circuit, commercial development	Commercial	No	Yes	0.5	0.5	1.0							
	B3 S12 - 20 Allara St, Apartment	Residential	No	Yes	0.5	0.5	0.5							

Zone Substation	Project Name	Load Type	Data Centre*	Probability**	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23	2023-24	2024-25	2025-26	2026-27
	B3 S3 – 33 London Circuit, mixed-use development	Mix Use	No	Yes	0.8									
	B27 S26 - 69 Northbourne Ave, Mix use	Mix Use	No	Yes	0.4	0.4	0.4							
	S96 - Canberra Centre extension	Commercial	No	Yes		1.0	1.0	2.0	2.5	1.8				
Civic/Molonglo	Whitlam new estate	Residential	No	No			1.3	1.5	1.3	1.3	1.0	0.8	0.5	0.3
East Lake	CDC Fyshwick 1 load forecast	Industrial	Yes	Yes	1.0	1.0	1.0	1.0			0.5			
	CDC Fyshwick 2 load forecast	Industrial	Yes	Yes	0.4	2.0	4.1	0.5	0.5	0.5	0.5	0.5		
	Brindabella Business Park	Commercial	No	Yes	1.0	1.0	1.0	1.6						
	Fairbairn Macquarie Telecom Data Centre	Industrial	Yes	Yes	0.4	0.6	0.5	0.3						
	Majura Defence Facility	Commercial	No	Yes	0.8									
	Pialligo Horticulture Expansion	Commercial	No	Yes	1.0									
Telopea Park/East Lake	Kingston Foreshore Development, Causeway	Residential	No	Yes	1.0	2.0	2.0	2.0	2.0	2.0				
	Kingston Arts Centre Precinct	Commercial	No	Yes			0.5	0.5	0.5					
Gilmore	20003535 - B11 S21 Recycling & fuel extraction plant	Commercial	No	Yes	1.5									
	20004191 - B4&5 S 29 Supply to commercial site	Commercial	No	Yes	0.6									
	20004081 - B4 S8 Supply to Commercial development	Commercial	No	Yes	0.2									
	20002704 - B7 S29 Supply to Warehouse	Commercial	No	Yes	0.2									
	20001257 - B31 S3 Canberra Data Centre Upgrade	Industrial	Yes	Yes	0.5									
	20001161 - B18 S3 Canberra Data Centre	Industrial	Yes	Yes	2.5	1.5								
	Miscellaneous small projects	Commercial	No	Yes	0.1									
	New West Industry Park	Industrial	No	Yes	0.3	0.9	0.6	0.6	0.3	0.3	0.3	0.3	0.3	0.3
Gold Creek	Gungahlin Town Centre Apartment	Residential	No	No			0.2	0.6	0.4	0.5				
	Moncrieff New Estate	Residential	No	No	0.3	0.3		0.1						
	Taylor New Estate	Residential	No	No	1.2	1.2	1.5	0.6	2.3					
	Jacka New Estate	Residential	No	No				1.5						

EVO Energy Peak Demand Forecast for period: 2018-2027   **EVO Energy**

Zone Substation	Project Name	Load Type	Data Centre*	Probability**	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23	2023-24	2024-25	2025-26	2026-27
	Throsby New Estate	Residential	No	No	1.2	0.1	0.2	0.2						
	Kenny New Estate	Residential	No	No					0.6	0.9	0.9	0.9	0.9	0.9
	Amaroo New Estate	Residential	No	No	0.0									
	Total Mix Use	Mix Use	No	Yes		0.7	0.8	0.8	0.9					
	Total Commercial Use	Commercial	No	Yes		2		4	2					
	Capital Metro TPS 1 (Kate Crace)	Industrial	No	No		3								
	Australian Data Centre	Industrial	Yes	Yes	0.6	0.6	0.6	0.6	0.6					
Latham/Strathnairn	Strathnairn New Estate	Residential	No	No	0.9	0.9	0.9	0.9	1.0	0.9	0.9	0.9	0.9	0.9
	Total Mix Use	Mix Use	No	Yes					0.2					
	Total Commercial Use	Commercial	No	Yes					0.2					
	School	Community	No	No					0.6					
Telopea Park	B50 S19, Eyre St, Kingston	Residential	No	Yes				2.5						
	Stuart Flats, Light St / Stuart St, Griffith	Residential	No	Yes				1.5						
	B13 S13, Canberra Ave, Forrest.	Residential	No	Yes					0.5					
	Red Hill Village, Discovery St, Red Hill	Residential	No	Yes		0.8								
	Gowrie Court Flats, B3 S62, McIntyre St, Narrabundah	Residential	No	Yes					0.4					
Wanniassa	B1, S78 - Anketell St / Oakden St, Apartment	Residential	No	Yes			0.4	0.4						
	B1 S74 – Anketell St / Limburg Way, Apartment	Residential	No	Yes	0.3									
	B1 S79 – Cynthia Teague Cres – Apartment	Residential	No	Yes			1.0	0.2						
	B5 S13 – Athllon Dr, townhouse development	Residential	No	Yes	0.4	0.4								
	Residential Use - PJR Supply to Erindale Group Centre	Residential	No	Yes						0.2	0.2	0.2		
	Mixed Use - PJR Supply to Erindale Group Centre	Mix Use	No	Yes							0.5	0.5		
	B4 S57 – Anketell St / Limburg Way, mixed-use	Mix Use	No	Yes		1.0								
	B1 S76 – Anketell St / Oakden St mixed-use	Mix Use	No	Yes	0.5	0.6								

Zone Substation	Project Name	Load Type	Data Centre*	Probability**	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23	2023-24	2024-25	2025-26	2026-27
	B2 S14 – Athllon Dr, office building	Commercial	No	Yes		1.0	1.0	0.9						
	Shopping Centre Extension	Commercial	No	Yes				0.3	0.5					
	Retail Use (4,000 m2/yr)	Commercial	No	Yes						0.4	0.4	0.4		
Woden/Molonglo	Coombs New Estate	Residential	No	No	0.6	0.5	0.8	0.5	0.3					
	Wright New Estate	Residential	No	No		0.9	0.6							
	Denman Prospect Estate	Residential	No	Yes	0.3	1.0	1.0	1.0	1.0	0.8	0.8	0.8	0.8	0.6
	Lyons New Estate	Residential	No	No				1.1						
	Phillip	Residential	No	No				1.2	0.3					
	Mawson	Residential	No	No				0.2	0.2					
	Total Mix Use	Mix Use	No	Yes	0.7	1.3	1.0	0.9	0.8					
	Total Commercial Use	Commercial	No	Yes	0.3		0.3		1.5					
	School	Community	No	No			0.3							
	Community Use	Community	No	Yes			0.2							

* All data centre block load are discounted by 50% before probability adjustment except Metronode data centre, who is exempt from both adjustments.

**The following categories are exempt from probability adjustment:

1) New estate from ILRP;

2) Government found school and hospital;

6.4 Other Important Information

6.4.1 Distribution Loss Factors

ActewAGL engages GHD Hill Michael annually to calculate and prepare the report of ActewAGL distribution loss factors (DLFs) to comply with the AER's regulatory requirement . The DLF methodology can be found at ActewAGL's website:

http://www.actewagl.com.au/~/media/ActewAGL/ActewAGL-Files/About-us/Publications/ACT-Distribution-loss-factor-methodology.ashx?la=en

And the ActewAGL DLF for each network level can be found publicly at AEMO's website:

https://www.aemo.com.au/-/media/Files/Electricity/NEM/Security_and_Reliability/Loss_Factors_and_Regional_Boundaries/2017/DLF_V1_2017_2018.pdf

6.4.2 Diversity Factors

Diversity Factors are calculated based on the load on the Zone Substation at the time of system peak demand as a percentage of the Zone Substation peak demand.

6.4.2.1 Summer Diversity Factor per Zone Substation

Zone	2016	2017	Average
Belconnen	98%	100%	99%
City East	97%	98%	98%
Civic	98%	97%	98%
East Lake	92%	73%	83%
Fyshwick	91%	71%	81%
Gilmore	92%	64%	78%
Gold Creek	84%	92%	88%
Latham	83%	91%	87%
Telopea Park	99%	96%	98%
Theodore	48%	88%	68%
Wanniassa	93%	99%	96%
Woden	99%	100%	100%

6.4.2.2   Winter Diversity Factor per Zone Substation

Zone	2016	2017	Average
Belconnen	100%	100%	100%
City East	98%	96%	97%
Civic	85%	94%	90%
East Lake	55%	55%	55%
Fyshwick	63%	53%	58%
Gilmore	92%	95%	94%
Gold Creek	97%	99%	98%
Latham	92%	100%	96%
Telopea Park	93%	93%	93%
Theodore	98%	87%	93%
Wanniassa	100%	100%	100%
Woden	98%	100%	99%

6.5 Reference

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