Appendix 3.1: Peak demand forecast PJR

Revised regulatory proposal for the ACT electricity distribution network 2019–24

November 2018

evoenergy

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Evoenergy

Peak Demand Forecast for period: 2019 – 2028

Version: 2.0

28 November 2018

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1 Introduction

This report provides the Evoenergy peak demand forecast for the period 2019-2028. The forecast includes both a total system forecast and individual Zone Substation forecast.

The report covers the following areas:

- Details of 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 connection point 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 growth, consumer price index, 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.

Figures 2.3.1 and 2.3.2 illustrate the comparison between the top-down forecast and the bottom-up 50% POE forecast for both summer and winter.

Table 2.3.1 shows the average discrepancy between top-down and bottom-up 50% POE forecasts for summer and winter are between 1% and 5%, which is considered as an acceptable range for the purpose of forecast reconciliation. However, the aggregate zone substation summer forecast indicates an upward trend whereas the system summer forecast predicts a downward trend. This is potentially caused by energy efficiency adjustments not being applied to Latham and Woden zone substations to avoid double accounting, because Energy efficiency is one of the independent variables in their average demand models.

Table 2.3.1: Average discrepancy between Top-Down and Bottom-Up forecasts

Year	Summer POE 50	Winter POE 50
2019	1%	5%
2020	-2%	4%
2021	-3%	3%
2022	-4%	1%
2023	-5%	1%
2024	-5%	0%
2025	-7%	0%
2026	-7%	-2%
2027	-7%	-1%
2028	-9%	-2%
Average	**-5%**	**1%**

Figure 2.3.1: Summer Maximum Demand Forecast

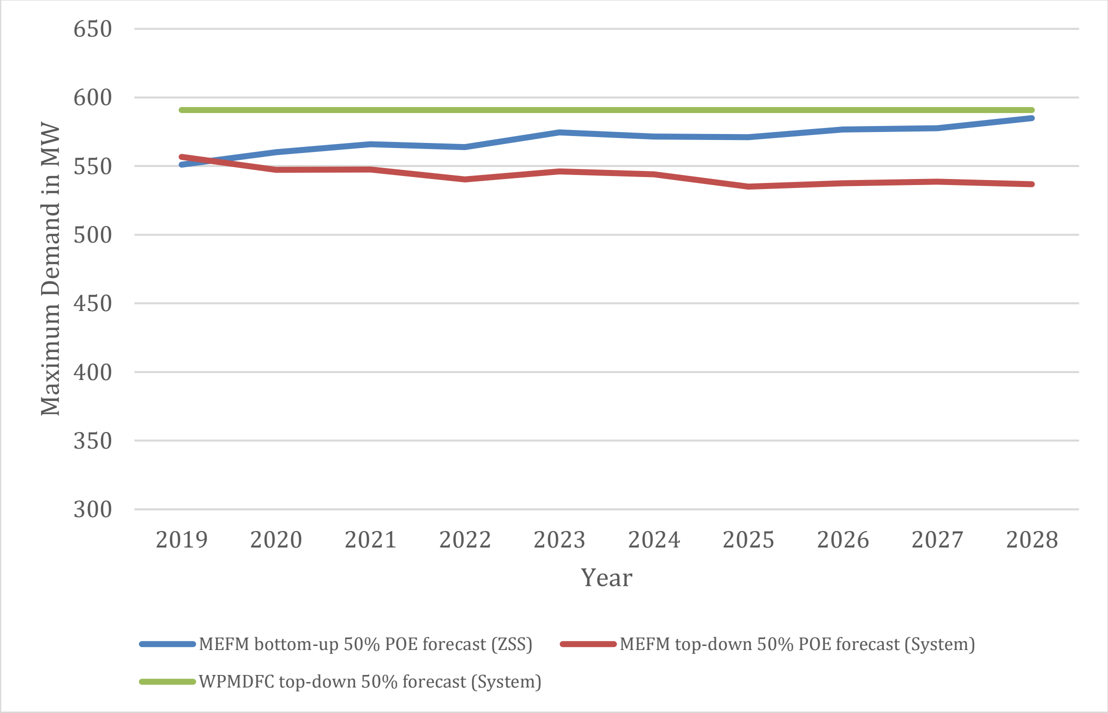
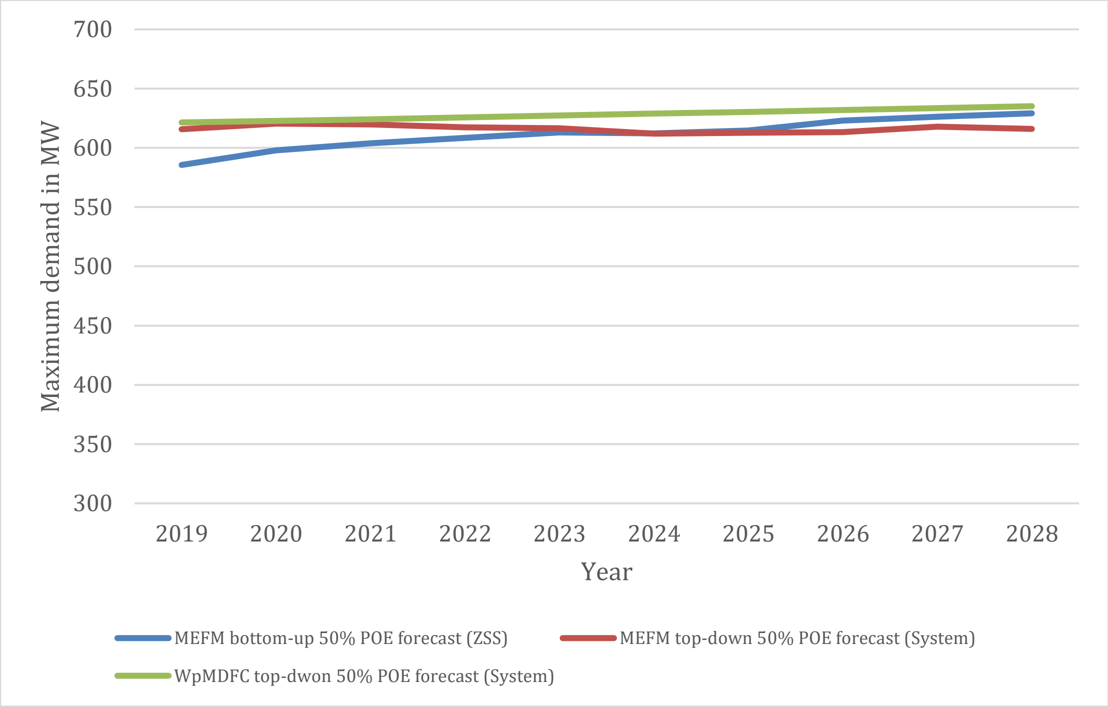


Figure 2.3.2: Winter Maximum Demand Forecast



3 Modelling/Forecasting Accuracy

At 1st September each year, Evoenergy examines and evaluates the previous year's forecast by comparing with the actual measured maximum demand. Tables 3.1 and 3.2 illustrate the accuracy of 2017 MEFM forecasts at both System and zone substation (ZSS) level. The majority of ZSS actual figures were between the 90% POE and 10% POE forecasted figures. City East summer and Gilmore summer and winter forecasts were inaccurate, due to the over-forecast of additional block loads applied to these two ZSS. Actuals maximum demands were just outside the 90% POE forecast.

Table 3.1: 2018 MEFM summer forecast results evaluation

Zone	Year	POE90	POE50	POE10	Actual	Performance
System	2018	526	587	649	565	Good
Belconnen	2018	51	58	65	54	Good
City East	2018	67	75	86	66	**Bad**
Civic	2018	51	57	65	55	Good
East Lake	2018	16	20	24	19	Good
Fyshwick	2018	24	29	33	28	Good
Gilmore	2018	26	34	42	26	**Bad**
Gold Creek	2018	48	60	73	62	Good
Latham	2018	44	52	59	52	Good
Telopea Park	2018	77	86	94	83	Good
Theodore	2018	19	24	30	24	Good
Wanniassa	2018	55	63	72	59	Good
Woden	2018	67	76	86	79	Good

Table 3.2: 2018 MEFM winter forecast results evaluation

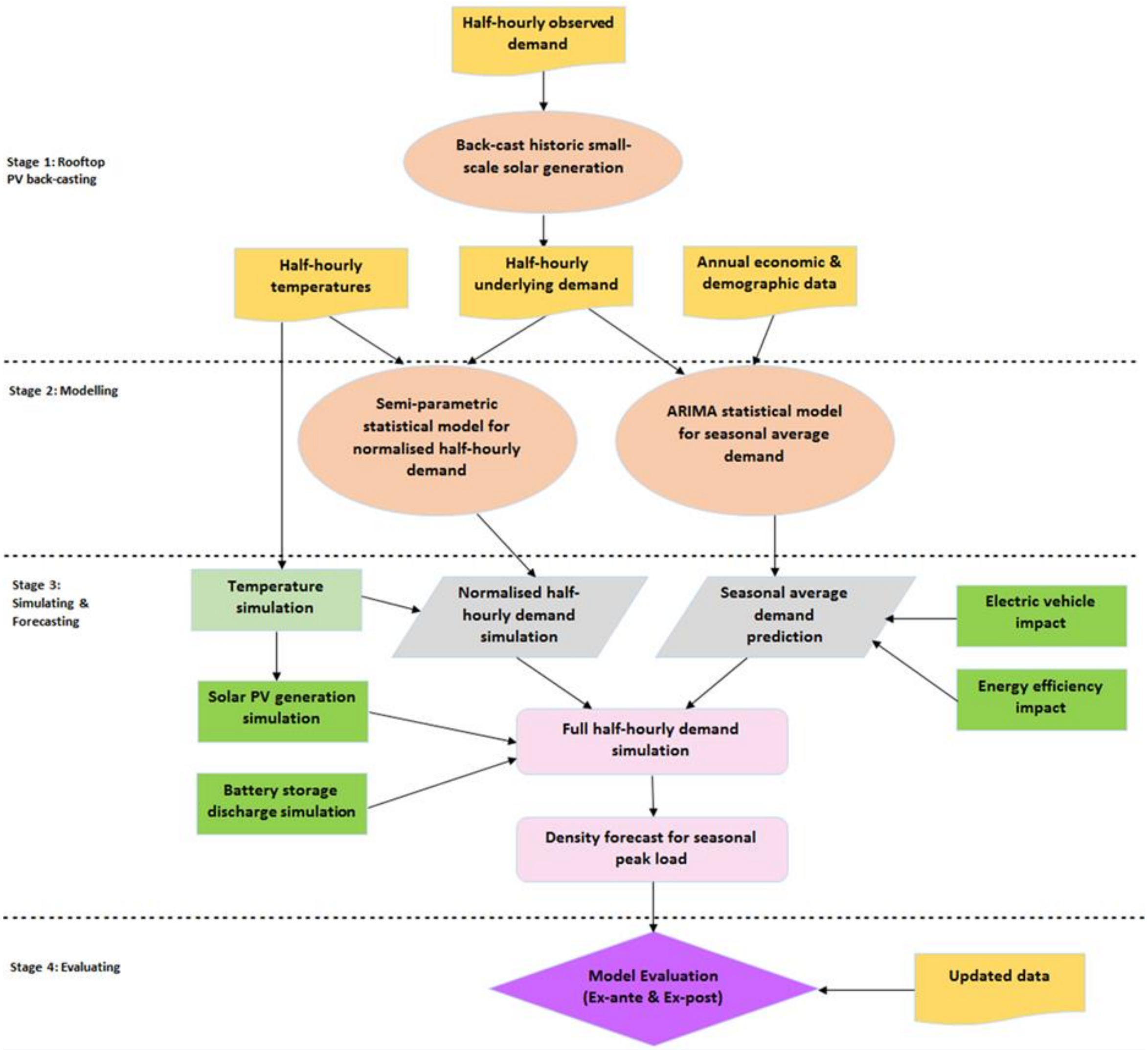
Zone	Year	POE90	POE50	POE10	Actual	Performance
System	2018	596	627	665	623	Good
Belconnen	2018	56	60	64	57	Good
City East	2018	63	68	74	67	Good
Civic	2018	45	49	54	51	Good
East Lake	2018	16	20	24	18	Good
Fyshwick	2018	19	23	27	24	Good
Gilmore	2018	30	35	41	30	**Bad**
Gold Creek	2018	60	68	76	71	Good
Latham	2018	63	68	73	67	Good
Telopea Park	2018	80	84	89	85	Good
Theodore	2018	26	29	33	28	Good
Wanniassa	2018	72	77	83	73	Good
Woden	2018	72	78	84	83	Good

4 Forecasting Methodology: Integrated MEFM

4.1 Overview of Current Approach

Evoenergy has adopted and implemented AEMO's maximum demand forecast methodology which uses the Monash Electricity Forecasting Model (MEFM), This 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

[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/

Figure 4.1.1 provides an overview 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 storage discharge 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 conditions;**
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 Evoenergy, and occurs ‘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. Evoenergy (and other DNSPs) also collects information on PV systems as part of connection agreements.

[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 has been developed in two stages (see Figure 4.2.1) as follows:

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 model. Solar output is modelled as a non-linear function of temperature. In addition, separate statistical models have been 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, two adjustments were made 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 dataset 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

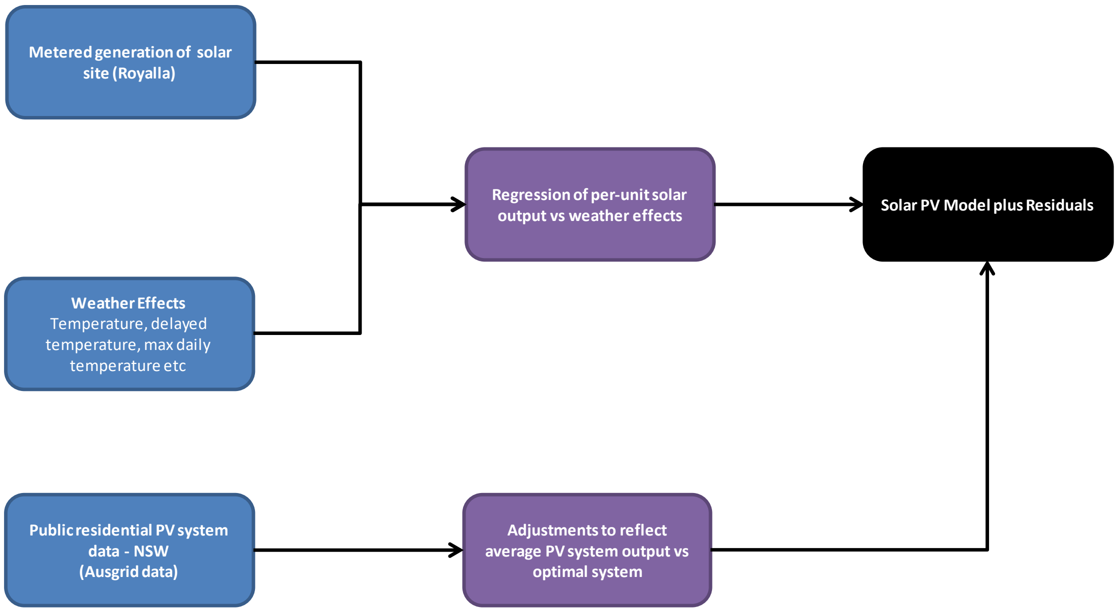


Figure *4.2.2*The average system output during peak solar production generally ranges from 60% to 80% of optimally sited systems, depending on the time of the day and the season. We applied these ratios to the forecast output of the solar model, which is based on an optimally orientated system.

We also applied an adjustment to reflect the smoothing effect on system output of multiple, geographically diverse generating systems. 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:

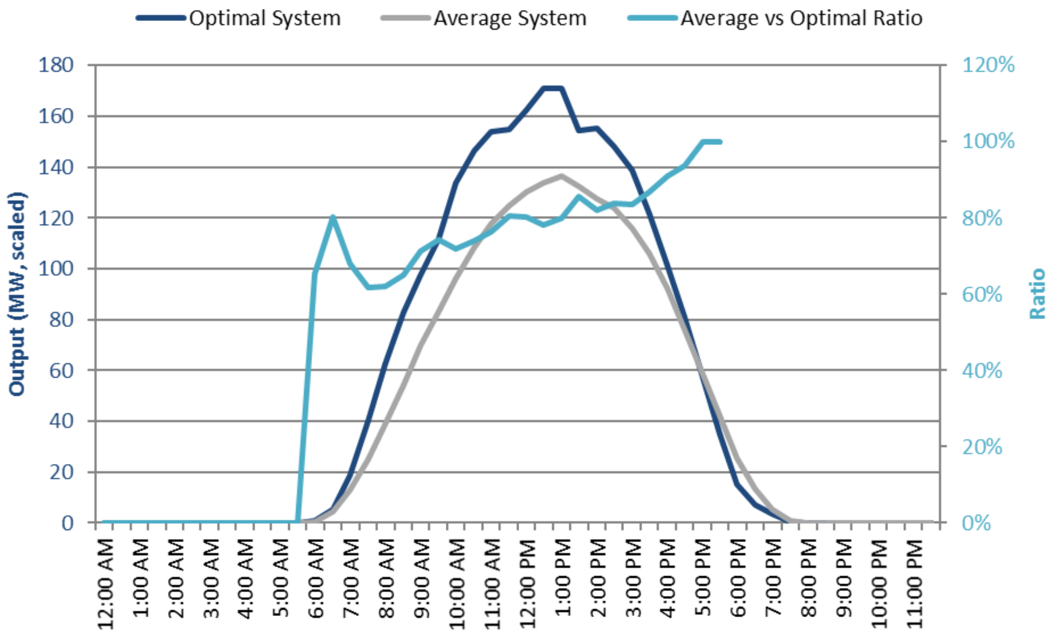
$$P_i^* = \frac{P_{i-1} + P_i + P_{i+1}}{3}$$

Where:

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

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

Figure 4.2.2: 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.

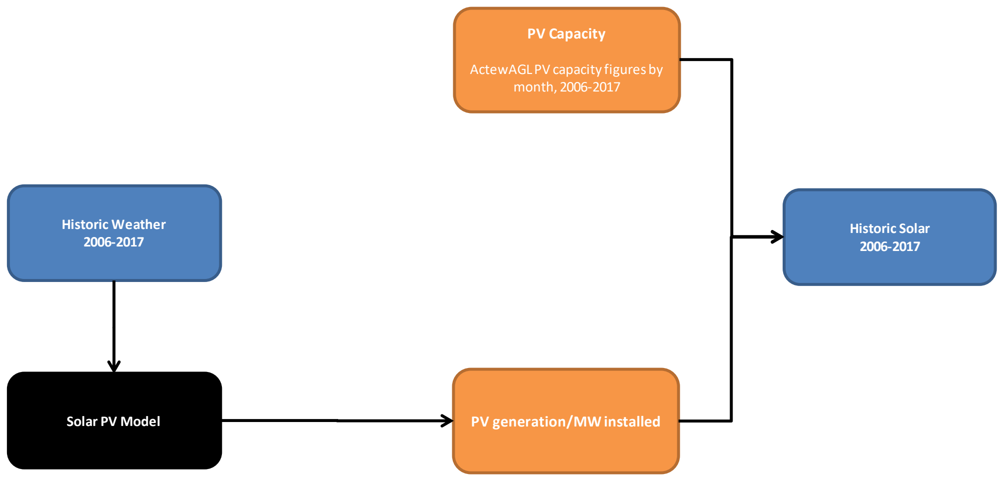
This process is illustrated in Figure 4.2.3.

Evoenergy's historic PV installed capacity by month was used to develop the back-cast. The data 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 verify 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 4.2.3: 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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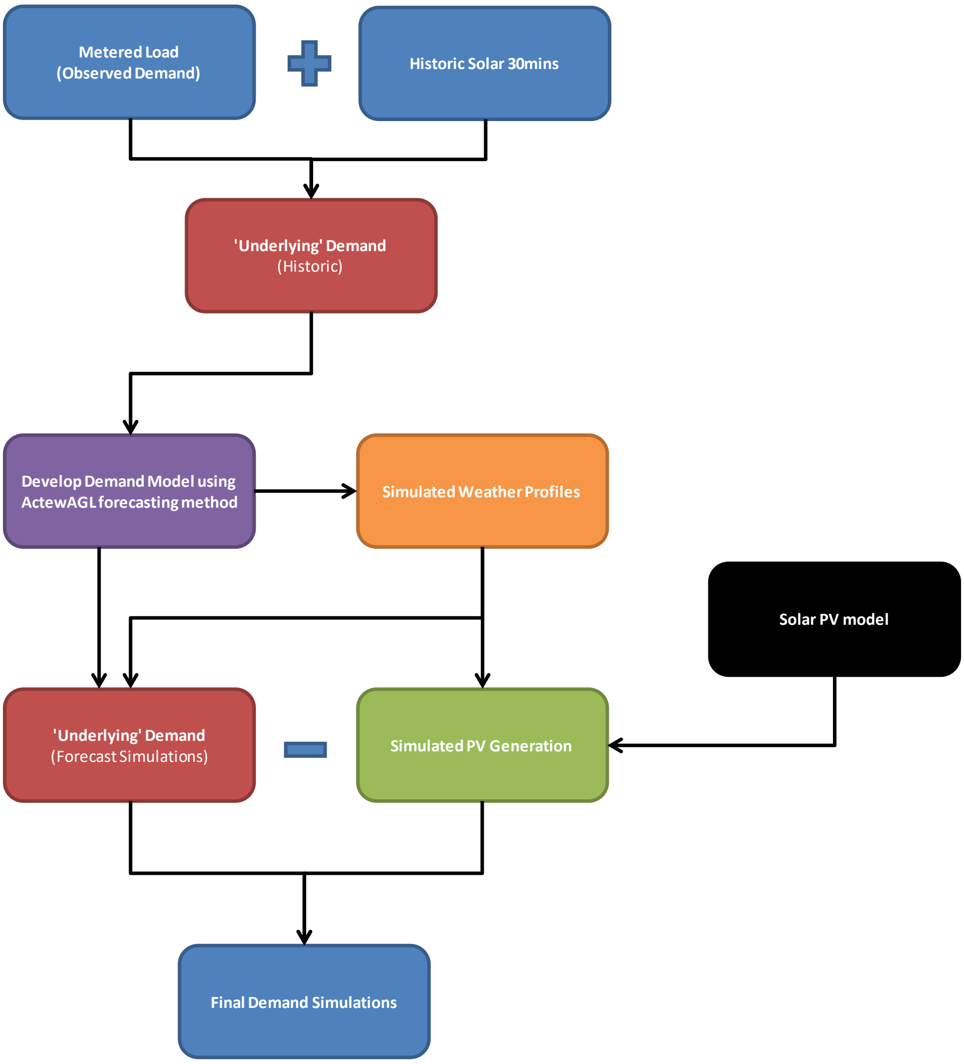
[3] One would typically use a process of adding on residuals from the model to our back-casts to assess the confidence intervals of our back-cast against actual outcomes, but in this case there are no benchmark data to assess against.

This process is illustrated visually in Figure 4.2.4

Figure 4.2.4: 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 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 dataset. 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 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; 6. The minimum	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; 9. Average electricity price (residential), in cents/kWh;

[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.

		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.	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[5] for details.

4.5 Structural Changes

Structural change technologies such as solar PV, battery storage, electric vehicle charging 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:

[5] Appendix 3.3, *Support information: Evoenergy - Energy customer numbers and peak demand forecasts - Appendices 3.1-3.3 - November 2018*

1) Rooftop PV and battery storage have now been integrated into the 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 vehicle charging using AEMO estimates of NSW and ACT electric vehicle penetration. This adjustment is made at Stage 3 of the Integrated MEFM process; and
3) Energy efficiency is treated as one of the average demand model inputs where applicable and relevant.[6]

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.[7] 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.

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 Evoenergy 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.

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[6] 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.

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

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 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 generation 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

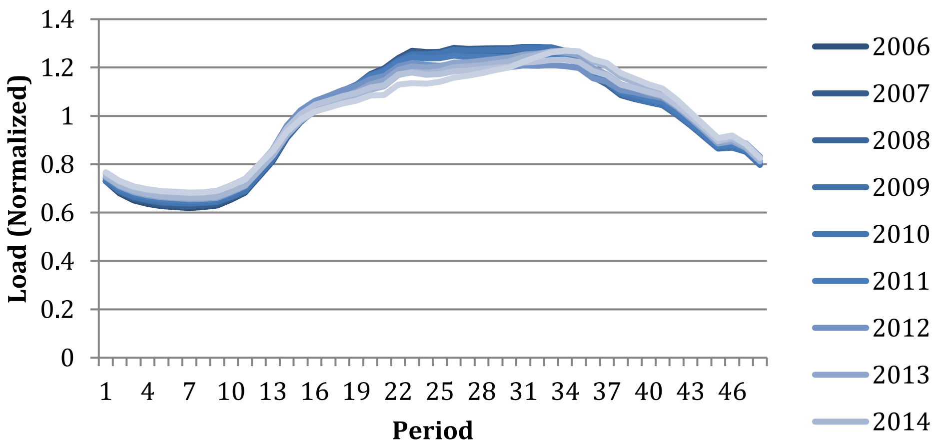
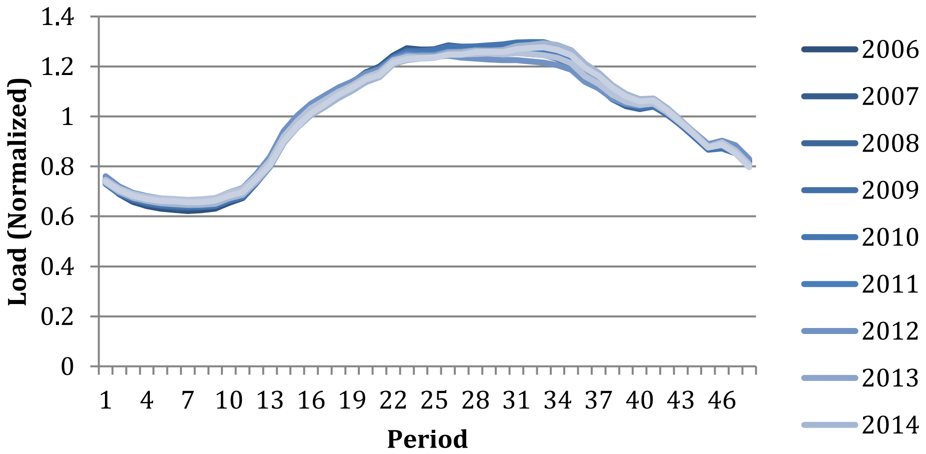


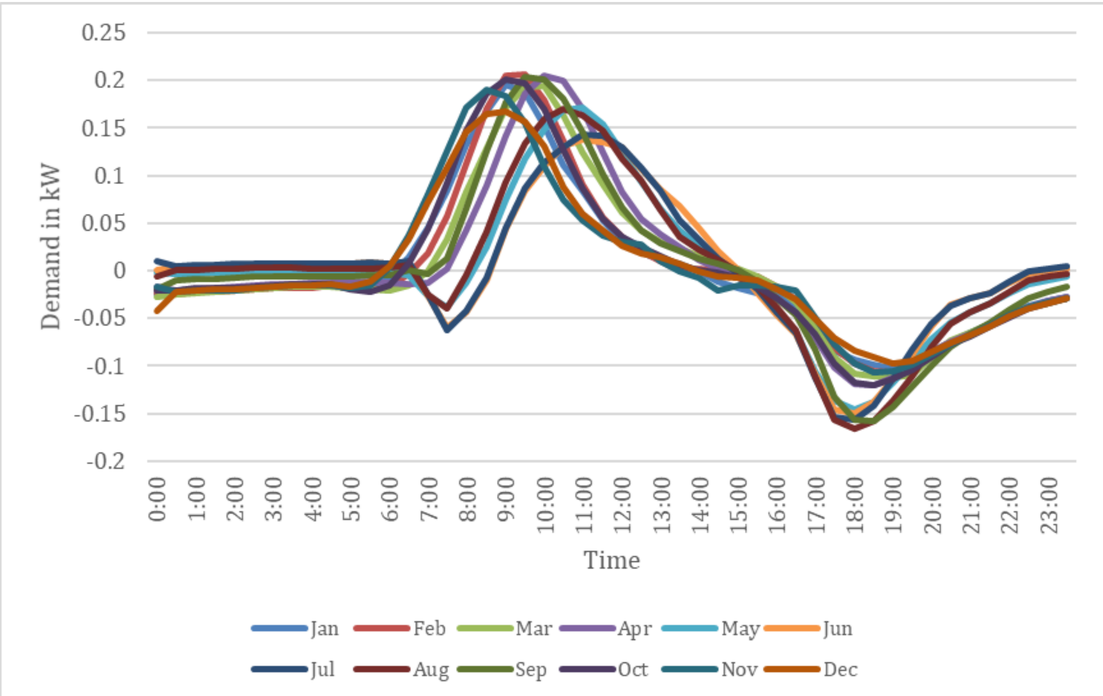
Figure 4.5.2: Normalized Underlying Demand, 2006-2016



4.5.2 Battery Storage

The battery storage model has been improved dramatically in 2018, because Evoenergy has been able to obtain a year's worth of battery storage data from approximately 400 Virtual Power Plant (VPP) project customers, who all installed solar PV panels with battery storage systems coupled with a Reposit software system installed behind the meter to measure all imports and exports from the Grid, Solar PV and battery. The figure 4.5.3 shows the monthly average charge and discharge load profile for a 1 kWh capacity battery storage system.

Figure 4.5.3: Monthly average battery storage charge and discharge profile for 1kWh system.



The battery impact is integrated into the MEFM process along with solar PV during full half-hourly demand simulation. Figure 4.5.4 demonstrates the ACT battery storage capacity forecast derived from AEMO's NSW forecast till Year 2050.

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 models 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. Figure 4.5.5 details the scenario forecast for energy efficiency changes in the next 20 years.

Figure 4.5.4: ACT battery storage charge capacity scenario forecast (derived from AEMO NSW forecast).

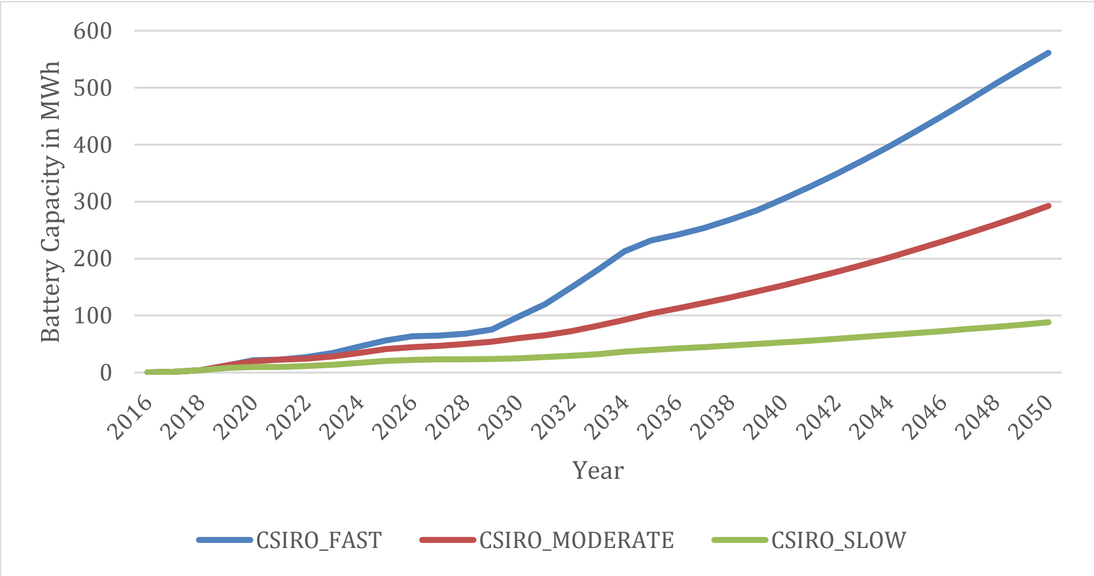
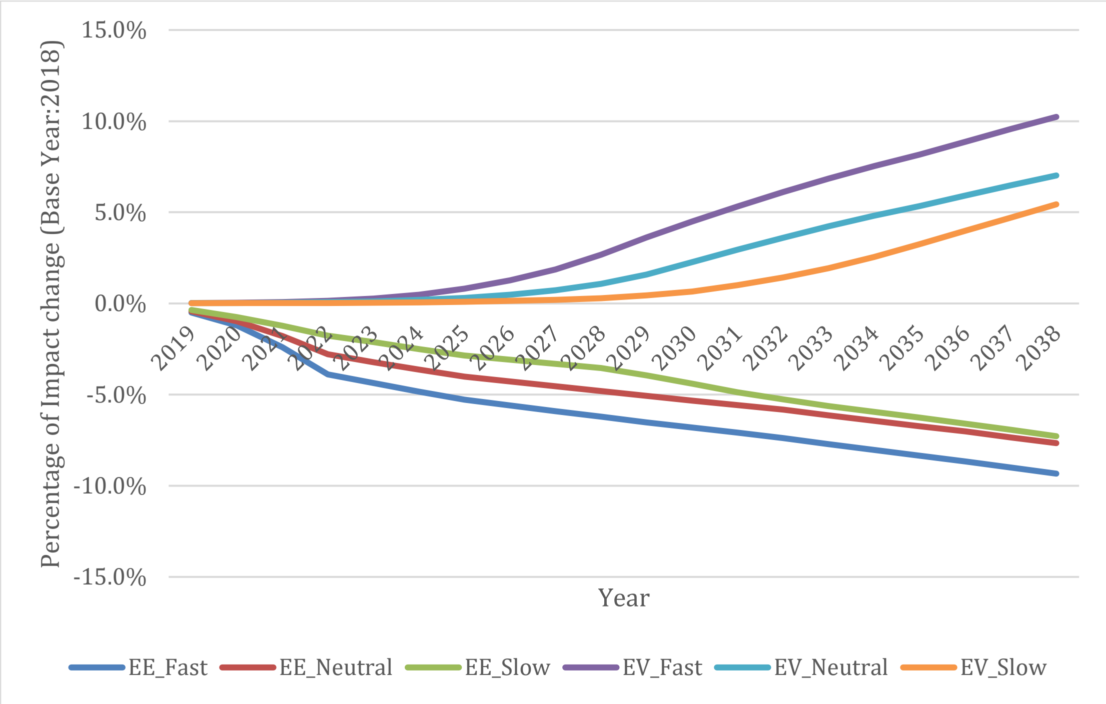


Figure 4.5.5: ACT Energy Efficiency and Electric Vehicles scenario forecast (derived from AEMO NSW forecast).



4.5.4 Electric Vehicles

Electric vehicles are not yet materially prevalent in the ACT, 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 EVs 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. Figure 4.5.5 highlights the percentage of change contributed towards underlying consumption from EVs in next 20 years.

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) The ACT Government Suburban Land Agency (SLA) annual **indicative land release program** (ILRP) 2017-21; and

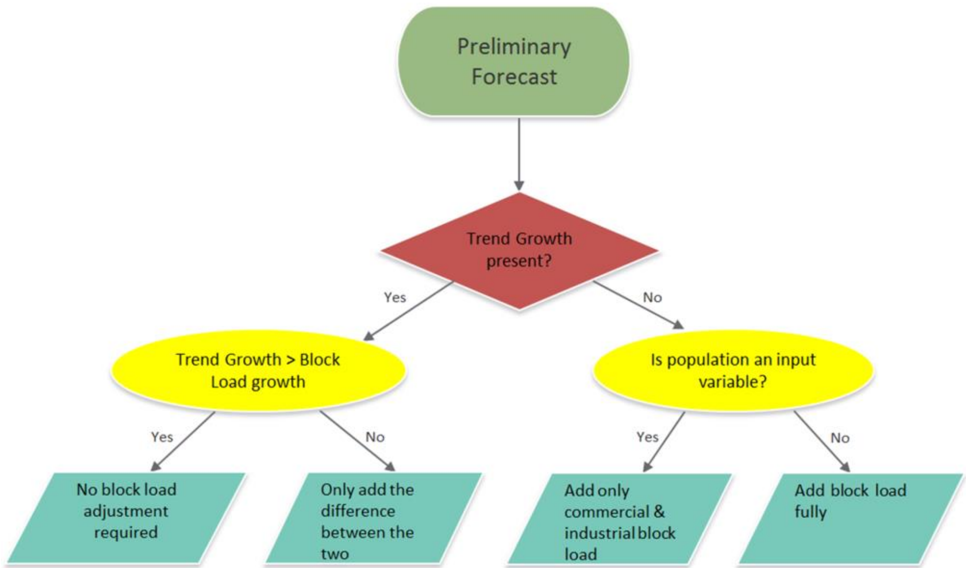
b) Connection requests received directly from customers. An estimated diversified maximum demand is calculated based on the type of connection and size of building or complex. The details of diversified maximum demand calculations can be provided on request.

4.6.2 Key Assumptions

Figure 4.6 provides an overview of the rules we applied for the block load allocation. The key assumptions are:

- ILRP is the base source of block loads for new Greenfield estates such as Gungahlin, Molonglo Valley, West Belconnen, and Tuggeranong 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 areas such as Canberra CBD, Hume and Belconnen Town Centre is rapid and driven by customer requests;

Figure 4.6: Rules for block load allocation



- 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.

Table 4.6.1: Block load probability adjustment rate by completion year

Completion Year (Financial Year)	Probability of Project going ahead
2019	100%
2020	90%
2021	70%
2022	50%
2023	30%
2024	10%
2025	10%
2026	10%
2027	10%
2028	10%

4.7 Forecast Accuracy Review Process

4.7.1 System and Zone Substation forecast evaluation

At Evoenergy, the previous period of forecast is typically reviewed and analysed before the next forecast cycle starts. For detailed accuracy analysis and comments, please refer to Chapter 3 of this document.

System and Zone Substation average demand models were prepared and developed by Jacobs. Please refer to Jacobs' report for details on the system and 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 where 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 solar PV.

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

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

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.

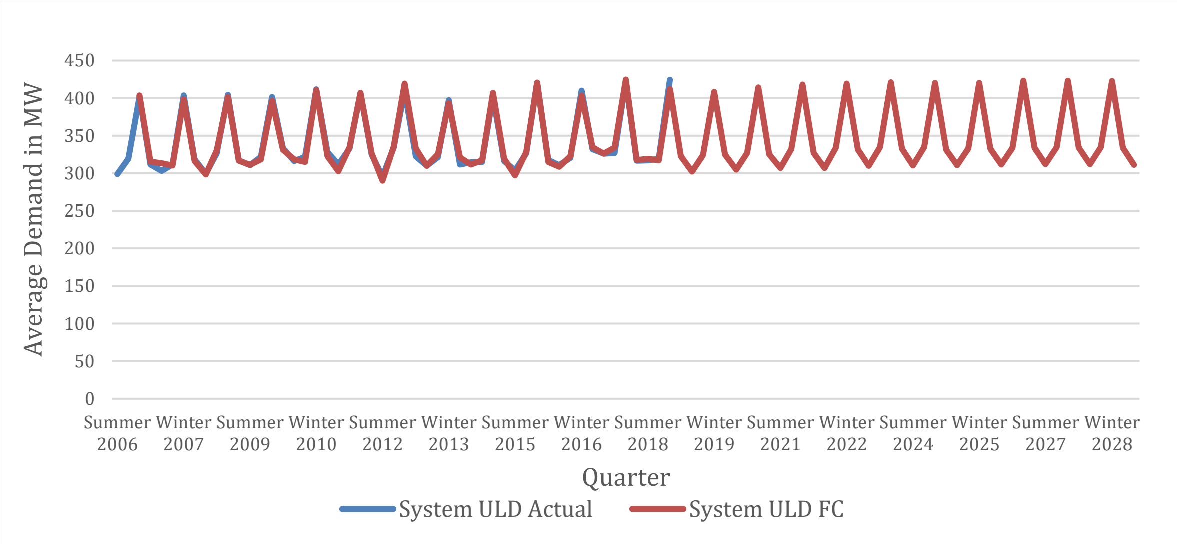
5 Forecast Results

5.1 System Forecast

5.1.1 Seasonal average demand

Jacobs produced the seasonal average demand model for the System and found that the key drivers were weather, ACT population, and retail price and retail energy efficiency. The model had an adjusted R-squared statistic of 98% and projections are displayed in Figure 5.1.1 – refer to the Jacobs report for more detail on the actual model.

Figure 5.1.1: Evoenergy system seasonal average demand – Model Fit and Forecast



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 5.1.1, which is applicable to all half-hourly models. A list of selected weather and calendar variables is provided in Table 5.1.2.

Table 5.1.1: 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:

Model output parameter	Description
	Various day type variables – that is, day of week, public holiday, etc Various temperature related variables in current or prior time periods
Residual standard error, R-squared values, F-statistics 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 5.1.2: 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 (2019-2028)

5.1.3.1 Forecast Summary

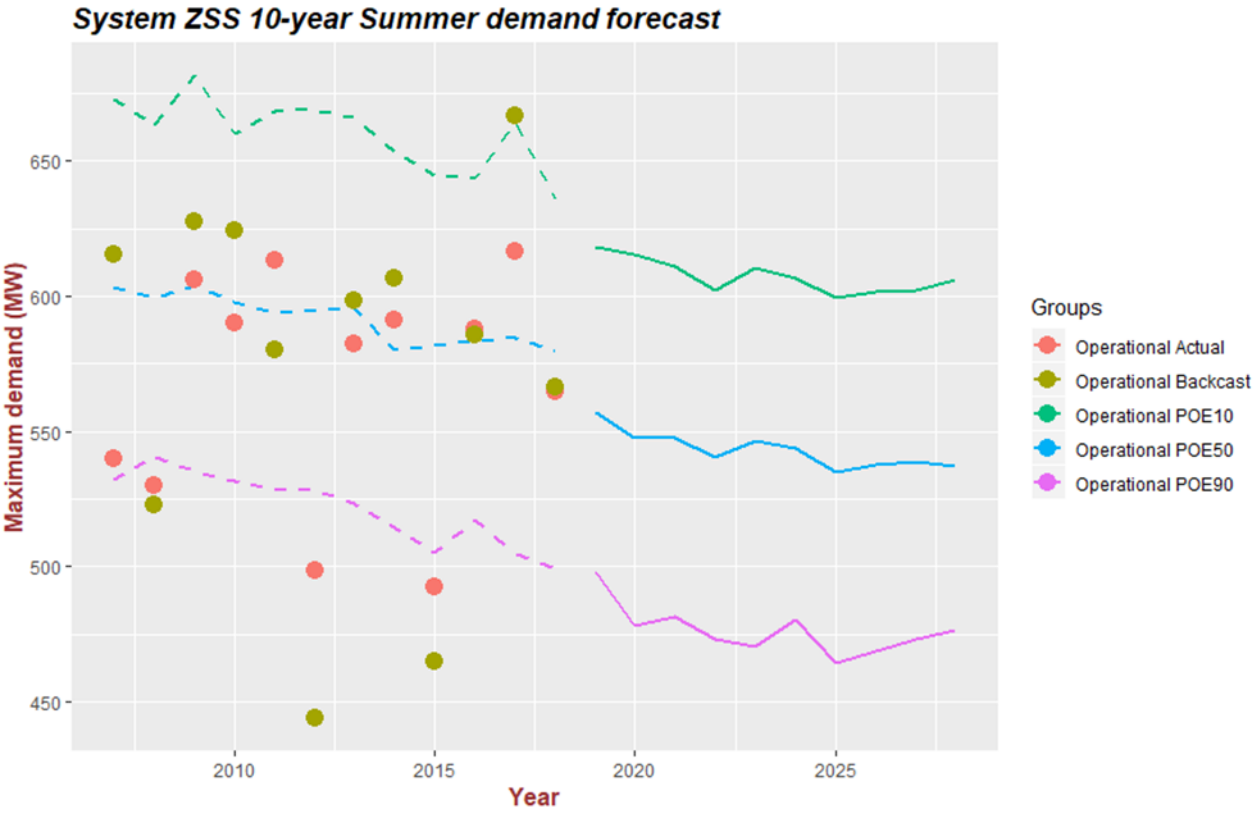
The historical, weather corrected historical and POE forecast are demonstrated in Figure 5.1.3

Key findings from Figure 5.1.2 are:

1) 2012 and 2015 summer peak demands were below 90% POE due to mild summer weather. This implies that ACT summer maximum demand is heavily dependent on weather conditions;
2) Figure 5.1.2 shows a clear downward trend for all POE forecasts from 2019 to 2025 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.

Figure 5.1.2: line graph (Horizontal) 10-year summer forecast (Operational Demand)



5.1.3.2 POE Forecast breakdown by structure change technology – Vertical analysis

Figure 5.1.3 and 5.1.4 demonstrates the vertical analysis of POE forecast. Both charts show the combined impact of rooftop PV and battery storage, and is expected to grow gradually over the next ten years as more PV and battery systems are 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 due to the increased impact from solar PV and battery storage, but the rate of decline is expected to slow due to more EV uptake from 2023 onwards.

Figure 5.1.3: 50% POE 10-year summer demand forecast stack charts

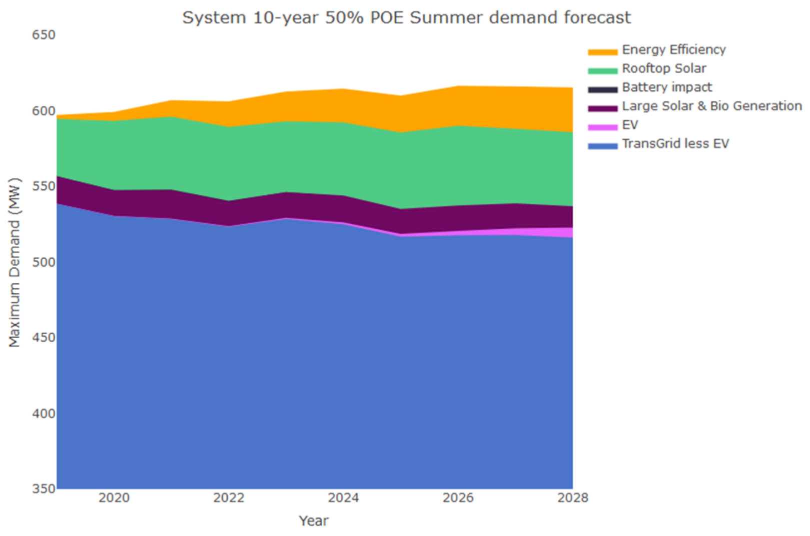
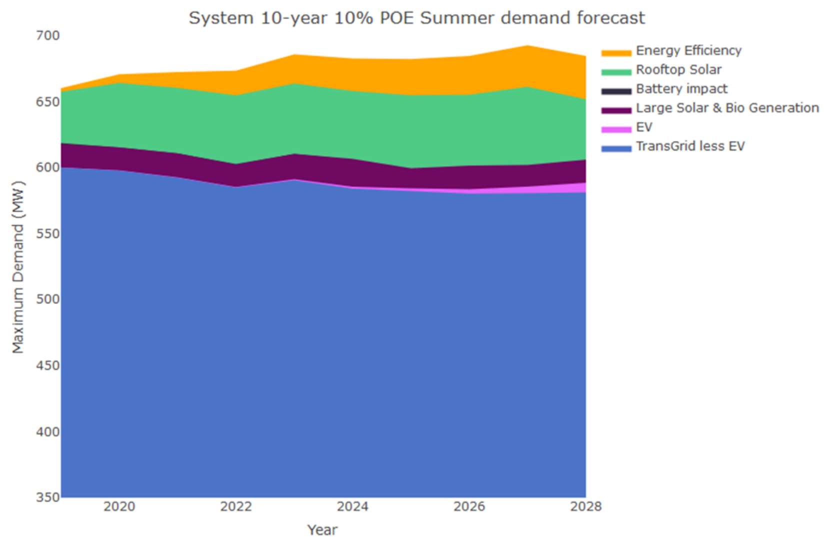


Figure 5.1.4: 10% POE 10-year summer demand forecast stack charts



5.1.3.3 Historical and forecast outcomes for Figure 5.1.2, 5.1.3 and 5.1.4

Table 5.1.3: Summer maximum demand historical and forecast POE trend.

Year	Actual	Fitted	Backcast			Forecast		
			90%	50%	10%	90%	50%	10%
2007	540	615	532	604	673			
2008	530	523	540	600	663			
2009	606	627	535	604	682			
2010	590	624	531	598	660			
2011	613	580	528	594	668			
2012	498	444	528	595	669			
2013	583	598	523	595	666			
2014	591	607	514	580	654			
2015	492	465	505	582	645			
2016	588	586	517	584	643			
2017	617	667	504	584	664			
2018	565	566	499	579	636			
2019						498	557	618
2020						478	547	615
2021						482	548	611
2022						473	540	602
2023						470	546	610
2024						480	544	607
2025						464	535	600
2026						468	537	602
2027						473	539	602
2028						477	537	606

Table 5.1.4: Summer maximum demand POE forecast vertical breakdown.

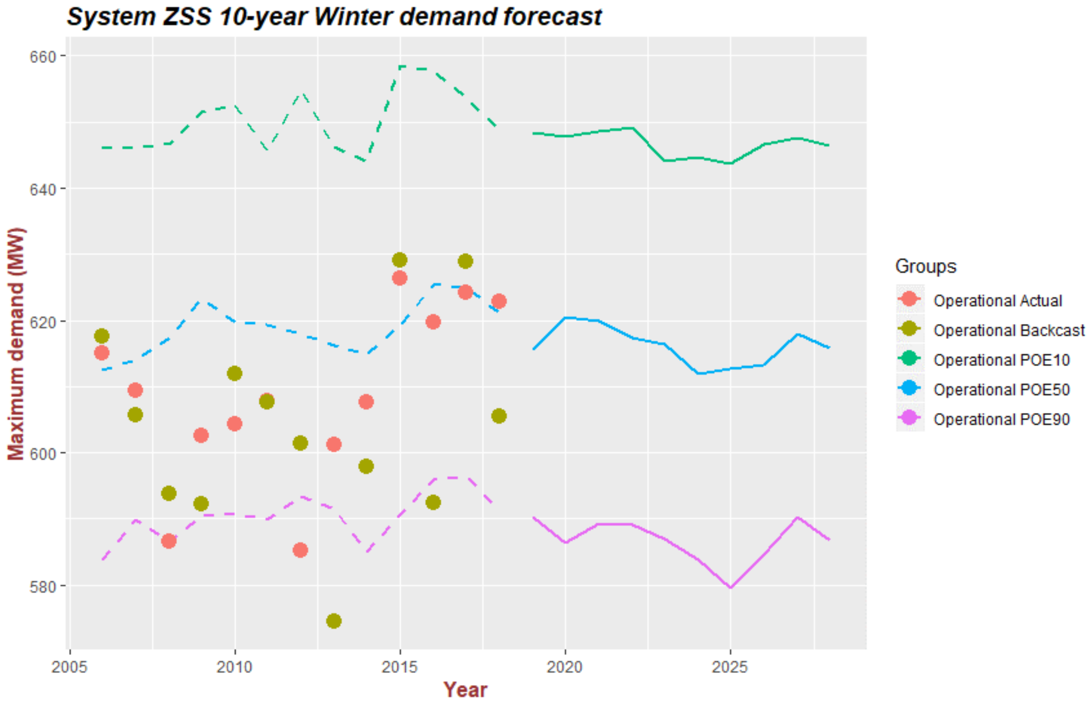
Summer	TG less EV		Plus EV (TG Import)		Plus Large Solar& Bio Gen (Operational demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	539	600	539	600	557	618	557	619	595	657	597	660
2020	530	598	530	598	547	615	548	615	593	664	599	671
2021	528	592	529	593	548	611	548	611	596	660	607	673
2022	523	585	524	585	540	602	540	603	589	655	606	674
2023	528	590	529	591	546	610	546	610	593	664	613	686
2024	525	584	526	586	544	607	544	606	592	658	615	683
2025	517	582	519	584	535	600	534	599	586	655	610	682
2026	518	580	521	584	537	602	536	599	590	655	616	685
2027	518	581	522	586	539	602	536	599	588	661	616	693
2028	516	581	523	589	537	606	532	600	586	652	615	685

5.1.4 Winter Forecast (2019 – 2028)

5.1.4.1 Forecast Summary

The historical, weather corrected historical and POE scenario winter forecast are demonstrated in Figure 5.1.5.

Figure 5.1.5: line graph (Horizontal) 10-year winter forecast (Operational Demand)



Key findings from Figure 5.1.5 are:

1) Historically, the winter peak demands have always been above 600 MW except 2008 and 2012 when milder winters occurred;

2) Rooftop PV has less impact on winter demand than summer demand because the sun has already gone down before the peak has hit (Figure 5.1.2 vs Figure 5.1.5) and Figure 5.1.6 and Figure 5.1.7 demonstrates the battery storage impact is growing and is expected to be influential in winter demand by the end of the 10-year period;

3) Similar to the summer forecast, the load growth is expected to be gradual, then accelerating from 2026 onwards due to higher uptake of EVs.

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. Figures 5.1.6 and 5.1.7 show nearly zero impact from solar PV compared with gradually increasing influence of battery storage. The electrcity demand from EVs is forecast to be small initially but noticable when more EVs are connected to the Grid, which consequently drvies up TransGrid import at the end of the 10-year period.

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

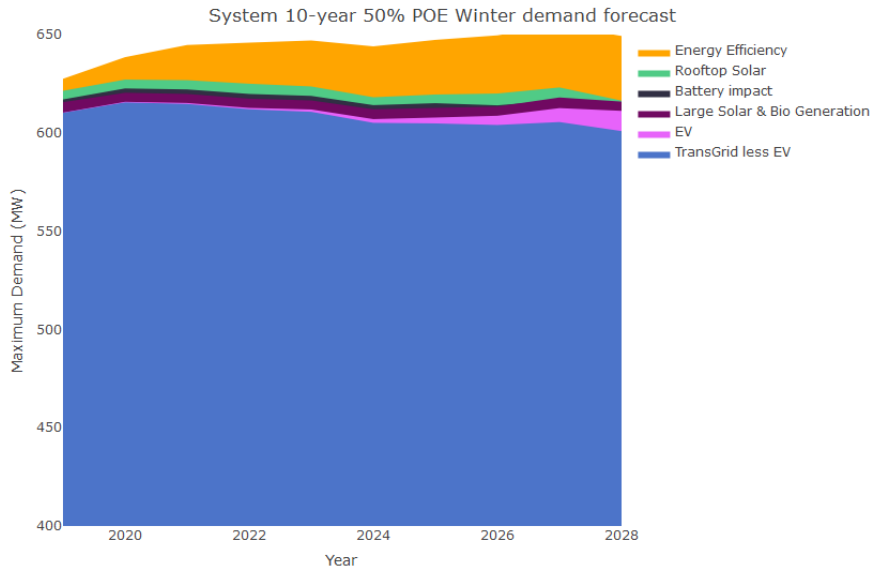
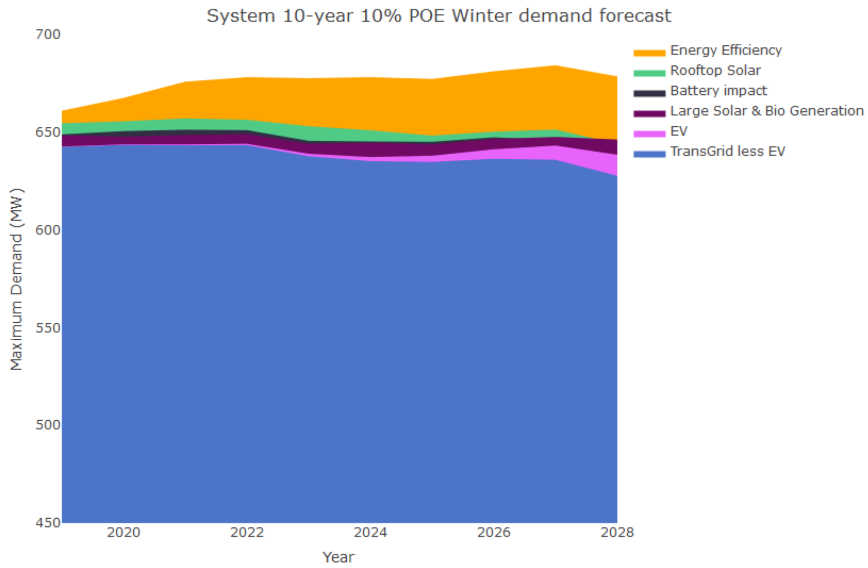


Figure 5.1.7: 10% POE 10-year winter demand forecast stack charts



5.1.4.3 Historical and forecast outcomes for Figure 5.1.5, 5.1.6 and 5.1.7

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

Year	Actual	Fitted	Backcast			Forecast		
			90%	50%	10%	90%	50%	10%
2006	615	617	584	613	646			
2007	609	606	590	614	646			
2008	587	594	587	617	647			
2009	603	592	591	623	652			
2010	604	612	591	620	652			
2011	608	608	590	619	646			
2012	585	601	593	618	655			
2013	601	574	591	616	646			
2014	608	598	585	615	644			
2015	626	629	591	619	659			
2016	620	592	596	625	658			
2017	624	629	597	625	654			
2018	623	605	591	621	649			
2019						590	616	648
2020						586	620	648
2021						589	620	649
2022						589	617	649
2023						587	616	644
2024						584	612	645
2025						580	613	644
2026						585	613	647
2027						590	618	648
2028						587	616	646

Table 5.1.6: Winter maximum demand POE forecast vertical breakdown.

Winter	TG less EV		Plus EV (TG Import)		Plus Large Solar& Bio Gen (Operational demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	610	643	610	643	616	648	617	649	621	655	628	661
2020	615	644	616	644	620	648	623	651	627	656	639	668
2021	615	643	615	644	620	649	622	651	627	657	645	676
2022	612	643	613	644	617	649	620	651	625	656	646	678
2023	611	638	612	639	616	644	619	646	624	653	647	678
2024	605	635	607	637	612	645	614	645	618	651	644	678
2025	605	635	608	638	613	644	615	645	620	648	647	677
2026	604	636	609	641	613	647	614	647	620	650	650	681
2027	606	636	613	643	618	648	617	646	623	651	655	684
2028	601	628	611	638	616	646	612	639	616	644	649	679

5.2 Zone Substation Forecasts

This 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 2019 - 2028 (in MVA)

Zone Substation	Continuous Rating	Emergency two-hour Rating	PoE Forecast	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
Belconnen	**55**	**63**	***50%***	56	62	66	68	69	69	68	68	68	68
			10%	63	68	73	75	76	76	75	75	75	75
City East	**95**	**95**	***50%***	73	81	88	93	100	98	98	99	99	101
			10%	85	92	99	104	111	110	111	112	114	114
Civic	**110**	**114**	***50%***	59	63	66	67	69	69	69	69	69	69
			10%	65	69	74	75	76	75	77	76	77	76
East Lake	**24**	**43**	***50%***	21	20	21	21	22	22	23	24	25	26
			10%	26	26	26	27	29	30	30	30	33	33
Fyshwick	**28**	**28**	***50%***	29	30	30	30	31	31	31	31	32	32
			10%	30	31	32	32	32	32	32	33	33	34
Gilmore	**45**	**62**	***50%***	31	32	34	35	36	38	39	41	42	44

			10%	39	40	42	43	44	47	48	49	51	53
Gold Creek	**57**	**76**	***50%***	67	69	74	73	78	79	82	84	86	89
			10%	79	83	88	88	93	97	98	102	104	108
Latham	**95**	**95**	***50%***	52	53	54	55	57	57	58	59	60	62
			10%	60	60	62	63	64	65	66	67	68	70
Telopea Park	**100**	**114**	***50%***	87	93	97	101	103	103	102	104	103	103
			10%	100	106	109	111	115	115	114	116	116	116
Tennent	**15**	**15**	***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	25	25	25	25	25	25	25	25	25
			10%	29	30	30	29	30	30	30	30	30	30
Wanniassa	**95**	**95**	***50%***	62	64	65	65	65	64	63	62	61	61
			10%	71	74	73	74	74	73	71	70	70	69
Woden	***95***	***95***	***50%***	77	80	84	86	88	88	88	88	88	88
			10%	87	91	95	96	98	99	98	99	99	98

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

Zone Substation	Continuous Rating	Emergency two-hour Rating	PoE Forecast	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
Belconnen	**55**	**76**	***50%***	59	65	69	70	71	71	71	71	71	71
			10%	62	68	72	74	74	74	74	74	75	75
City East	**95**	**112**	***50%***	68	77	85	90	93	92	93	95	94	95
			10%	76	85	93	98	100	100	102	103	103	103
Civic	**110**	**143**	***50%***	53	57	59	61	62	62	62	63	63	63
			10%	56	59	62	63	65	65	65	66	66	66
East Lake	**30**	**54**	***50%***	18	18	19	19	20	20	21	22	22	23

			10%	20	20	20	21	22	22	23	24	24	25
Fyshwick	**28**	**28**	***50%***	24	25	25	26	27	28	29	30	31	31
			10%	24	25	26	27	28	28	29	30	31	32
Gilmore	**45**	**69**	***50%***	32	33	34	35	36	37	38	39	40	42
			10%	35	36	37	38	39	40	42	43	44	46
Gold Creek	**57**	**76**	***50%***	71	75	78	81	83	85	87	90	92	94
			10%	76	82	85	88	91	93	95	99	101	102
Latham	**95**	**114**	***50%***	67	69	70	72	73	74	74	76	77	78
			10%	71	73	75	76	77	78	78	80	81	83
Telopea Park	**100**	**114**	***50%***	85	91	96	99	99	99	99	100	100	100
			10%	90	97	101	104	106	106	105	106	107	107
Tennent	**15**	**15**	***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%***	28	28	29	29	29	29	28	29	29	29
			10%	30	31	31	31	31	31	31	31	31	31
Wanniassa	**95**	**114**	***50%***	73	76	77	76	75	74	73	72	72	70
			10%	79	82	82	81	81	80	79	78	78	76
Woden	**95**	**114**	***50%***	82	87	89	90	92	92	92	93	93	93
			10%	88	94	97	98	99	99	98	100	100	99

Notes:

1 East Lake Zone Substation is equipped initially with one transformer only (ie N security). Second transformer is to be installed by 30 June 2019.

2 Strathnairn Zone Substation will be equipped initially with 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 Belconnen Zone Substation Forecast

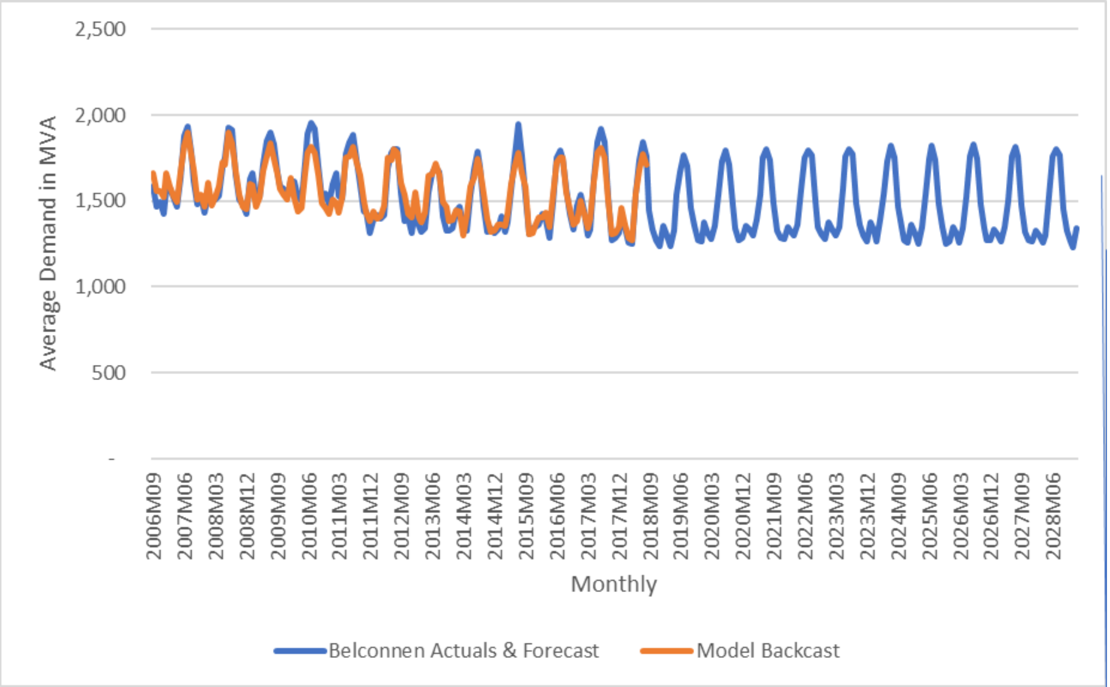
5.2.2.1 Seasonal average model

5.2.2.1.1 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 retail energy efficiency. The model had an adjusted R-squared statistic of 95% and projections are displayed in Figure 5.2.2.1 – more detail in Jacobs report on the actual model.

5.2.2.1.2 Forecast trend and block load analysis

Figure 5.2.2.1: Belconnen ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis:

1) Figure 5.2.2.1 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;
3) Detailed block load information are shown in Table 5.2.2.1:

5.2.2.2 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.

5.2.2.3 Summer and Winter Demand forecast

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

- Figure 5.2.2.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.2.3: Stack Chart by structure change impact;
- Table 5.2.2.2 to 5.2.2.5: Actual or forecast figures for Figure 5.2.2.2 and 5.2.2.3

Key findings from Figure 5.2.2.2 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 have been noted directly from key customers constantly from Belconnen area shown in Table 5.2.2.1, 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.

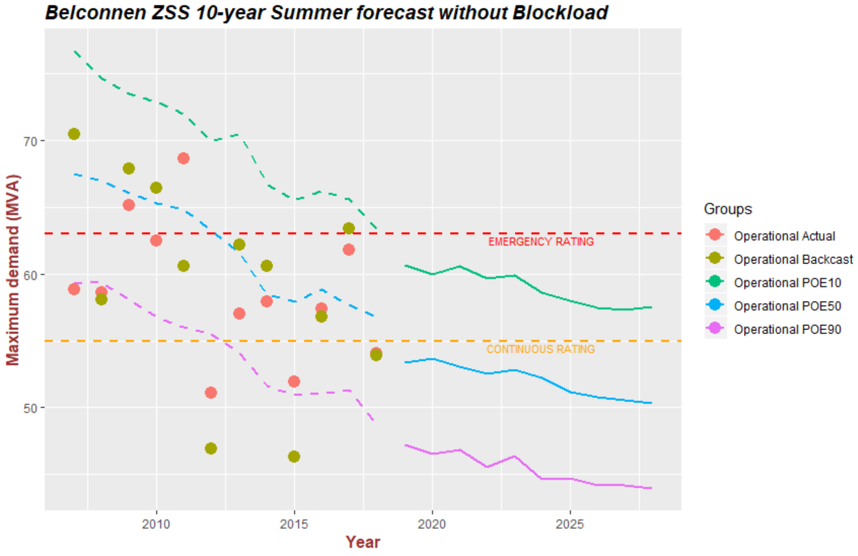
In conclusion, Belconnen Zone Substation network could be easily constrained by future extreme summer weather as experienced in February 2017 (3 consecutive days of hot weather). It is proposed to install a third 132/11 kV 30/55 MVA transformer at Belconnen Zone Substation in the 2024-29 Regulatory Control Period.

Figure 5.2.2.3 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.

Table 5.2.2.1: Belconnen ZSS detailed block load in MVA

Block Load Project	2019	2020	2021	2022	2023	2024
PN 20002104 Calvary Hospital expansion	1					
PN 20000938 University of Canberra Hospital	1					
PN 20003743 S48 B8 Residential and commercial	0.5					
PN 20004977 Supply to Cancer Clinic UoC Hospital	0.7					
PN 20003008 S48 B19, Residential and commercial, Republic Stage 1		1.8				
PN 20005391 S52 B37, Emu Bank, Residential and commercial	1.3					
PN 20005940 S49 B4, Cohen St, Residential development	0.4					
PN 20006035 S200 B2, Residential & commercial, Republic Stage 2 & 3		1.2	2.4			
PN 20006119 S32 B16, Ibbott Lane, Commercial development		0.5				
PN 20006170 S32 B12-13 Thynne St, Residential and commercial/retail	0.5	1				
Lawson North Village, Defence Housing Australia		1.5				
University of Canberra Residential development 3,300 units			1.8	2	2.5	2
Belconnen Trades Centre Commercial and light industrial development			1	1	1	1

Figure 5.2.2.2: Belconnen ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



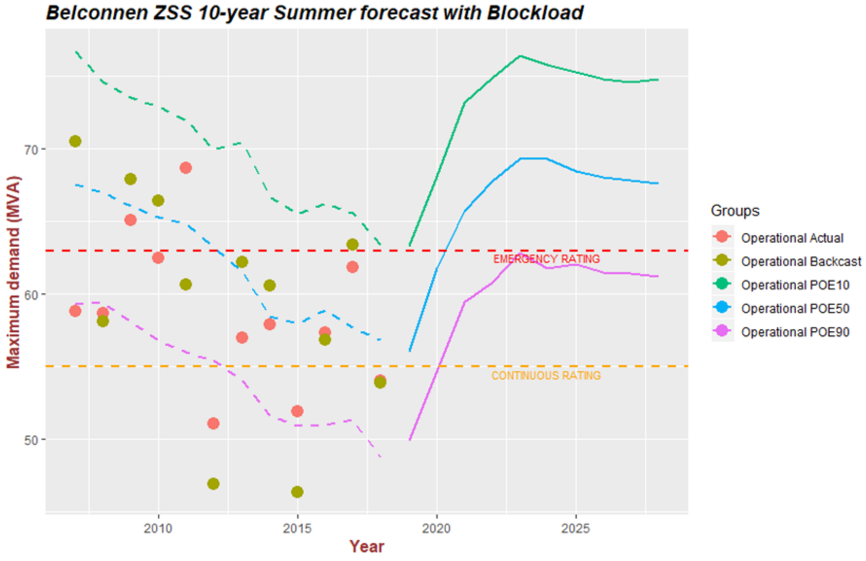


Figure 5.2.2.2: Belconnen ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

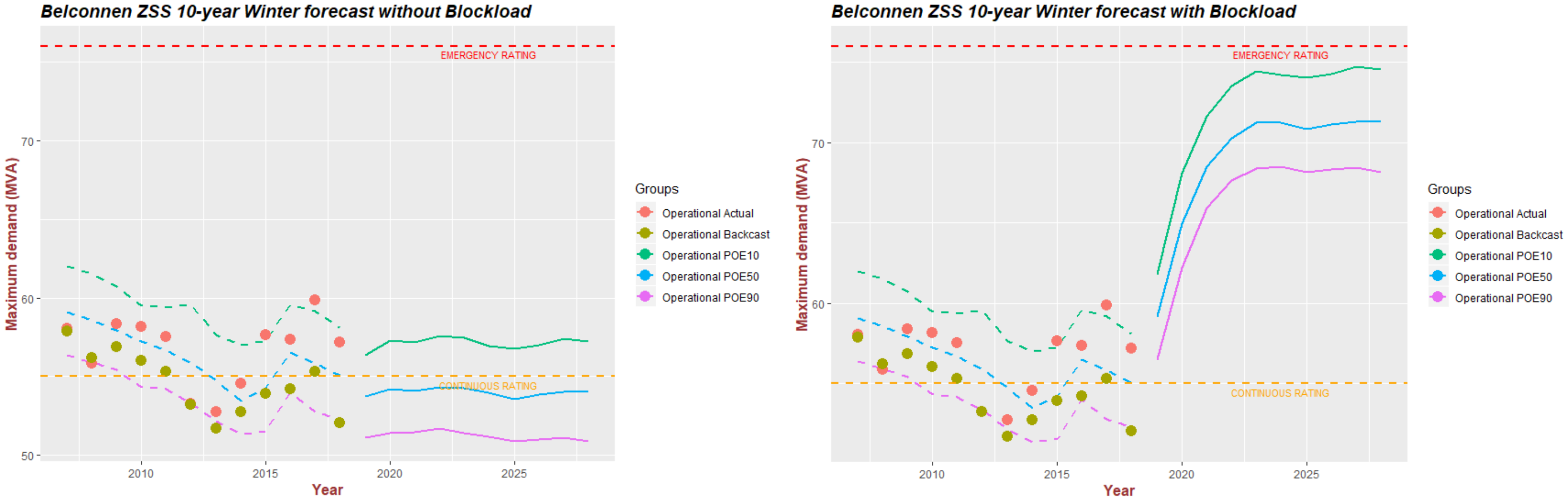


Figure 5.2.2.3: POE Forecast breakdown by structure change technology – Vertical analysis

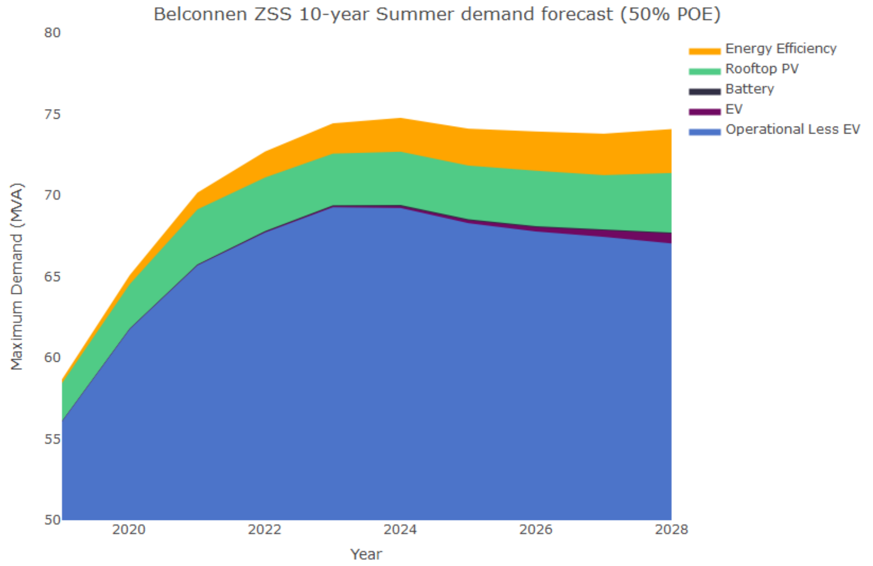
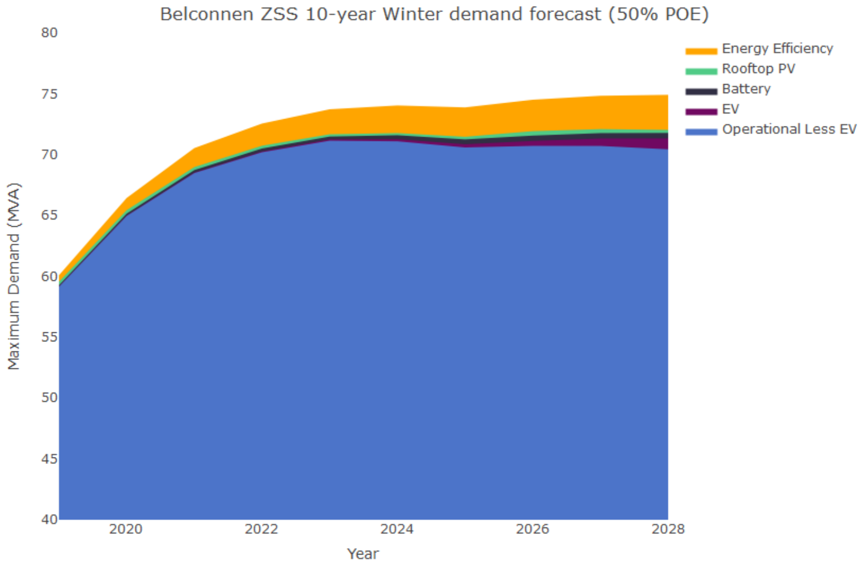
Summer POE Forecasts	***Winter POE Forecasts***
	

Figure 5.2.2.3: POE Forecast breakdown by structure change technology – Vertical analysis

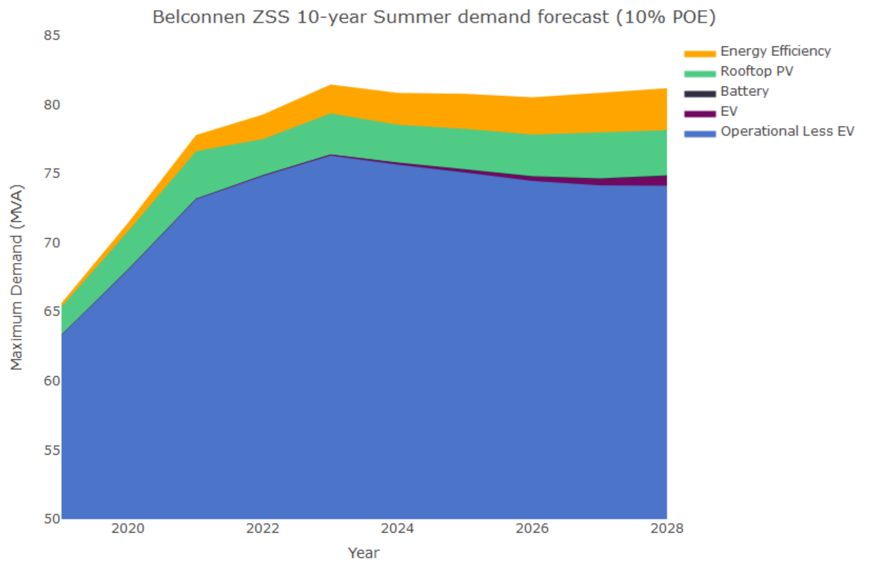
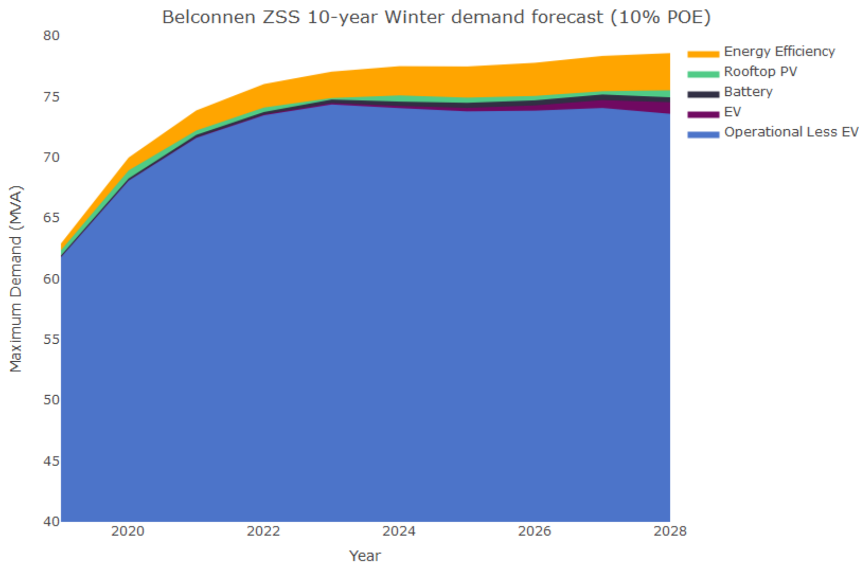
Summer POE Forecasts	*Winter POE Forecasts*
	

Table 5.2.2.2: Belconnen ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	59	70	59	68	77
2008	59	58	59	67	75
2009	65	68	58	66	73
2010	63	66	57	65	73
2011	69	61	56	65	72
2012	51	47	55	63	70
2013	57	62	54	62	70
2014	58	61	52	58	67
2015	52	46	51	58	66
2016	57	57	51	59	66
2017	62	63	51	58	66
2018	54	54	49	57	63

Table 5.2.2.3: Belconnen ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	56	63	56	63	56	63	58	65	59	66
2020	62	68	62	68	62	68	65	71	65	72
2021	66	73	66	73	66	73	69	77	70	78
2022	68	75	68	75	68	75	71	78	73	79
2023	69	76	69	76	69	76	73	79	74	81
2024	69	76	69	76	69	76	73	79	75	81
2025	68	75	68	75	69	75	72	78	74	81
2026	68	74	68	75	68	75	72	78	74	81
2027	67	74	68	75	68	75	71	78	74	81
2028	67	74	68	75	68	75	71	78	74	81

Table 5.2.2.4: Belconnen ZSS winter back-cast and weather correction in MVA

Winter			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	59	70	59	68	77
2008	59	58	59	67	75
2009	65	68	58	66	73
2010	63	66	57	65	73
2011	69	61	56	65	72
2012	51	47	55	63	70
2013	57	62	54	62	70
2014	58	61	52	58	67
2015	52	46	51	58	66
2016	57	57	51	59	66
2017	62	63	51	58	66
2018	54	54	49	57	63

Table 5.2.2.5: Belconnen ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	59	62	59	62	59	62	60	62	60	63
2020	65	68	65	68	65	68	65	69	66	70
2021	68	72	69	72	69	72	69	72	71	74
2022	70	73	70	74	71	74	71	74	73	76
2023	71	74	71	74	71	75	72	75	74	77
2024	71	74	71	74	72	75	72	75	74	78
2025	71	74	71	74	71	74	71	75	74	77
2026	71	74	71	74	72	75	72	75	75	78
2027	71	74	71	75	72	75	72	75	75	78
2028	70	74	71	75	72	75	72	76	75	79

5.2.3 City East Zone Substation Forecast

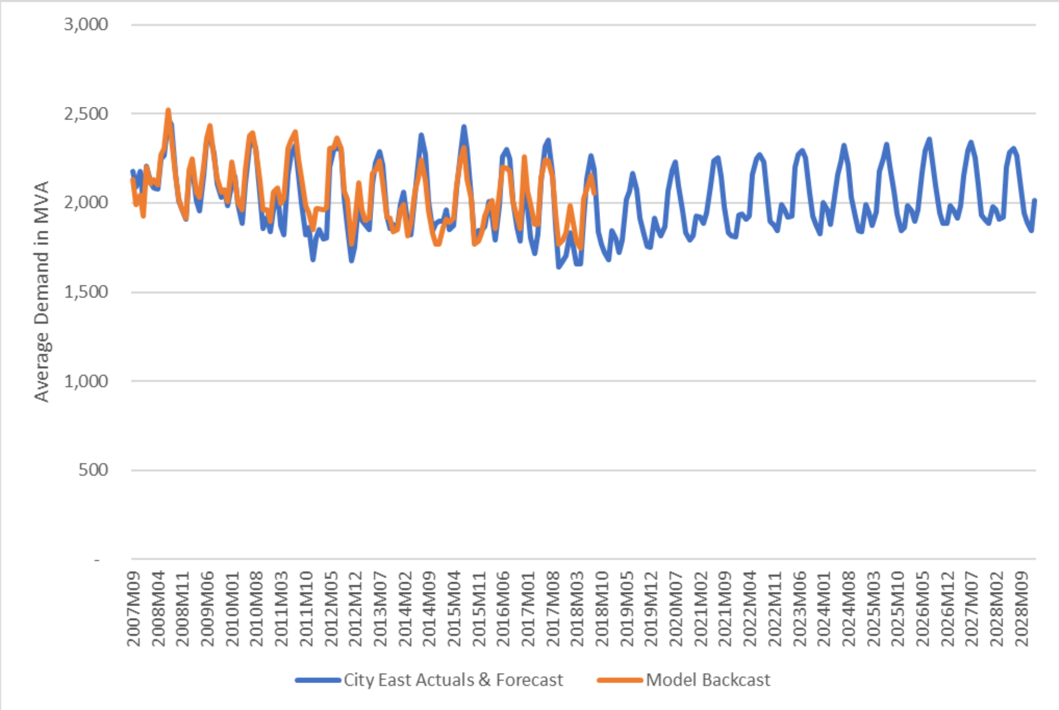
5.2.3.1 Seasonal average model

5.2.3.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, North Canberra regional population, residential electricity price and retail energy efficiency. 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: City East ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis:

- Figure 5.2.3.1 demonstrates neither an upward nor downward trend over the next ten years. Therefore, block load adjustment is required;
- the regional population is forecast to grow in next ten years;
- Strong load growth forecast in the Civic, City East and Dickson area and was driven by the high volume of customer connection requests due to the expansion of Canberra CBD and redevelopment of Northbourne Corridor. Please see Table 5.2.3.1 for more details about those future projects;
- A new feeder was proposed from City East ZSS to support the growth and ensure the reliability of electricity supply in those areas.

5.2.3.2 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.

5.2.3.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by 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 5.2.3.2 to 5.2.3.5: Actual or forecast figures for Figure 5.2.3.2 and 5.2.3.3.

Key findings from Figure 5.2.3.2 are:

- Both summer and winter historical actuals show a strong downward trend;
- But the downward trending is expected to overturned due to the expansion of CBD area and redevelopment of Northbourne Corridor;
- The summer 50% POE forecast is forecast to exceed the summer emergency rating by 2023. It seems that there will be no constraint issue during winter period in next ten years as winter 10% POE forecast is trending below the winter continuous rating.

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 3 PM whereas its winter peak normally occurs either at 9 AM in the morning or at 6 PM in the evening.

Table 5.2.3.1: City East ZSS detailed block load in MVA

Block Load Project	2019	2020	2021	2022	2023	2024	2025	2026
PN20003655 - B1-12 S48, 54 Northbourne Avenue, Commercial 1600 m².	0.08							
PN20003928 - B27 S26 - Corner Northbourne Ave & Cooyong St. Commercial 14,590m², Retail 215m², Car park 7600m², Plant 791m².	1.34							
PN20004555 - B3 S12 - 20 Allara St. Residential 346 units, Commercial 1400 m², Car park 13000 m².	0.5	1						
PN20005626 - B19 S26, 16 Lonsdale St. Residential 50 units, Commercial 535 m², Car park 3500 m².		0.25						
PN20006231 - B24 S19 - Hotel & Commercial Development : Corner London Circuit and Constitution Ave		0.5	2	2				
B23 S19, Corner Northbourne Ave & London Circuit. New Canberra Theatre.			0.5	0.5				
B8 S3, Between Constitution Ave & Parkes Way (CIT car park). Residential & Commercial 9450 m².		0.5	1.5					
B6 S3, Corner Constitution Ave & Parkes Way. UNSW campus 35190 m².			0.5	1.5	1.5	2		
Expansion and redevelopment of National War Memorial, Treloar Cres, Campbell.			1	1				
B13 S63, Corner Northbourne Ave & London Circuit. Commercial 9372 m².					0.5	0.5		
B14 S63, Corner Vernon Circle & Northbourne Ave. Commercial 2362 m².					0.25			

B20 S63, Corner Vernon Circle & Commonwealth Ave. Mixed use 168,000 m².			2	2.1	0			
Canberra Metro traction power station TPS8 - corner Constitution Ave & Coranderrk St.							1.9	
Canberra Metro traction power station TPS9 - 51 Russell Dr.							1.9	
PN20005471 - B6 S30 - 11 Donaldson St Braddon. Commercial development 3800 m².		0.36						
PN20005138 - B5 S30 - 7 Donaldson St Braddon. Mixed development: 140 units Residential; 2080 m² Commercial; 6500 m² Car park.		0.95						
PN20004917 - B7-9 S18 - 92 Northbourne Ave Braddon. Mixed develoment: 250 units Residential; 189 rooms hotel; Commercial and Car park.		1.23						
PN20005855 - B12 S50 - Northbourne Ave Lyneham: Residential development	0.83							
PN20003452 - S96 - Corner Cooyong St and Donaldson St. Commercial development: Canberra Centre Extension.		1	1	2	2.5	1.8		
PN20005209 - B19 S33 - Challis St, Dickson. Mixed development: 144 units Residential; 14900 m² Commercial; 1470 m² Community child-care facility.		2						
Lyneham on Northbourne - 253 Northbourne Ave. Mixed development: 1044 units Residential; 2000m² Commercial.					2.3			
B1 S6 Dickson - 242 Northbourne Ave. Mixed development: 406 units Residential; 949 m² Commercial; Car park.			1.2					

PN20002255 - B3 S28 32 Mort St. Mixed development: 60 units Residential; 1195 m^2 Commercial; 4200 m^2 Car park.	0.29							
PN20003882 - B17 S61 corner Bradfield St and Melba St. 282 units Residential.		0.96						
Yowani Development - corner Barton Highway and Northbourne Ave. Residential Development.							2	2.5

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

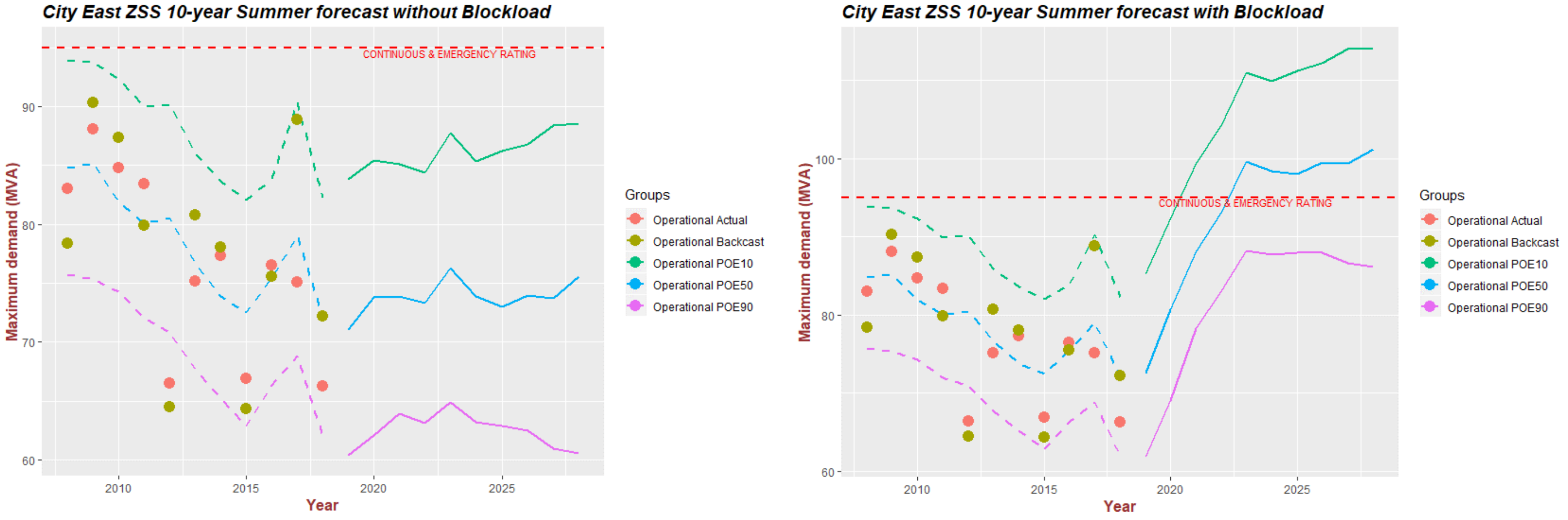
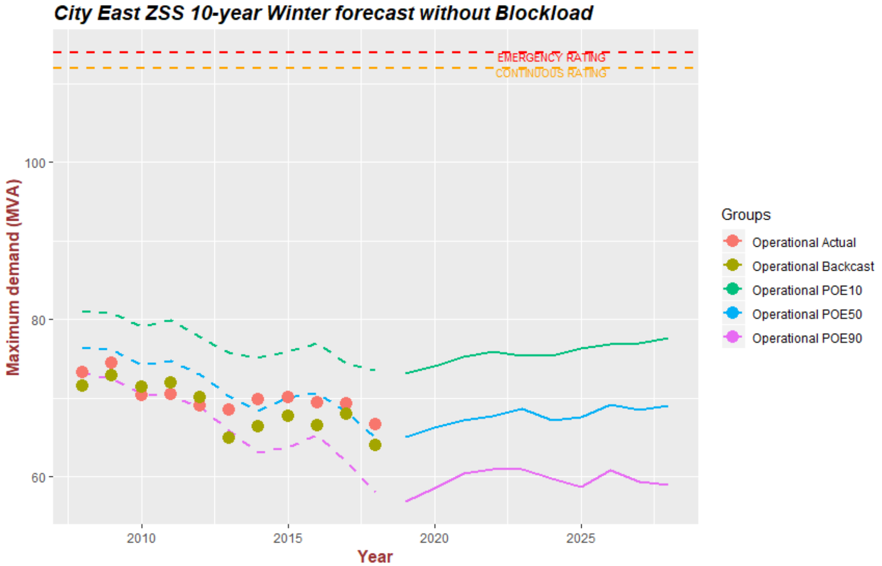


Figure 5.2.3.2: City East ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



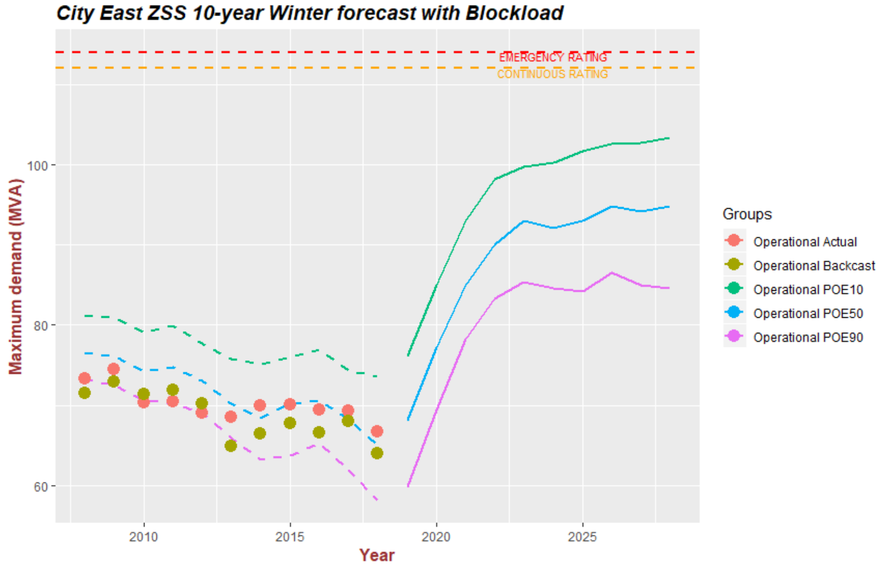


Figure 5.2.3.3: POE Forecast breakdown by structure change technology – Vertical analysis

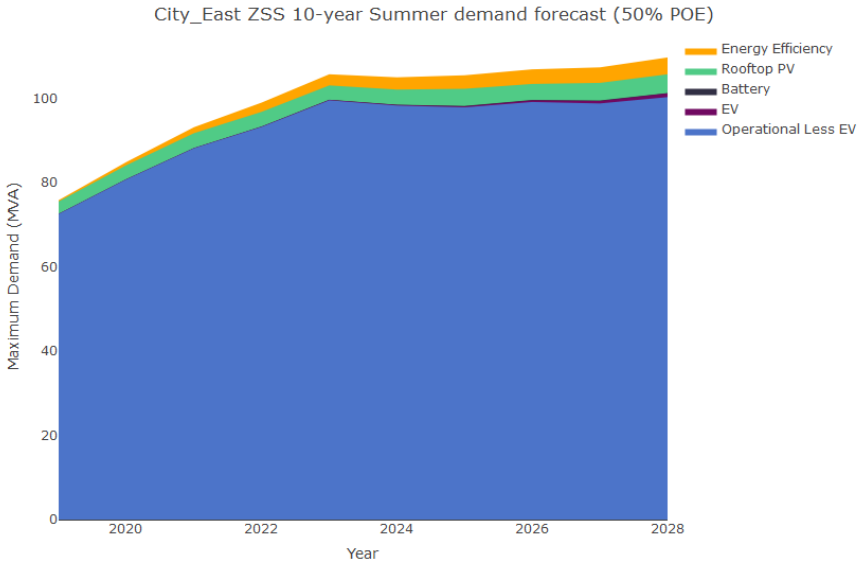
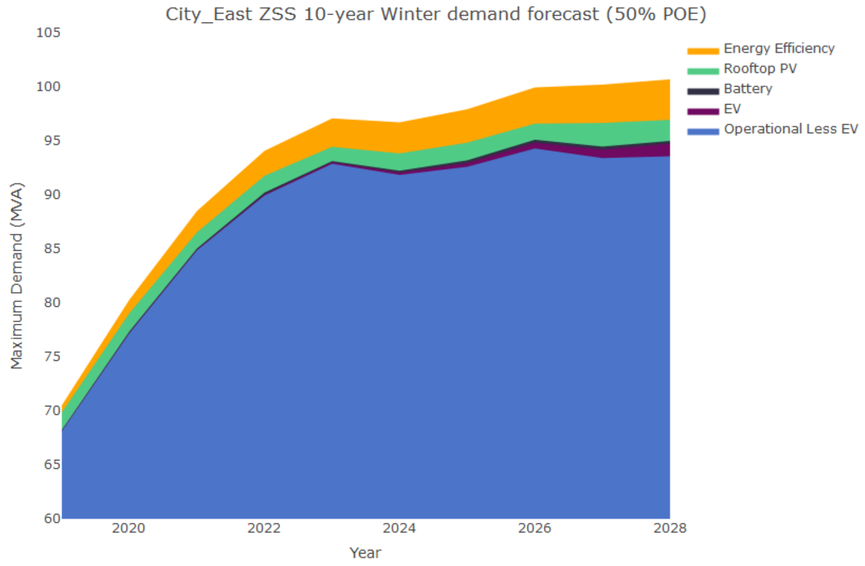
Summer POE Forecasts	***Winter POE Forecasts***
	

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

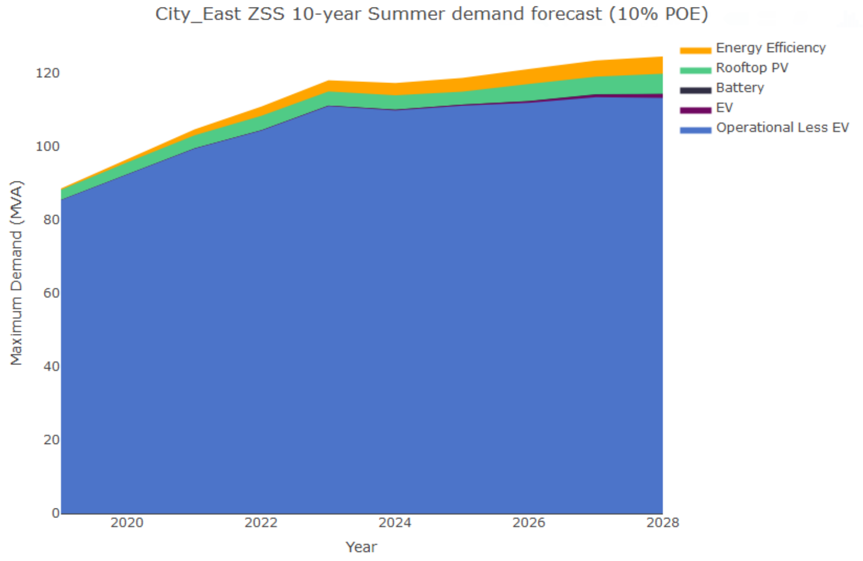
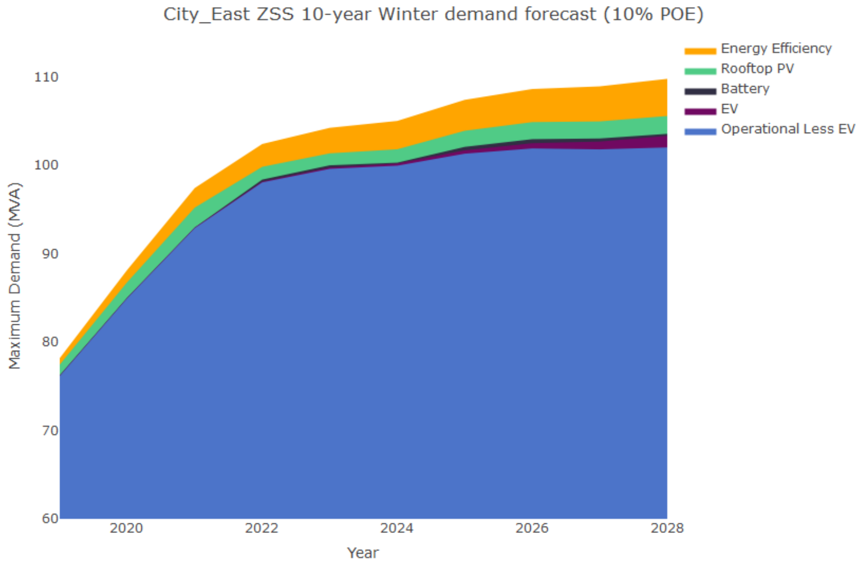
Summer POE Forecasts	*Winter POE Forecasts*
	

Table 5.2.3.2: City East ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2008	83	78	76	85	94
2009	88	90	75	85	94
2010	85	87	74	82	92
2011	83	80	72	80	90
2012	66	64	71	81	90
2013	75	81	68	77	86
2014	77	78	65	74	84
2015	67	64	63	72	82
2016	77	76	66	75	84
2017	75	89	69	79	90
2018	66	72	62	72	82

Table 5.2.3.3: City East ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	73	85	73	85	73	85	75	88	76	88
2020	81	92	81	92	81	92	84	96	85	97
2021	88	99	88	99	88	99	92	103	93	105
2022	93	104	93	104	93	104	97	108	99	111
2023	100	111	100	111	100	111	103	115	106	118
2024	98	110	98	110	98	110	102	114	105	117
2025	98	111	98	111	98	111	102	115	105	119
2026	99	112	99	112	100	112	103	117	107	121
2027	99	113	99	114	99	114	104	119	107	123
2028	100	113	101	114	101	114	106	120	110	124

Table 5.2.3.4: City East ZSS winter back-cast and weather correction in MVA

Winter			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2008	73	72	73	77	81
2009	74	73	72	76	81
2010	70	71	71	74	79
2011	70	72	70	75	80
2012	69	70	69	73	78
2013	69	65	66	70	76
2014	70	66	63	68	75
2015	70	68	64	70	76
2016	69	67	65	71	77
2017	69	68	62	68	74
2018	67	64	58	65	74

Table 5.2.3.5: City East ZSS winter forecast breakdown in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	68	76	68	76	68	76	70	77	71	78
2020	77	85	77	85	77	85	79	87	80	88
2021	85	93	85	93	85	93	87	95	89	97
2022	90	98	90	98	90	98	92	100	94	102
2023	93	100	93	100	93	100	94	101	97	104
2024	92	100	92	100	92	100	94	102	97	105
2025	93	101	93	102	93	102	95	104	98	107
2026	94	102	95	103	95	103	97	105	100	109
2027	93	102	94	103	94	103	97	105	100	109
2028	94	102	95	103	95	104	97	106	101	110

5.2.4 Civic Zone Substation Forecast

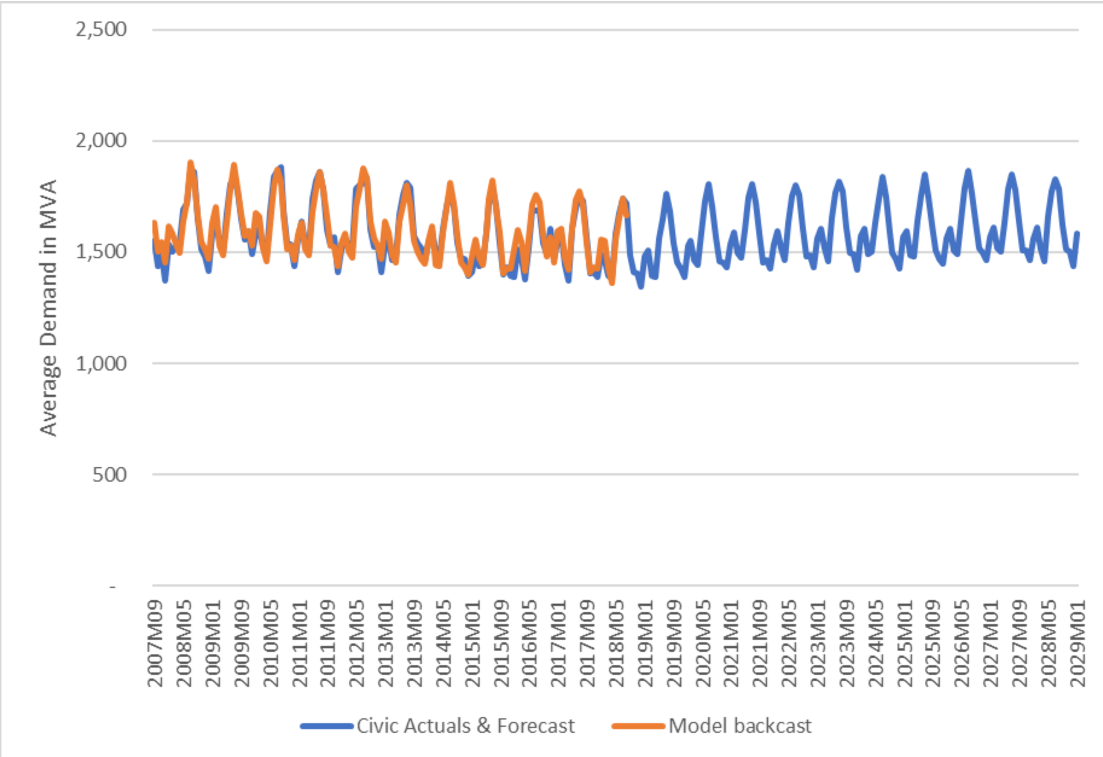
5.2.4.1 Seasonal average model

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, lagged retail price and business energy efficiency. The model had an adjusted R-squared statistic of 95% 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: Civic ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis and assumptions:

- Figure 5.2.4.1 demonstrates a clear downward trend up until the end of 2017/18 financial year. A positive trend is forecast from year 2018/19 onwards;
- Same like City East ZSS, strong commercial and residential development interests or projects such as ANU network upgrade, CBD expansion and City to Lake project were either confirmed or proposed by various developers and ACT government agencies;
- A new feeder was proposed from Civic ZSS to meet the demand of the above huge volume of developments;

- Civic ZSS will start supplying the new Whitlam estate via back mountain feeder from 2019/20 when Woden ZSS and its feeders are constraint at their maximum capacity;
- All future Civic ZSS block load (projects) are listed in Table 5.2.4.1.

5.2.4.2 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.

5.2.4.3 Final summer and Winter Demand forecast

The final forecast results and historical analysis are presented by 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 5.2.4.2 to 5.2.4.5: Actual or Forecast figures for Figure 5.2.4.2 and 5.2.4.3.

Key notes from Figure 5.2.4.2:

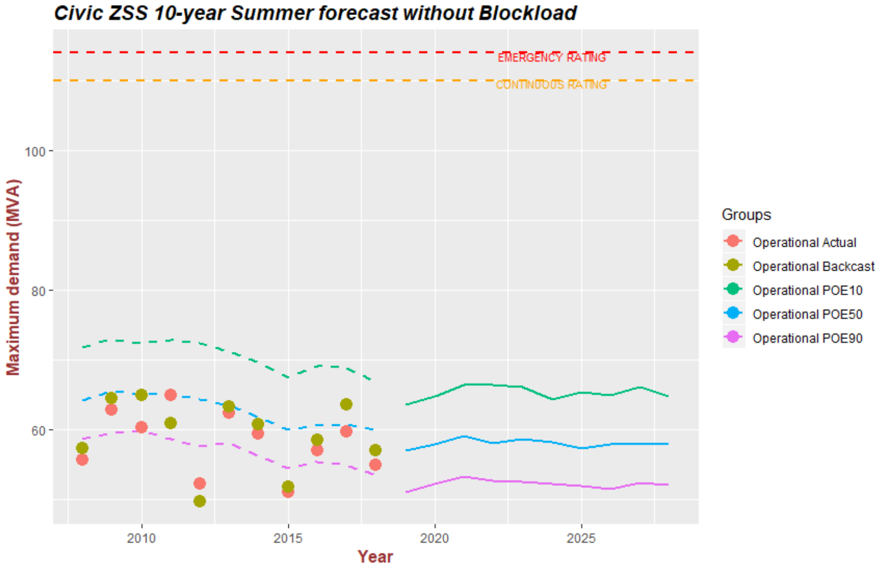
- Civic ZSS's maximum demand has been steady and below both continuous and emergency rating;
- With large capacity, Civic ZSS will play a key role in supplying load growth in the following areas:
  - Molonglo Valley developments (Whitlam new estate) prior to commissioning of Molonglo ZSS;
  - A new feeder to support Canberra City & Northbourne Avenue developments;
- No augmentation is required at zone level, because both summer and winter continuous rating are not expected to be exceeded in next 10 years.

Figure 5.2.4.3 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 PV system is still active and it is much more economic to use the energy generated directly from solar PV system.

Table 5.2.4.1: Civic ZSS detailed block loads in MVA

Block Load Project	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
PN20004045 -. Canberra Metro traction power station TPS 4	2.6									
20005206 - B20 S33 Dickson - Residential 102 apartments, commercial 3770 m² & car park 16124 m²			1							
Dickson on Northbourne - 25 Karuah St. Mixed development: 945 units Residential; 7538 m² Commercial; Hotel 96 rooms. (SOHO)			1.4		1.8	2.1	2			
PN20002983 - B3,5 & 15 S3 - 31 London Circuit. Residential 201 units, Commecial 668 m², Car park 7000 m².	0.75									
"PN20003048 - B20 & 21, S 63 - Corner London Cicruit & Knowles Place. Residential 84,500 m², Commercial 11,800 m², Retail 8,100 m², Car park 71,000 m².		1.3	1.5	1.5	1.5	0.7				
CSIRO Black mountain campus redevelopment		1.5								
City to Lake development Stage 1 - Corner Commonwealth Ave & London Circuit. Residential 607 units, Commercial 107,068 m², Community 32883 m².					1					
City to Lake development Stage 2 - Corner Commonwealth Ave and Parkes Way. Residential 2,130 units, Commercial 37,583 m².									1	3.3
B27 S19, Corner Vernon Circle & Constitution Ave. Commercial 5702 m².					0.5					
Whitlam New Estate			1.5	1.5						

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



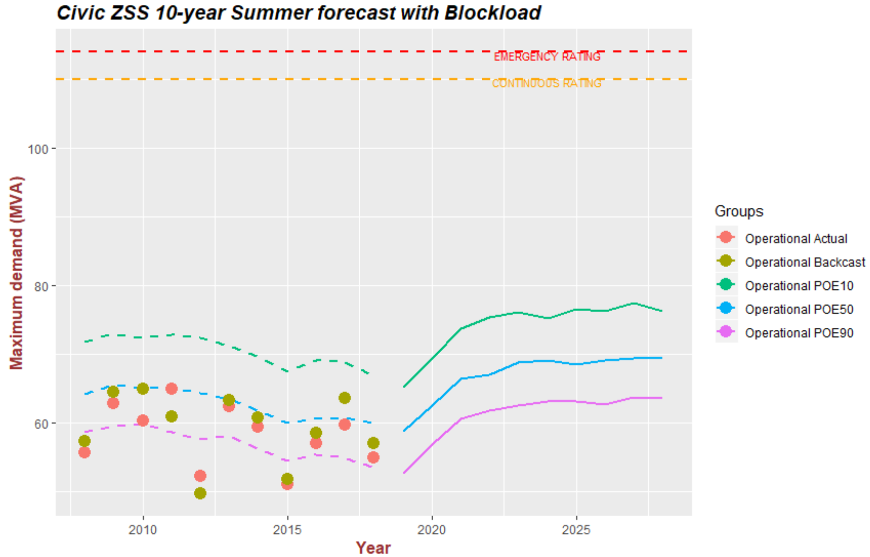
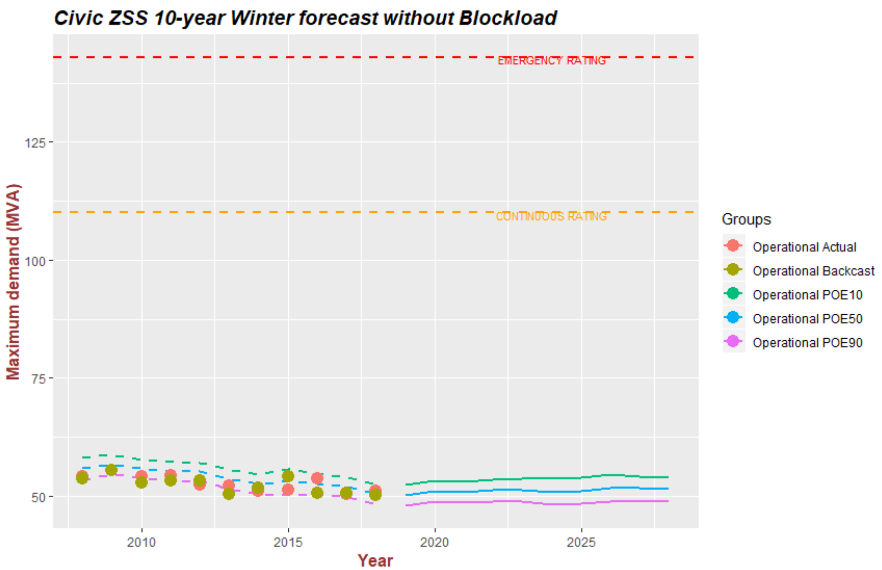


Figure 5.2.4.2: Civic ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



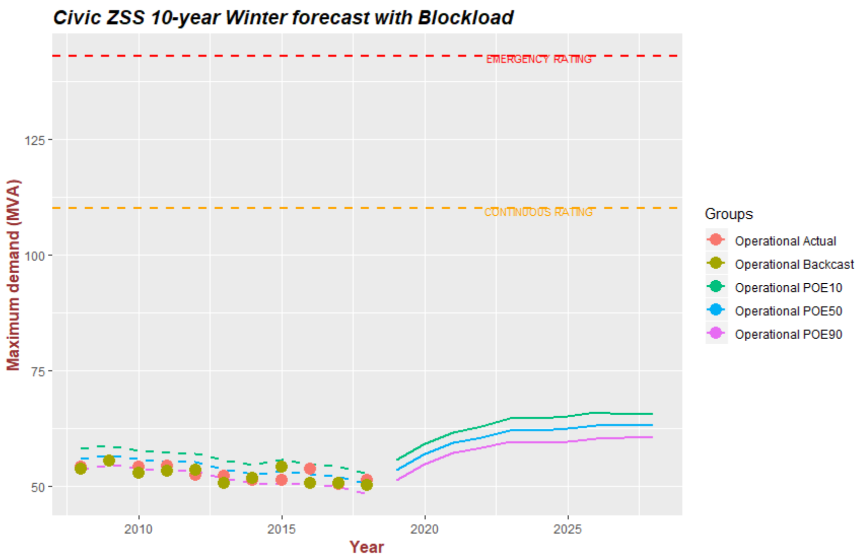


Figure 5.2.4.3: POE Forecast breakdown by structure change technology – Vertical analysis

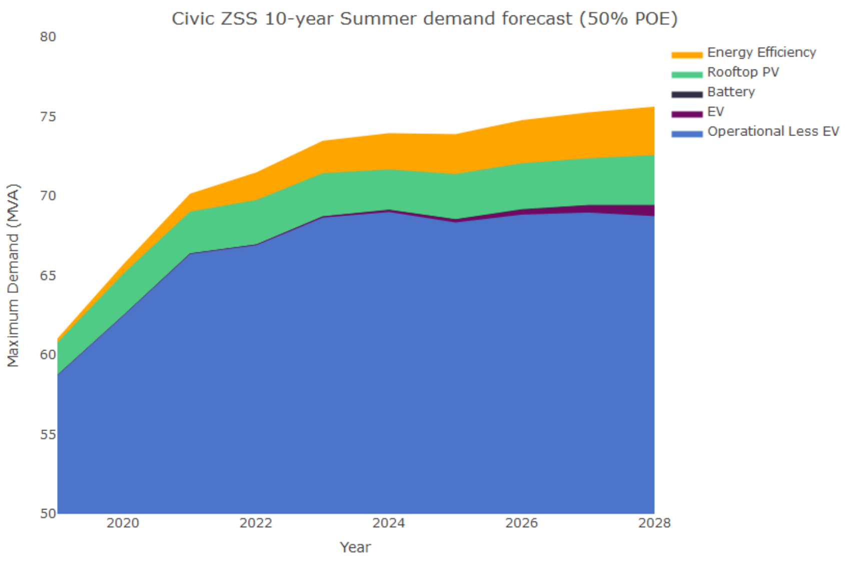
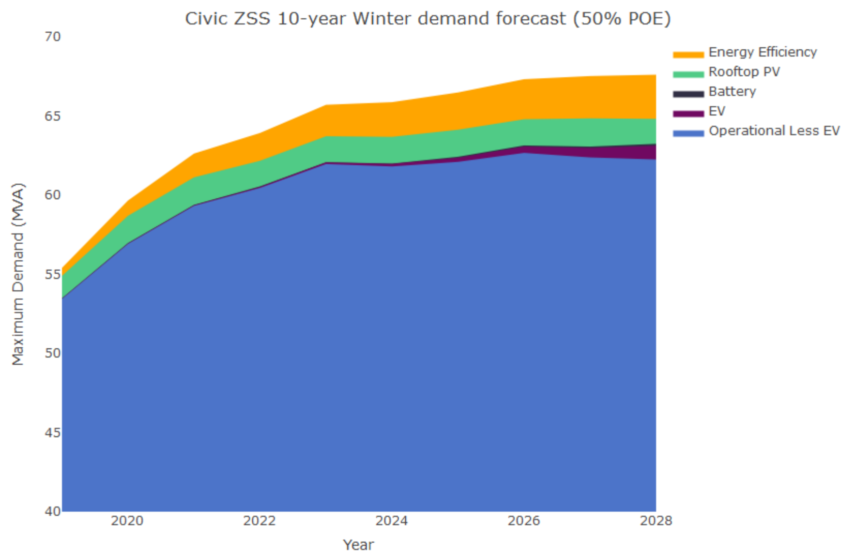
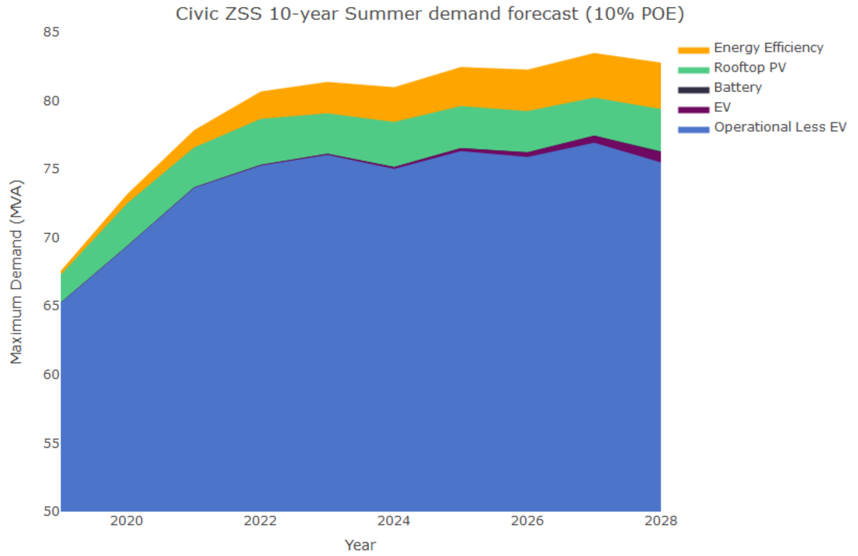
Summer POE Forecasts	Winter POE Forecasts
	

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

Summer POE Forecasts	Winter POE Forecasts



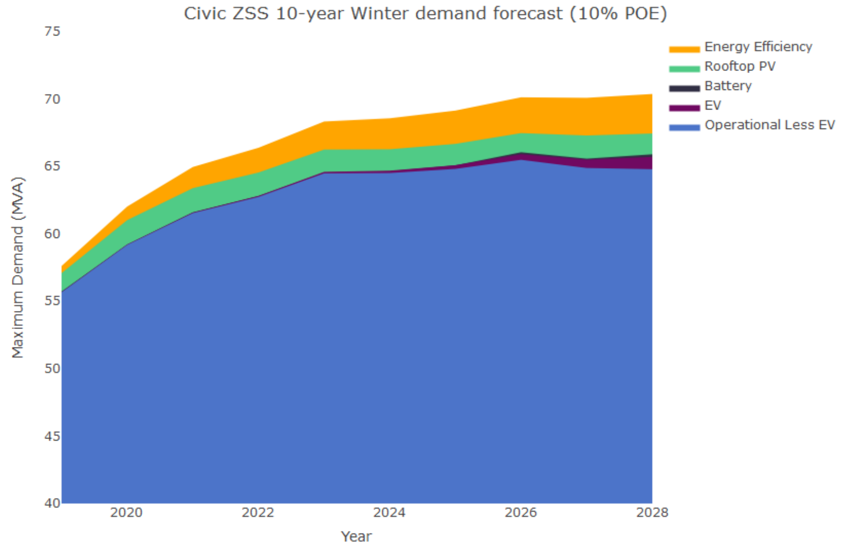


Table 5.2.4.2: Civic ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2008	56	57	59	64	72
2009	63	64	60	65	73
2010	60	65	60	65	72
2011	65	61	59	65	73
2012	52	50	58	64	72
2013	62	63	58	63	71
2014	59	61	56	62	70
2015	51	52	54	60	67
2016	57	58	55	61	69
2017	60	63	55	61	69
2018	55	57	53	60	67

Table 5.2.4.3: Civic ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	59	65	59	65	59	65	61	67	61	68
2020	62	69	63	69	63	69	65	73	66	73
2021	66	74	66	74	66	74	69	77	70	78
2022	67	75	67	75	67	75	70	79	71	81
2023	69	76	69	76	69	76	71	79	73	81
2024	69	75	69	75	69	75	72	78	74	81
2025	68	76	69	77	69	77	71	80	74	82
2026	69	76	69	76	69	76	72	79	75	82
2027	69	77	69	77	69	77	72	80	75	83
2028	69	75	69	76	69	76	73	79	76	83

Table 5.2.4.4: Civic ZSS winter back-cast and weather correction in MVA

Winter			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2008	54	54	54	56	64
2009	55	55	55	57	64
2010	54	53	54	56	63
2011	54	53	53	55	62
2012	52	53	53	55	62
2013	52	50	52	54	61
2014	51	52	50	53	60
2015	51	54	50	53	59
2016	54	51	50	53	60
2017	50	51	50	52	59
2018	51	50	48	50	57

Table 5.2.4.5: Civic ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	53	56	53	56	53	56	55	57	55	58
2020	57	59	57	59	57	59	59	61	60	62
2021	59	62	59	62	59	62	61	63	63	65
2022	60	63	61	63	61	63	62	65	64	66
2023	62	64	62	65	62	65	64	66	66	68
2024	62	65	62	65	62	65	64	66	66	69
2025	62	65	62	65	62	65	64	67	66	69
2026	63	65	63	66	63	66	65	67	67	70
2027	62	65	63	66	63	66	65	67	68	70
2028	62	65	63	66	63	66	65	67	68	70

5.2.5 East Lake Zone Substation Forecast

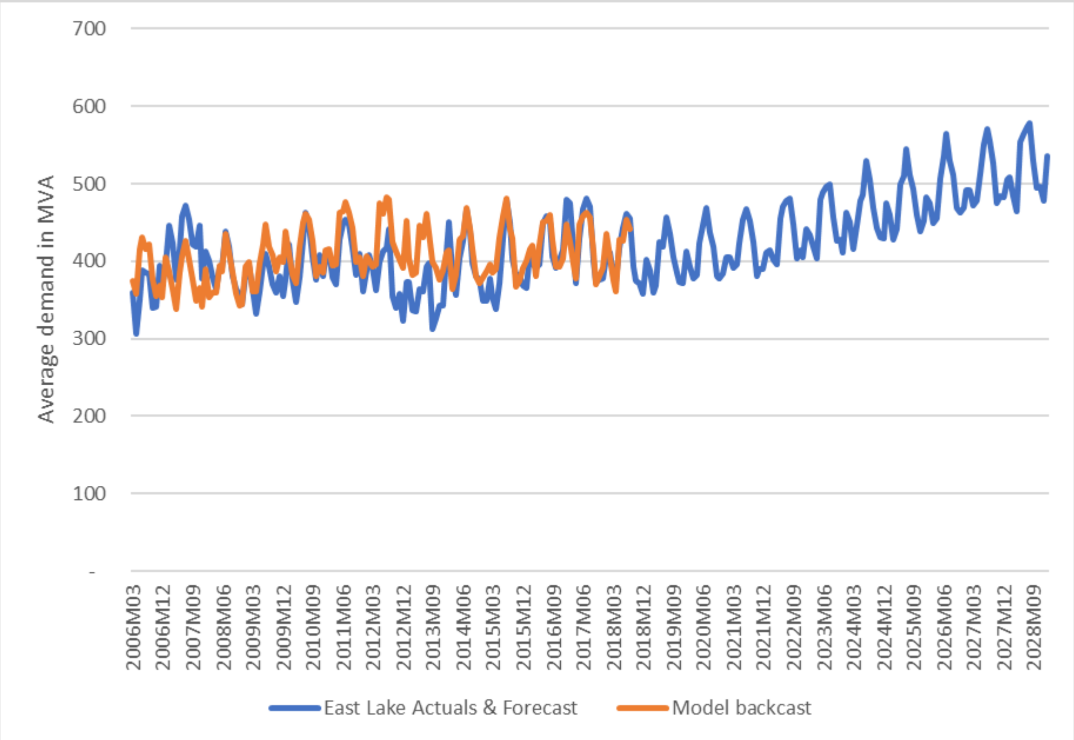
5.2.5.1 Seasonal average model

5.2.5.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Fyshwick regional population and lagged retail price. The model had an adjusted R-squared statistic of 72% 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: East Lake ZSS seasonal average demand – Model Fit and Forecast



Block load analysis and assumptions:

- A clear upward trend is indicated in Figure 5.2.5.1. Therefore, block load adjustment may not be required if any;
- The trend growth is consistent with the projection of ACT government planning and customer connection enquires and requests from potential customers;
- Fyshwick ZSS is planned to be decommissioned at the end of 2021/22 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 31.7 MVA and 26.7MVA and then each will be treated as a block load and fully transferred to East Lake ZSS at June 2022.

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 6.1.4.

5.2.5.3 Final summer and Winter Demand forecast

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

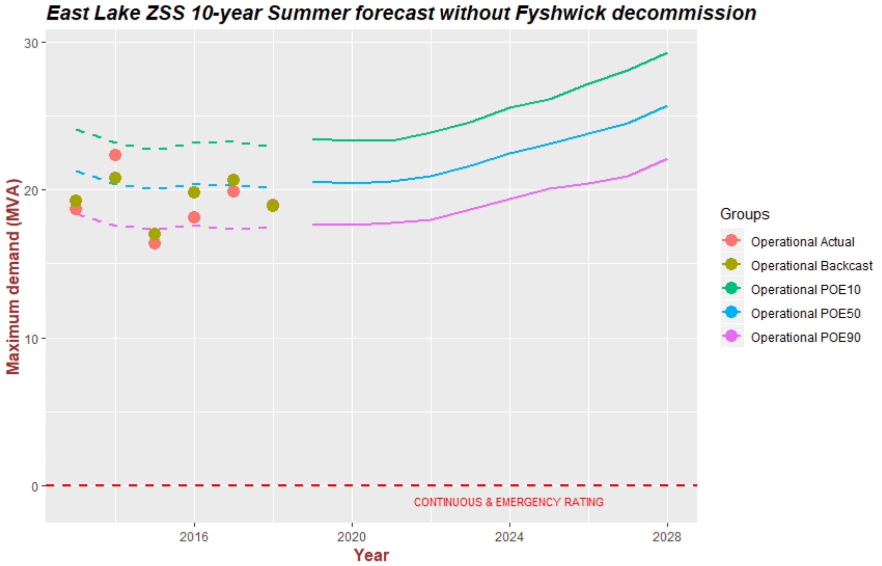
- Figure 5.2.5.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.5.3: Stack Chart by structure change impact;
- Table 5.2.5.1 to 5.2.5.4: Actual figures for Figure 5.2.5.2 and 5.2.5.3.

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 5.2.5.3 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 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 5.2.5.2: East Lake ZSS summer and winter demand forecast before and after Fyshwick decommission - Horizontal Analysis



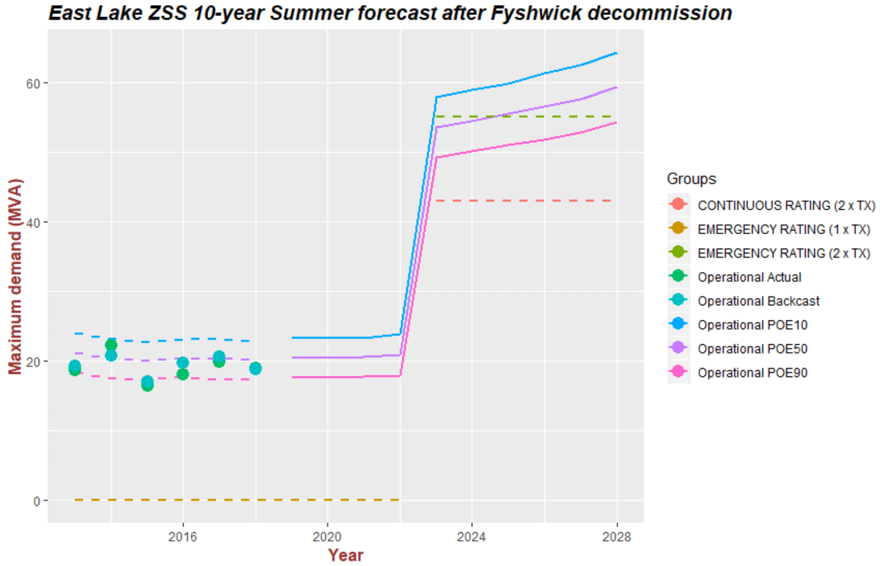
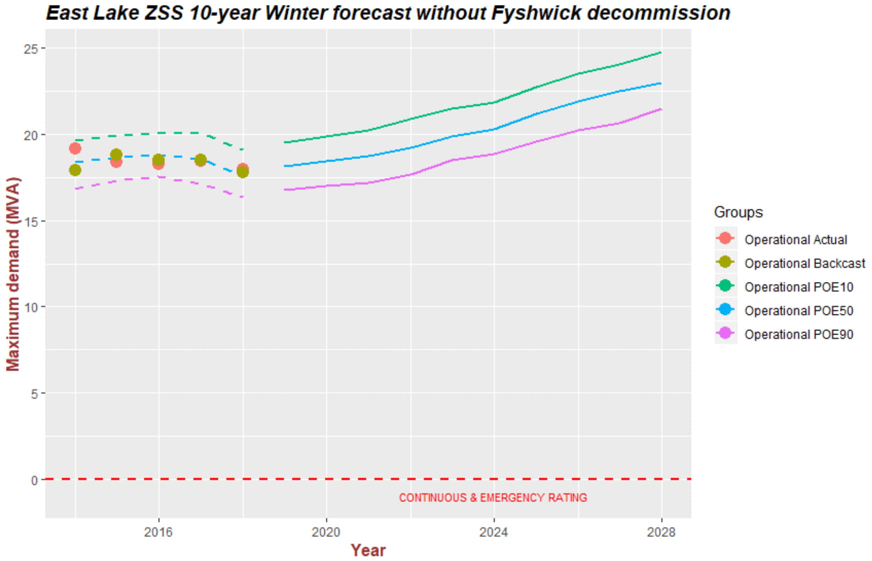


Figure 5.2.5.2: East Lake ZSS summer and winter demand forecast before and after Fyshwick decommission - Horizontal Analysis



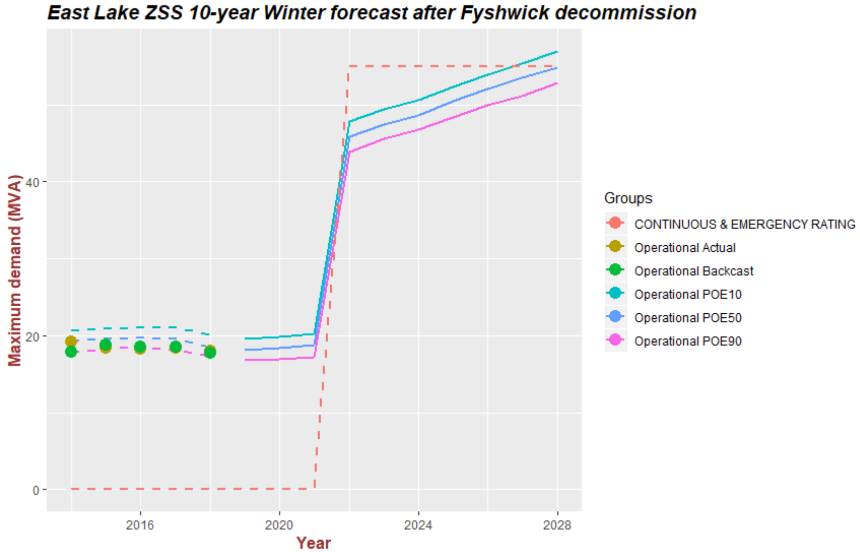


Figure 5.2.5.3: POE Forecast breakdown by structure change technology – Vertical analysis

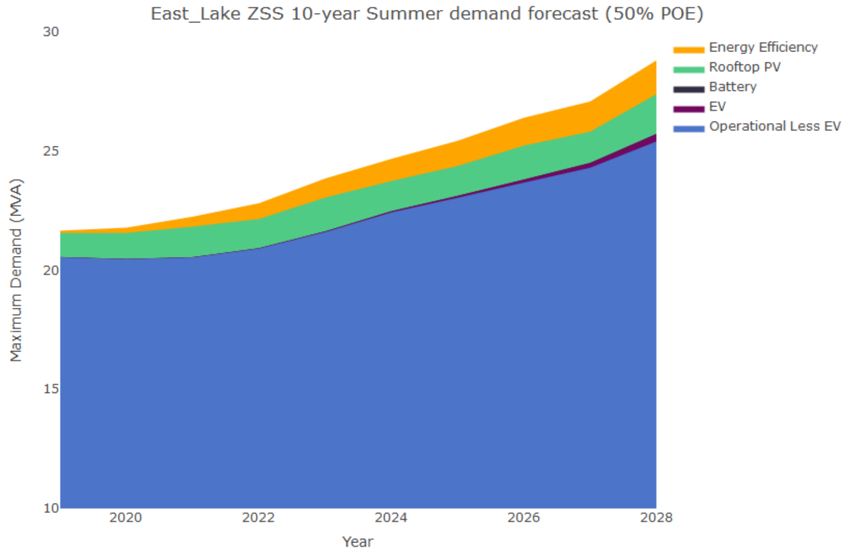
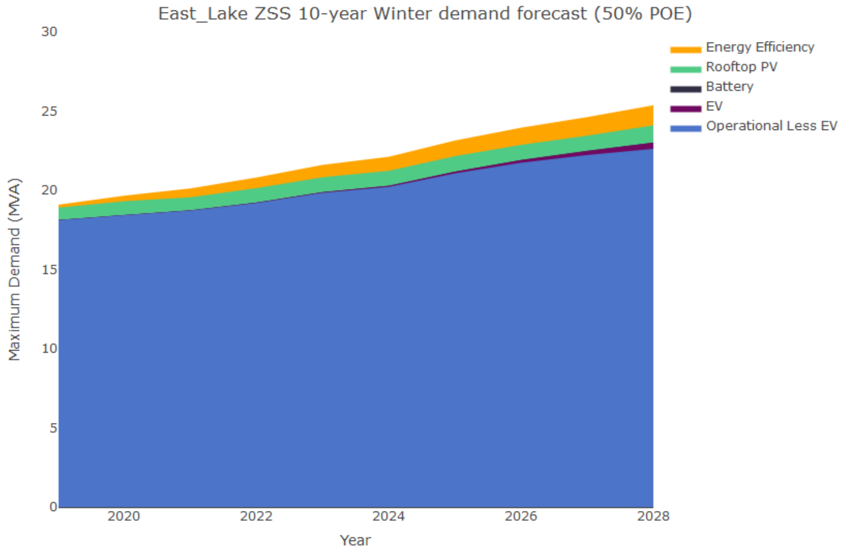
Summer POE Forecasts	***Winter POE Forecasts***
	

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

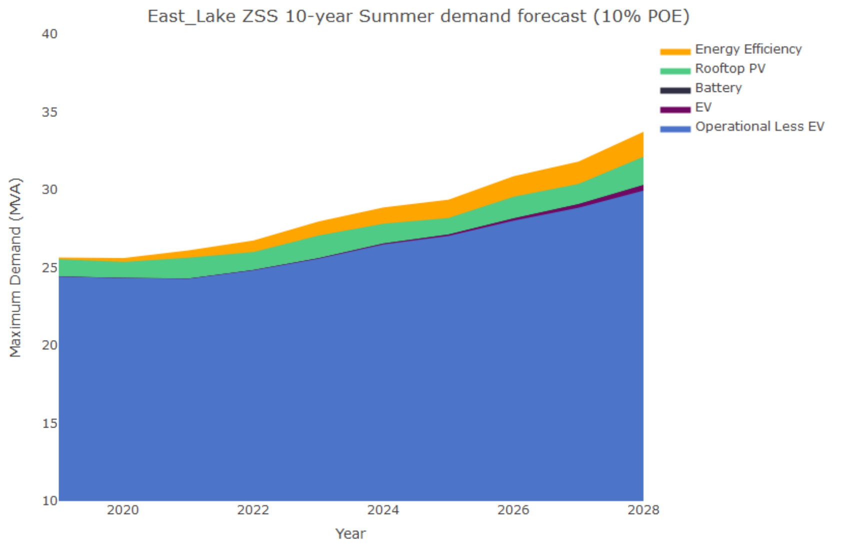
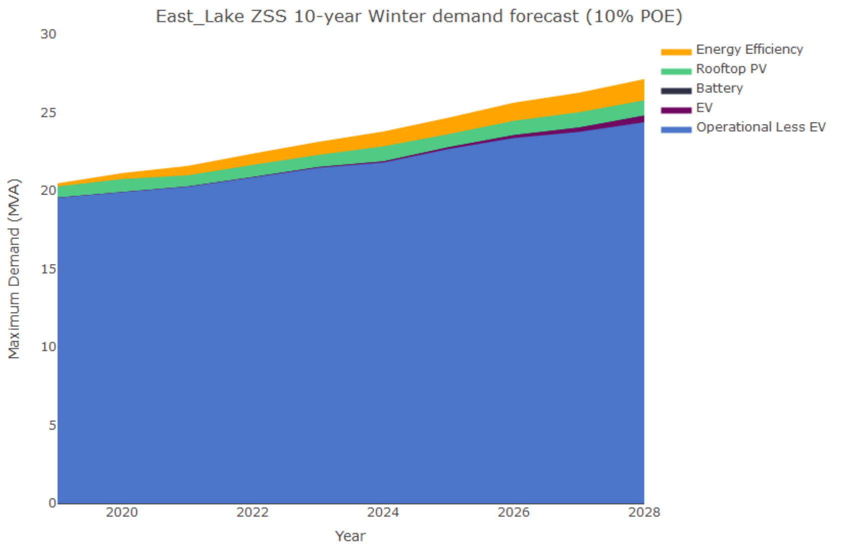
Summer POE Forecasts	***Winter POE Forecasts***
	

Table 5.2.5.1: East Lake ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2013	19	19	18	21	27
2014	22	21	17	20	26
2015	16	17	17	20	27
2016	18	20	17	20	26
2017	20	21	17	20	27
2018	19	19	17	20	25

Table 5.2.5.2: East Lake ZSS summer forecast before and after Fyshwick decommission in MVA

Summer	Before Fyshwick Decommission			After Fyshwick Decommission		
Year	POE90	POE50	POE10	POE90	POE50	POE10
2019	18	21	26	18	21	23
2020	18	20	26	18	20	23
2021	18	21	26	18	21	23
2022	18	21	27	18	21	24
2023	19	22	29	49	54	58
2024	19	22	30	50	54	59
2025	20	23	30	51	55	60
2026	20	24	30	52	57	61
2027	21	25	33	53	58	62
2028	22	26	33	54	59	64

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

Winter			Weather Correction		
Year	**Actual**	**Fitted**	**POE90**	**POE50**	**POE10**
2014	19	18	17	18	20
2015	18	19	17	19	20
2016	18	19	18	19	20
2017	18	19	17	19	20
2018	18	18	16	18	19

Table 5.2.5.4: East Lake ZSS winter forecast before and after Fyshwick decommission in MVA

Winter	Before Fyshwick Decommission			After Fyshwick Decommission		
Year	**POE90**	**POE50**	**POE10**	**POE90**	**POE50**	**POE10**
2019	17	18	20	17	18	20
2020	17	18	20	17	18	20
2021	17	19	20	17	19	20
2022	18	19	21	44	46	48
2023	19	20	22	46	47	49
2024	19	20	22	47	49	51
2025	20	21	23	48	50	52
2026	20	22	24	50	52	54
2027	21	22	24	51	53	55
2028	21	23	25	53	55	57

5.2.6 Fyshwick Zone Substation Forecast

5.2.6.1 Seasonal forecast model

5.2.6.1.1 Methodology Description

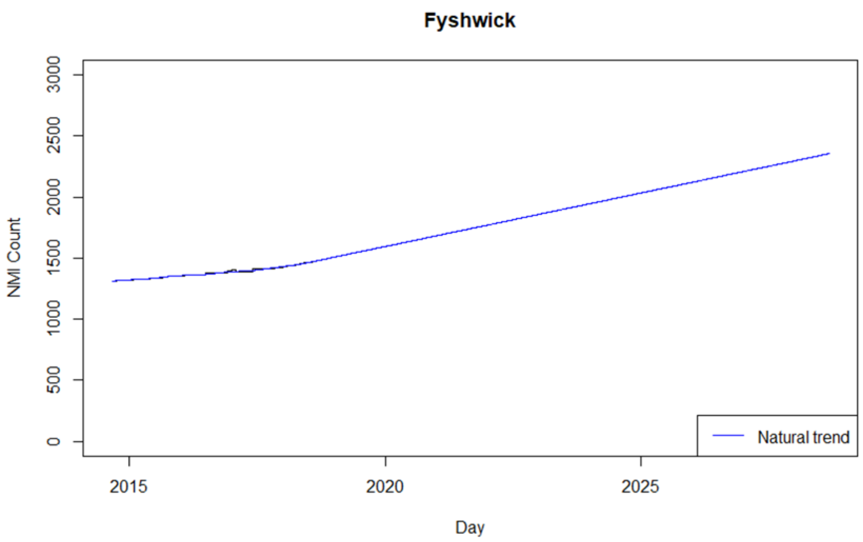
Western Power maximum demand forecast (WPMDFC) methodology was used for Fyshwick ZSS demand forecast. Evoenergy was very grateful and thankful the kindly support from Dr Yun Li, who is the Senior Forecasting and Modelling Analyst of Western Power. The detailed methodology is not going to be discussed in this report, because Dr Li's research paper regarding to the WPMDFC methodology is still under consideration of board of *IEEE Transactions on Power Systems* before officially publication. However, a brief description of the WPMDFC methodology quoted from the paper's abstract states:

"…To support long term planning, utilities typically complete energy consumption and maximum demand forecasts, are often forecast separately through two different process, which can lead to inconsistent trends and messages. To address these shortcomings, a point process approach from extreme value theory is proposed to model substation maximum demand as a function of trends in three common factors (including the customer count, the energy throughput and installed photovoltaic capacity). The point process model can be parameterized as a nonstationary generalized extreme value distribution with location and scale parameters dependent on the trends in these factors. As the generalized extreme value distribution governs the behaviors of block maxima (annual maximum demand), with forecast trends in three common factors, substation maximum demand can be estimated as per quantiles required by planning standards…"

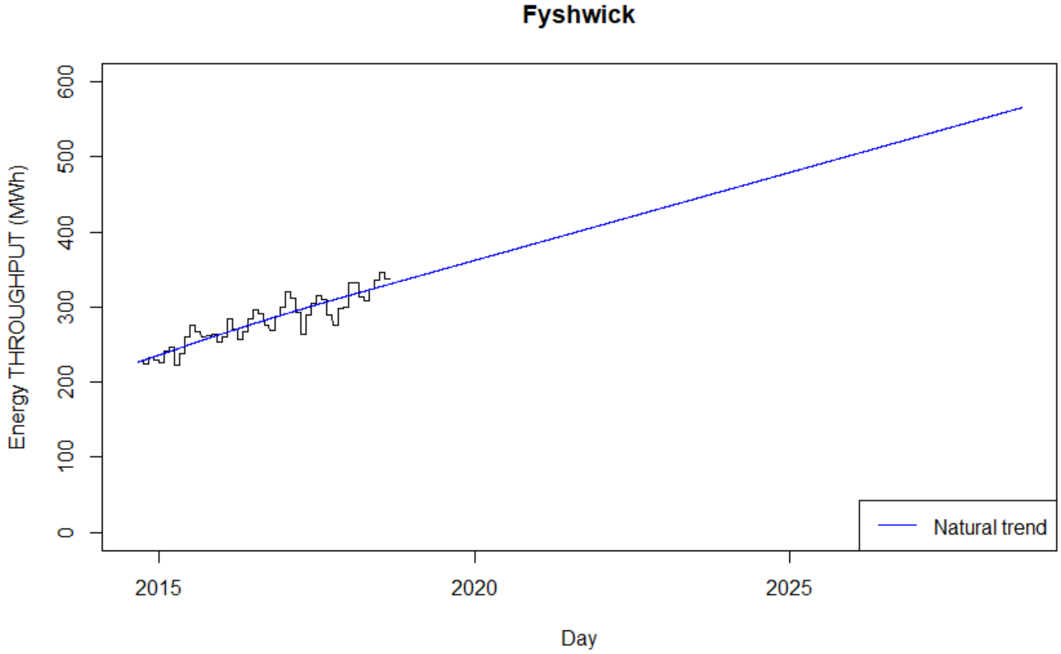
5.2.6.1.2 Model parameters

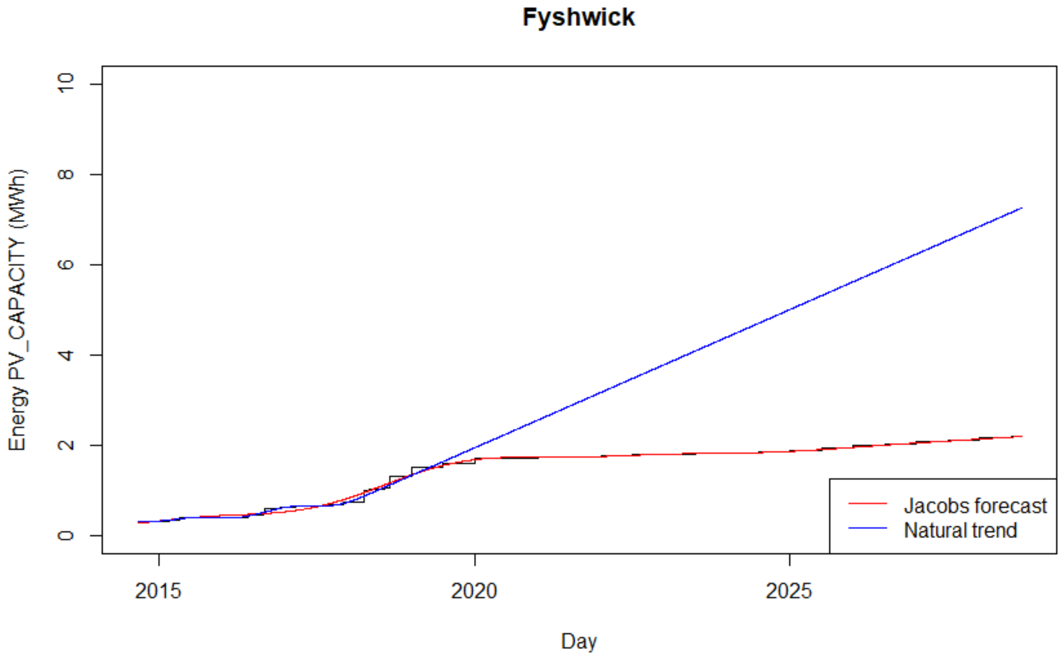
As the above abstract mentions, there are three key model inputs under WPMDFC framework:

Figure 5.2.6.1: three key model inputs



Fyshwick


Fyshwick
Energy THROUGHPUT (MWh)
0
100
200
300
400
500
600
2015
2020
2025
Day
Natural trend


Fyshwick
Energy PV_CAPACITY (MWh)
0
2
4
6
8
10
2015
2020
2025
Day
Jacobs forecast
Natural trend

5.2.6.2 Model Selection Summary and final Models

Table 5.2.6.1: Fyshwick ZSS seasonal average demand – Model Fit and Forecast

<table>
<tr><th>Season</th><th>Model Selection Summary</th><th>Select PP Model</th><th>Comments</th></tr>
<tr><td>Summer</td><td>
<table>
<tr><th>k</th><th>nllh</th><th>AIC</th><th>BIC</th><th>Model</th><th>Rank</th></tr>
<tr><td>4.0</td><td>6.7</td><td>21.5</td><td>24.0</td><td>mu3</td><td>1</td></tr>
<tr><td>3.0</td><td>14.3</td><td>34.5</td><td>36.4</td><td>Stationary</td><td>2</td></tr>
<tr><td>6.0</td><td>64.5</td><td>140.9</td><td>144.8</td><td>mu123</td><td>3</td></tr>
<tr><td>5.0</td><td>67.0</td><td>144.1</td><td>147.3</td><td>mu12</td><td>4</td></tr>
<tr><td>5.0</td><td>68.5</td><td>147.0</td><td>150.2</td><td>mu2_sig3</td><td>5</td></tr>
<tr><td>4.0</td><td>70.2</td><td>148.4</td><td>151.0</td><td>mu2</td><td>6</td></tr>
</table>
</td><td>Model: mu3
$$\mathrm{POE}(\mathrm{t,p}) = 23.12 + 4.76Z_{3t} + \frac{0.79}{-1.16}\{[-ln(1-p)]^{1.16} - 1\}$$</td><td>Z_{3t} is the trend of PV Capacity.</td></tr>
<tr><td>Winter</td><td>
<table>
<tr><th>k</th><th>nllh</th><th>AIC</th><th>BIC</th><th>Model</th><th>Rank</th></tr>
<tr><td>6.0</td><td>-7.3</td><td>-2.6</td><td>3.4</td><td>mu123</td><td>1</td></tr>
<tr><td>5.0</td><td>-6.0</td><td>-2.1</td><td>2.9</td><td>mu12</td><td>2</td></tr>
<tr><td>6.0</td><td>-5.7</td><td>0.5</td><td>6.5</td><td>mu12_sig3</td><td>3</td></tr>
<tr><td>7.0</td><td>-6.4</td><td>1.2</td><td>8.2</td><td>mu123_sig3</td><td>4</td></tr>
<tr><td>4.0</td><td>-3.2</td><td>1.5</td><td>5.5</td><td>mu3</td><td>5</td></tr>
<tr><td>3.0</td><td>9.8</td><td>25.6</td><td>28.6</td><td>Stationary</td><td>6</td></tr>
</table>
</td><td>Model: mu12
$$\mathrm{POE}(\mathrm{t,p}) = 13.28 - 0.0084Z_{1t} + 0.068Z_{2t} + \frac{0.34}{-0.65}\{[-ln(1-p)]^{0.65} - 1\}$$</td><td>Z_{1t} is the trend of NMI count on day t and Z_{2t} is the trend of energy throughput on day t.</td></tr>
</table>

5.2.6.3 Final summer and Winter Demand forecast

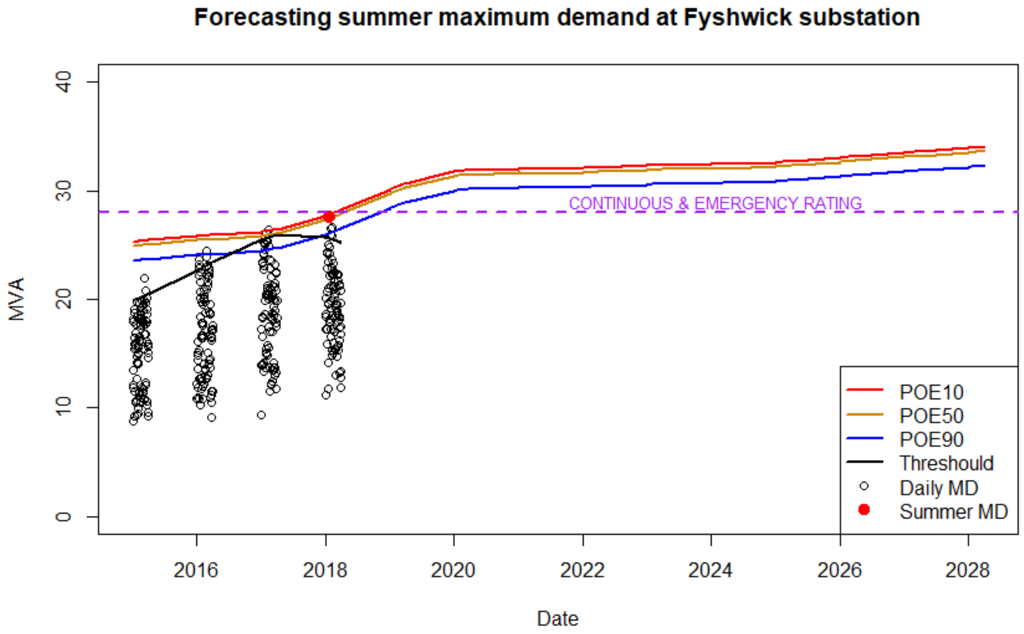
The final forecast results and historical load analysis are presented by following formats:

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

Key findings:

- See section 5.2.5 for the impact of Fyshwick ZSS decommission towards the East Lake ZSS;
- The load growth trend demonstrates in the forecast is consistent with government's future master planning in Fyshwick and Kingston area.

Figure 5.2.6.2: Fyshwick ZSS summer and winter demand forecast



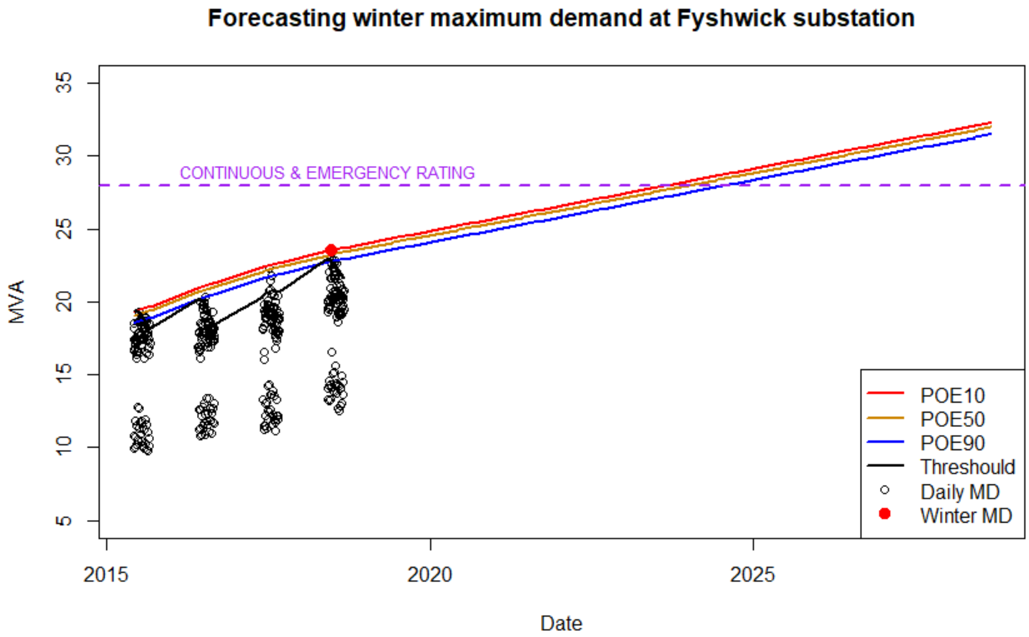


Figure 5.2.6.3: Residual analysis

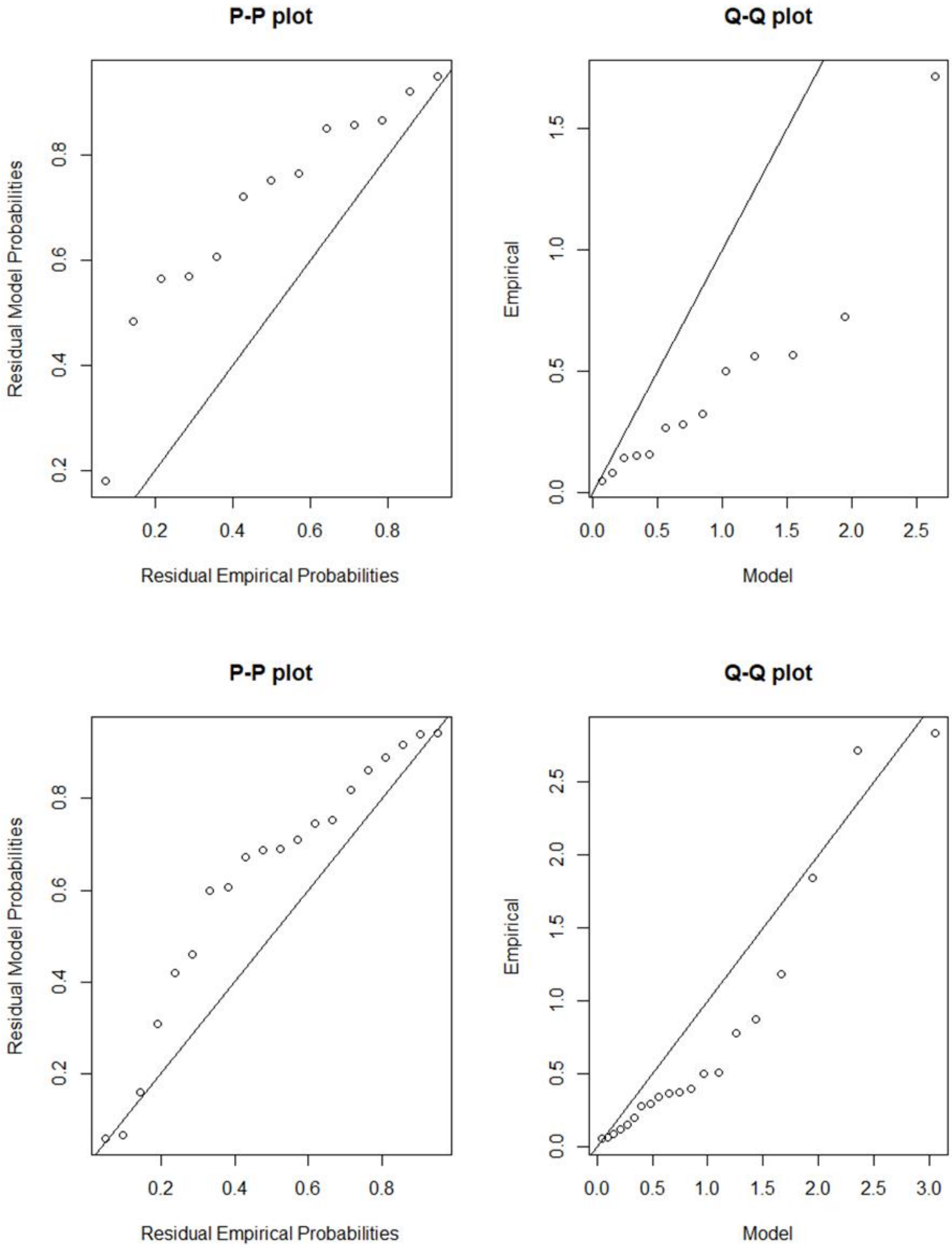


Table 5.2.6.1: Fyshwick ZSS summer back-cast and weather correction in MVA

Summer		Weather Correction		
Year	Actual	POE90	POE50	POE10
2015	21.9	23.6	24.9	25.3
2016	24.5	24.1	25.5	25.9
2017	26.4	24.6	25.9	26.3
2018	27.5	26.2	27.6	27.9

Table 5.2.6.2: Fyshwick ZSS summer POE forecast in MVA

Summer	Forecast		
Year	POE90	POE50	POE10
2019	28.6	30.0	30.4
2020	30.1	31.4	31.8
2021	30.3	31.6	32.0
2022	30.3	31.7	32.1
2023	30.6	31.9	32.3
2024	30.7	32.0	32.4
2025	30.9	32.3	32.6
2026	31.3	32.7	33.1
2027	31.8	33.1	33.5
2028	32.2	33.6	34.0

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

Winter		Weather Correction		
Year	**Actual**	**POE90**	**POE50**	**POE10**
2015	19.3	18.7	19.2	19.5
2016	20.4	20.3	20.8	21.1
2017	22.3	21.7	22.2	22.5
2018	23.5	22.8	23.3	23.6

Table 5.2.6.4: Fyshwick ZSS winter POE forecast in MVA

Winter	Forecast		
Year	**POE90**	**POE50**	**POE10**
2019	23.7	24.2	24.5
2020	24.5	25.0	25.3
2021	25.4	25.9	26.2
2022	26.2	26.7	27.0
2023	27.1	27.6	27.9
2024	28.0	28.4	28.7
2025	28.8	29.3	29.6
2026	29.7	30.2	30.4
2027	30.5	31.0	31.3
2028	31.4	31.9	32.2

5.2.7 Gilmore Zone Substation Forecast

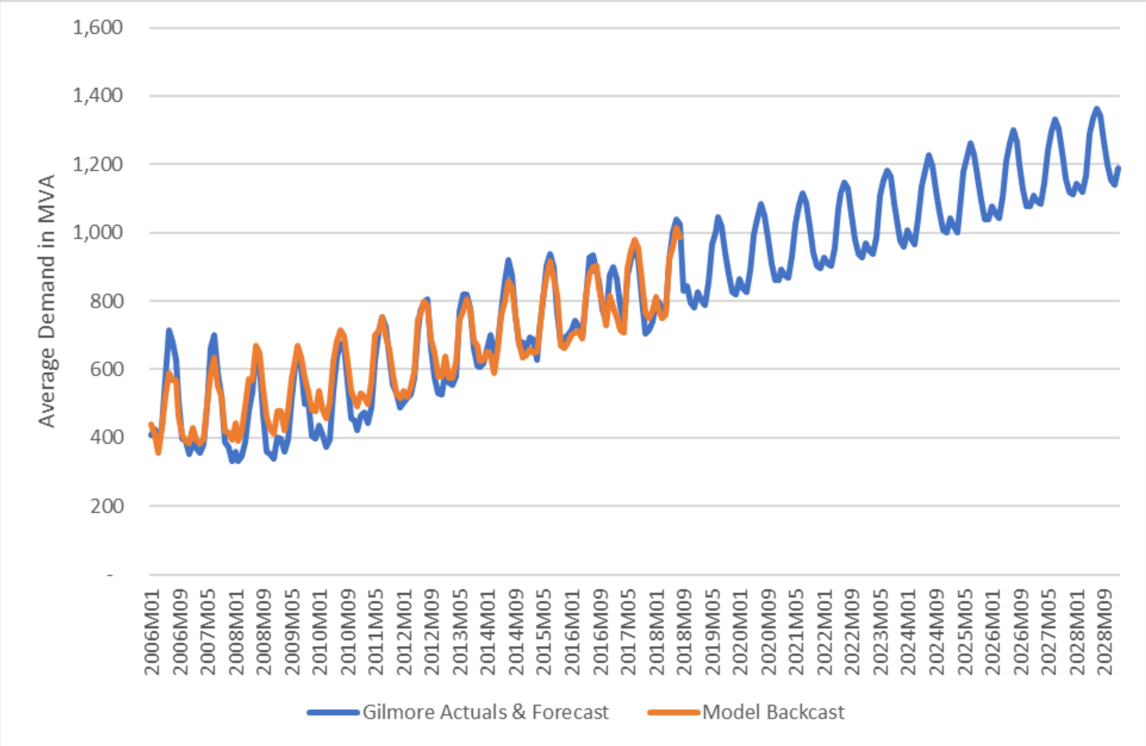
5.2.7.1 Seasonal average model

5.2.7.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, trend and Tuggeranong population. The model had an adjusted R-squared statistic of 98% 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: Gilmore ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis and assumptions:

- Figure 5.2.7.1 demonstrates a clear upward trend over the next ten years;
- The yearly trend growth is consistent with feedback from customers and in line with Government's plan of Hume Industry Park expansion.

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 6.1.6.

5.2.7.3 Final summer and Winter Demand forecast

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

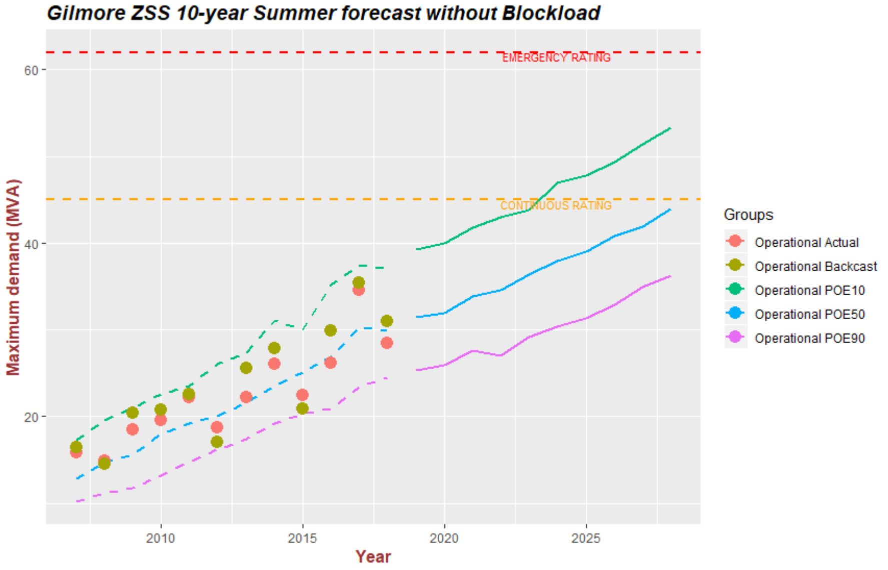
- Figure 5.2.7.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.7.3: Stack Chart by structure change impact;
- Table 5.2.7.1 to 5.2.7.4: Actual or Forecast figures for Figure 5.2.7.2 and 5.2.7.3.

Key notes from Figure 5.2.7.2 are:

- Industrial load growth has been consistent in Hume, which drives the growth of electricity demand at Gilmore ZSS;
- Figure 5.2.7.2 indicates that 10% POE forecast for both summer is forecast to exceed the continuous rating approximately by 2 MVA by 2024;
- Gilmore ZSS is capable to meet all electricity demand in the surrounding area for the next ten years under the "N-1" standard.

Figure 5.2.7.3 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 5.2.7.2: Gilmore ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



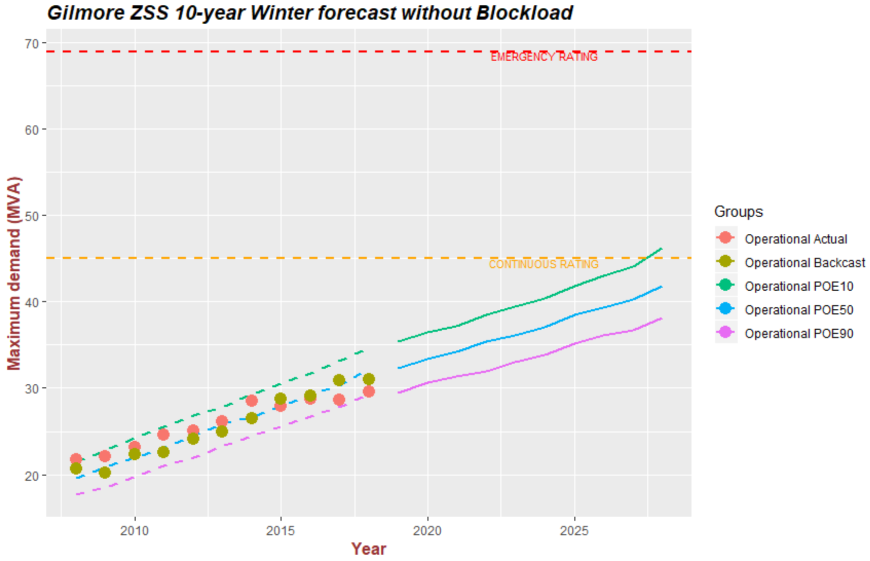


Figure 5.2.7.3: POE Forecast breakdown by structure change technology – Vertical analysis

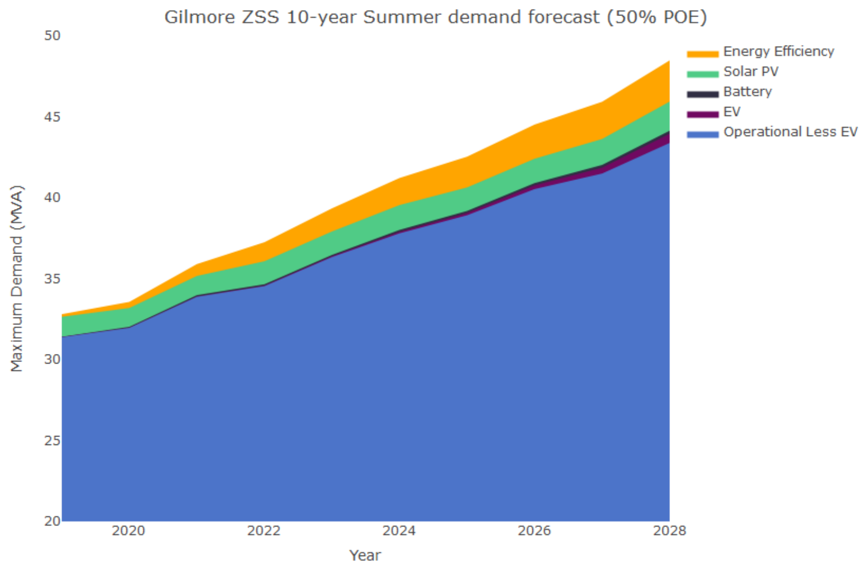
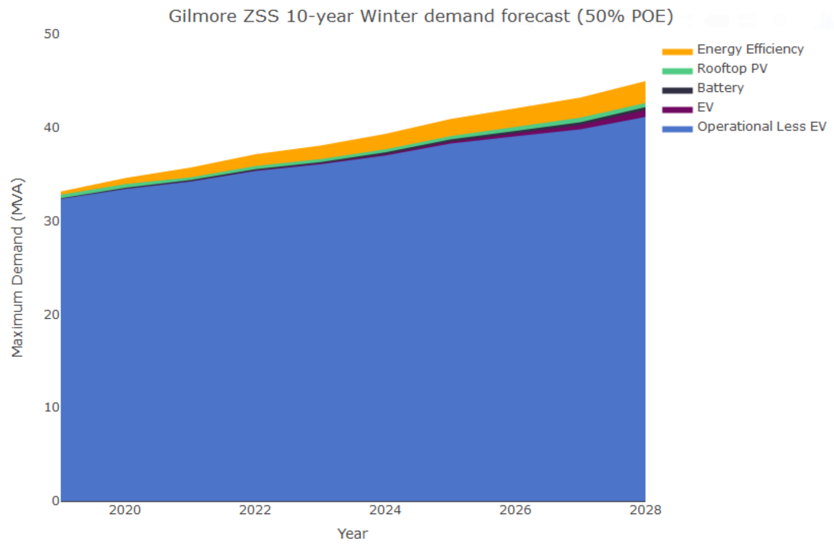
Summer POE Forecasts	***Winter POE Forecasts***
	

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

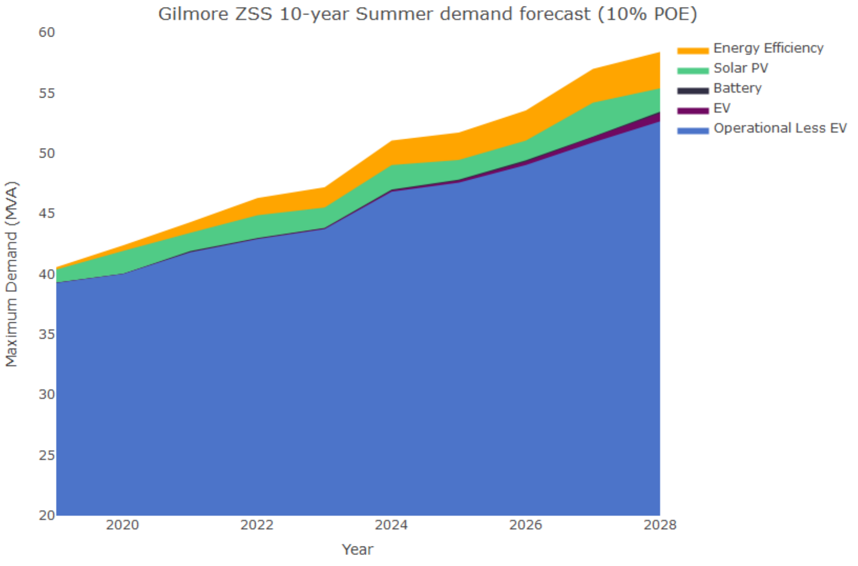
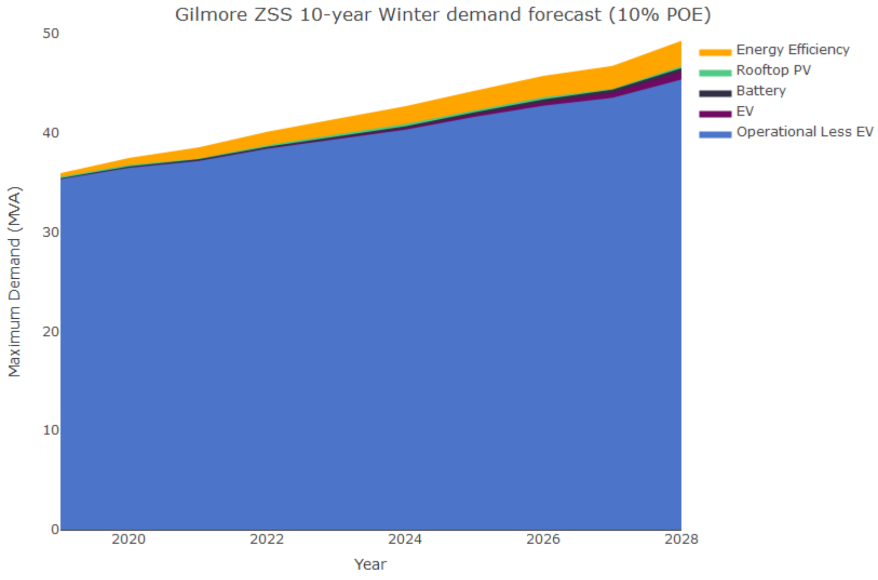
Summer POE Forecasts	*Winter POE Forecasts*
	

Table 5.2.7.1: Gilmore ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	**Actual**	**Fitted**	**POE90**	**POE50**	**POE10**
2007	16	16	10	13	17
2008	15	15	11	15	20
2009	19	20	12	16	21
2010	20	21	13	18	23
2011	22	23	15	19	23
2012	19	17	16	20	26
2013	22	26	17	22	27
2014	26	28	19	23	31
2015	22	21	20	25	30
2016	26	30	21	27	35
2017	35	35	23	30	38
2018	28	31	24	30	37

Table 5.2.7.2: Gilmore ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**	**POE50**	**POE10**
2019	31	39	31	39	31	39	33	40	33	41
2020	32	40	32	40	32	40	33	42	34	42
2021	34	42	34	42	34	42	35	43	36	44
2022	35	43	35	43	35	43	36	45	37	46
2023	36	44	36	44	36	44	38	46	39	47
2024	38	47	38	47	38	47	40	49	41	51
2025	39	48	39	48	39	48	41	49	43	52
2026	41	49	41	49	41	49	42	51	45	54
2027	41	51	42	51	42	51	44	54	46	57
2028	43	53	44	53	44	53	46	55	48	58

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

Winter			Weather Correction		
Year	**Actual**	**Fitted**	**POE90**	**POE50**	**POE10**
2008	22	21	18	20	21
2009	22	20	18	21	23
2010	23	22	20	22	24
2011	25	23	21	23	26
2012	25	24	22	25	27
2013	26	25	23	26	28
2014	29	26	24	27	29
2015	28	29	26	28	31
2016	29	29	27	29	32
2017	29	31	28	30	33
2018	30	31	29	32	35

Table 5.2.7.4: Gilmore ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	32	35	32	35	32	35	33	36	33	36
2020	33	36	33	36	34	37	34	37	35	37
2021	34	37	34	37	34	37	35	37	36	39
2022	35	38	35	38	36	39	36	39	37	40
2023	36	39	36	39	36	40	37	40	38	41
2024	37	40	37	40	37	41	38	41	39	43
2025	38	42	38	42	39	42	39	42	41	44
2026	39	43	39	43	40	43	40	44	42	46
2027	40	44	40	44	41	44	41	44	43	47
2028	41	45	42	46	42	47	43	47	45	49

5.2.8 Gold Creek Zone Substation Forecast

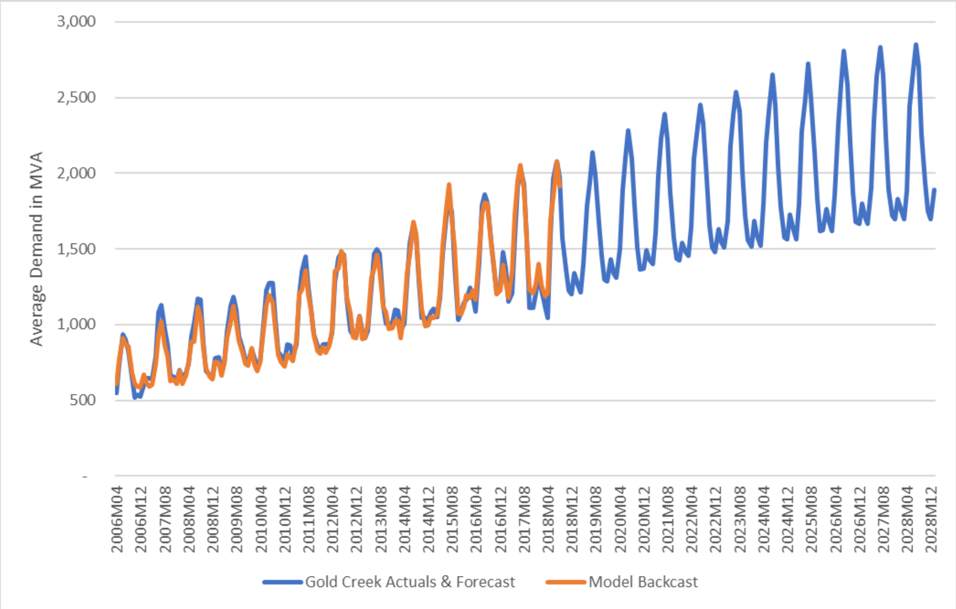
5.2.8.1 MEFM Seasonal average model

5.2.8.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Gungahlin regional population and retail price. The model had an adjusted R-squared statistic of 98% 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: Gold Creek ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis and assumptions:

- The 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;
- Therefore, a clear upward trend is demonstrated in Figure 5.2.8.1;
- Additional block load is not required for this instance to avoid double accounting as the trend has well explained the load growth in the past and future;

5.2.8.2 MEFM 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.

5.2.8.3 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 5.2.8.1 to 5.2.8.4: Actual or Forecast figures for Figure 5.2.8.2 and 5.2.8.3.

Key notes from Figure 5.2.8.2 are:

- The summer 2 hour emergency rating is forecast to be exceeded during the 2019-24 Regulatory Control Period by its 50% POE forecast in 2023 under MEFM and in 2021 under WPMDFC;
- The winter 2 hour emergency rating is forecast to be exceeded during the 2019-24 Regulatory Control Period by its 50% POE forecast in 2021 under MEFM and in 2020 under WPMDFC;
- MEFM and WPMDFC's winter forecasts are almost identical whereas MEFM's summer forecast has wider spread than WPMDFC's summer forecast;
- Winter maximum demand is hardly impacted or offset by rooftop PV as its peak time is always after daylight;
- Table 5.2.8.5 lists detailed WPMDFC model information;
- A third 132/11 kV 30/55 MVA transformer is proposed to be installed at Gold Creek Zone Substation in the 2024-29 Regulatory Control Period.

Figure 5.2.8.3 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 5.2.8.2: POE Forecast by MEFM and WPMDFC– Vertical analysis

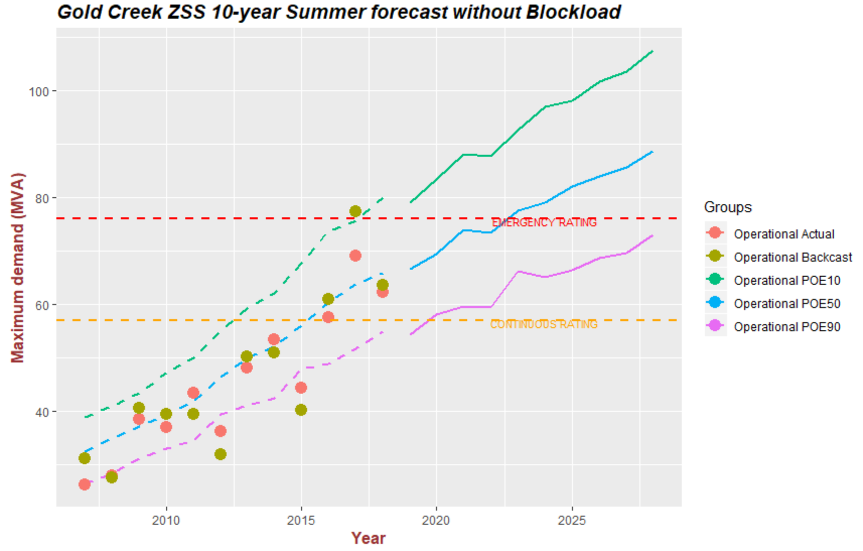
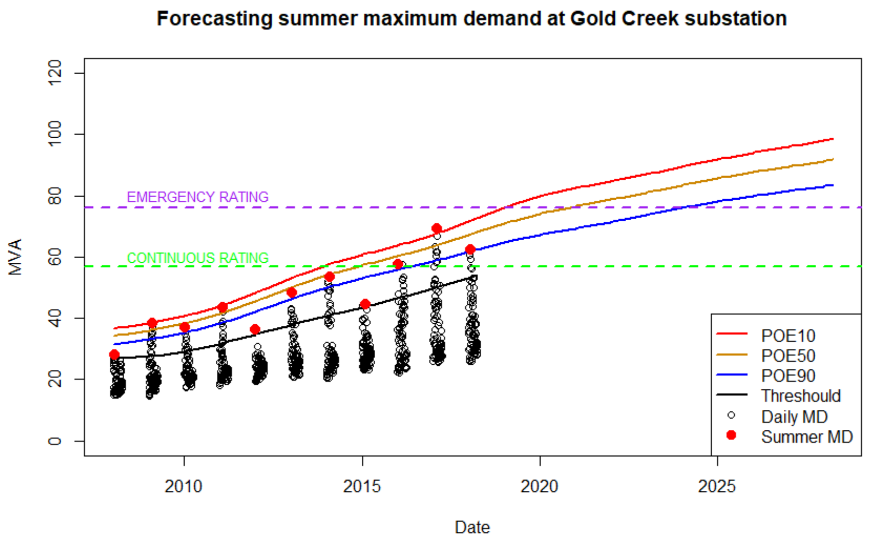
MEFM Forecast	WPMDFC Forecast
	

Figure 5.2.8.2: POE Forecast by MEFM and WPMDFC– Vertical analysis

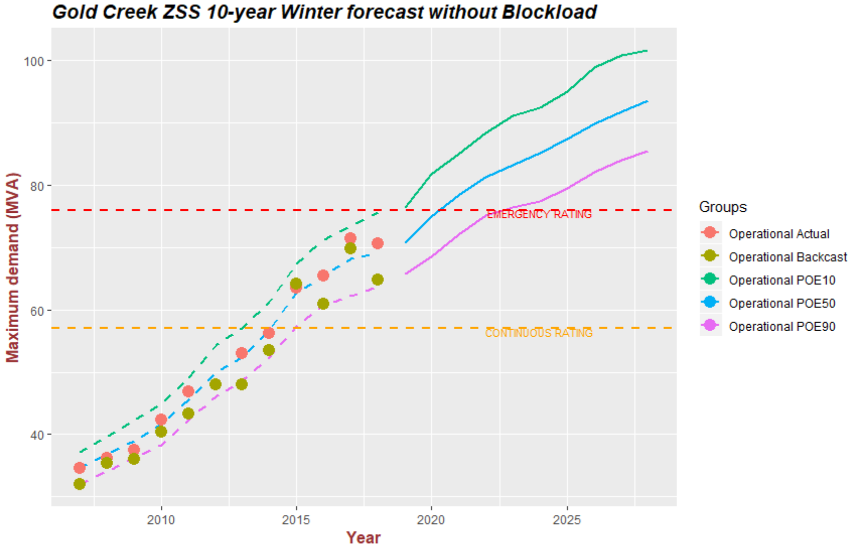
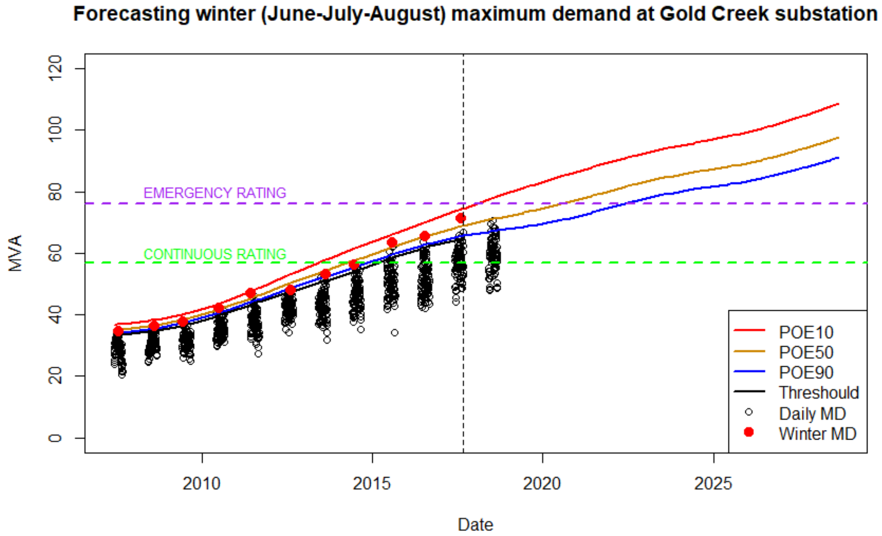
MEFM Forecast	***WPMDFC Forecast***
	

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

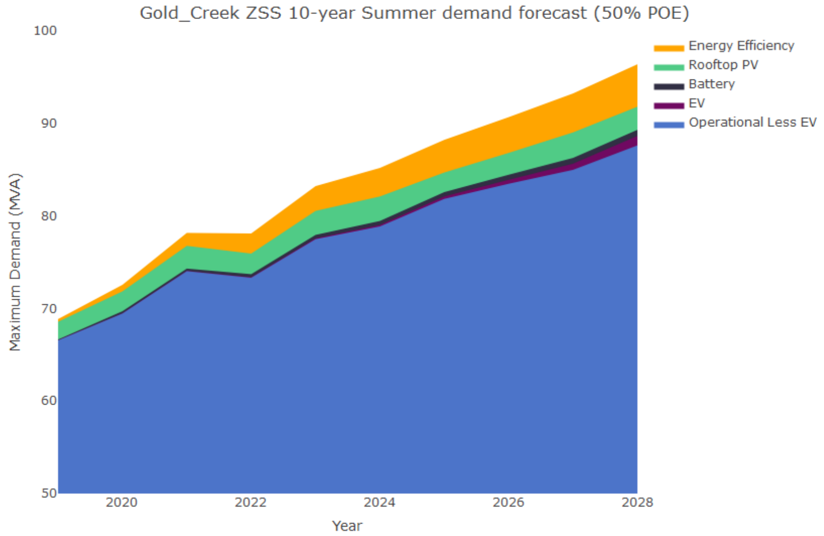
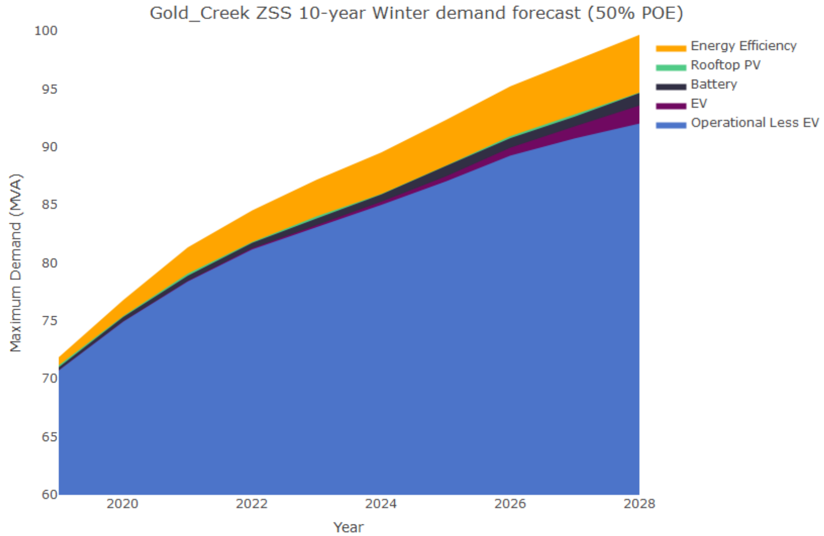
Summer POE Forecasts	***Winter POE Forecasts***
	

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

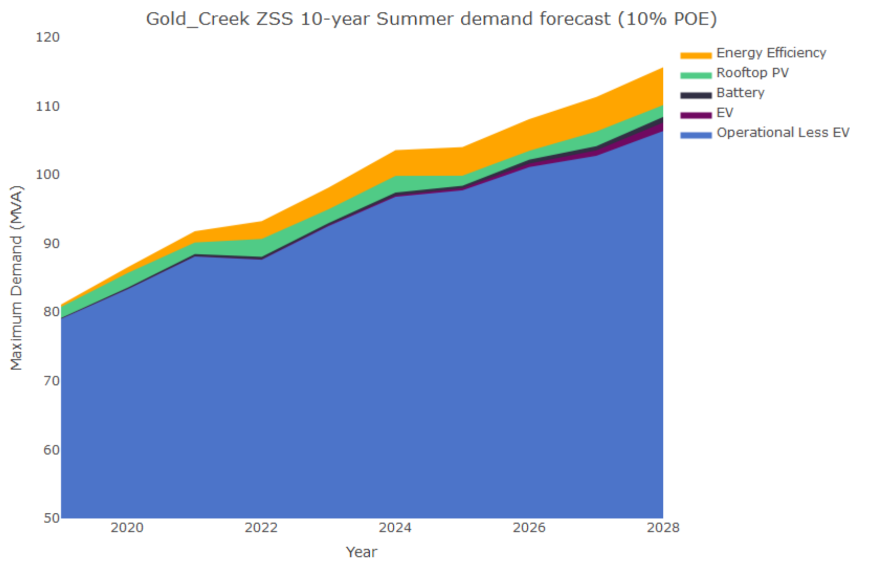
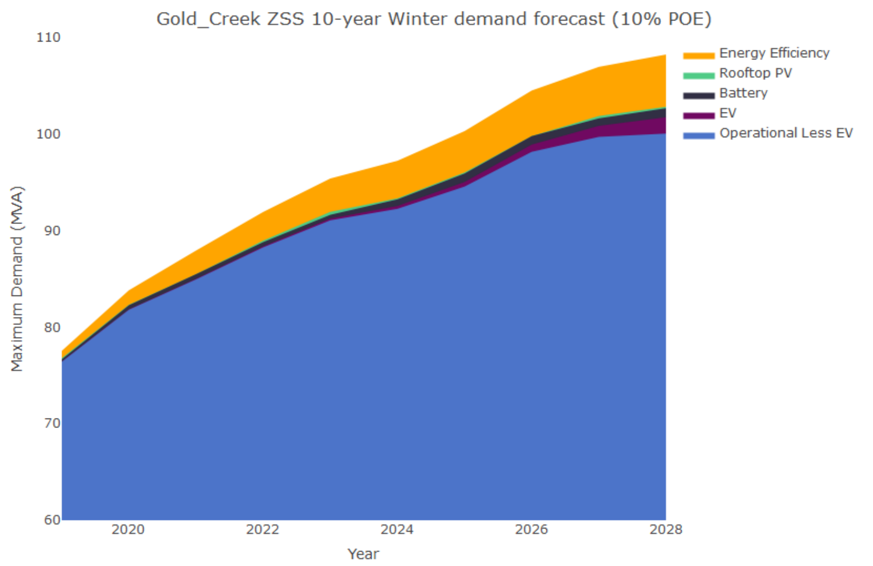
Summer POE Forecasts	***Winter POE Forecasts***
	

Table 5.2.8.1: 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 5.2.8.2: Gold Creek ZSS summer forecast for MEFM and WPMDFC

Summer	MEFM			WPMDFC		
Year	**POE90**	**POE50**	**POE10**	**POE90**	**POE50**	**POE10**
2019	54	67	79	65	71	77
2020	58	69	83	67	74	80
2021	60	74	88	70	77	83
2022	60	73	88	72	79	85
2023	66	78	93	74	81	87
2024	65	79	97	76	84	90
2025	66	82	98	78	86	92
2026	69	84	102	80	88	94
2027	70	86	104	82	90	96
2028	73	89	108	83	92	98

Table 5.2.8.3: Gold Creek ZSS winter back-cast and weather correction in MVA

Winter			Weather Correction		
Year	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 5.2.8.4: Gold Creek ZSS winter forecast breakdown in MVA

Winter	MEFM			WPMDFC		
Year	POE90	POE50	POE10	POE90	POE50	POE10
2019	66	71	76	69	73	82
2020	69	75	82	71	76	85
2021	72	78	85	74	79	88
2022	75	81	88	77	82	91
2023	76	83	91	79	85	94
2024	77	85	93	81	87	96
2025	80	87	95	83	88	98
2026	82	90	99	85	91	101
2027	84	92	101	87	94	104
2028	86	94	102	91	97	108

Table 5.2.8.5: Gold Creek ZSS WPMDFC model description

<table>
<tr><th>Season</th><th>Model Selection Summary</th><th>Select PP Model</th></tr>
<tr><td>Summer</td><td>

nllh	AIC	BIC	Model	Rank
135.09	280.18	293.25	mu1_sig3	1
135.49	280.98	294.05	mu2_sig3	2
134.96	281.93	297.62	mu12_sig3	3
134.39	282.78	301.08	mu123_sig3	4
138.14	284.28	294.74	mu2	5
138.87	285.73	296.2	mu1	6

</td><td>

Model: mu1_sig3

$$\mathrm{POE(t,p)} = 0.099 + 0.0025Z_{1t} + \frac{2.17 + 0.15Z_{3t}}{-0.44}\{[-ln(1-p)]^{0.44} - 1\}$$

Z_{1t} is the trend of NMI count on day t and Z_{3t} is the trend of PV Capacity.

</td></tr>
<tr><td>Winter</td><td>

nllh	AIC	BIC	Model	Rank
42.73	97.46	108.69	mu12_sig3	1
71.9	151.81	159.29	mu1	2
72.55	155.11	164.46	mu13	3
111.94	233.88	243.23	mu1_sig3	4
115.43	236.85	242.47	Stationary	5
173.72	357.44	366.79	mu2_sig3	6

</td><td>

Model: mu12_sig3

$$\mathrm{POE(t,p)} = -2.14 + 0.0017Z_{1t} + 0.017Z_{2t} + \frac{0.84 + 0.17Z_{3t}}{-0.057}\{[-ln(1-p)]^{0.057} - 1\}$$

Z_{1t} is the trend of NMI count on day t, $Z_{2t}$is the trend of energy throughput on day t and Z_{3t} is the trend of PV Capacity.

</td></tr>
</table>

5.2.9 Latham Zone Substation Forecast

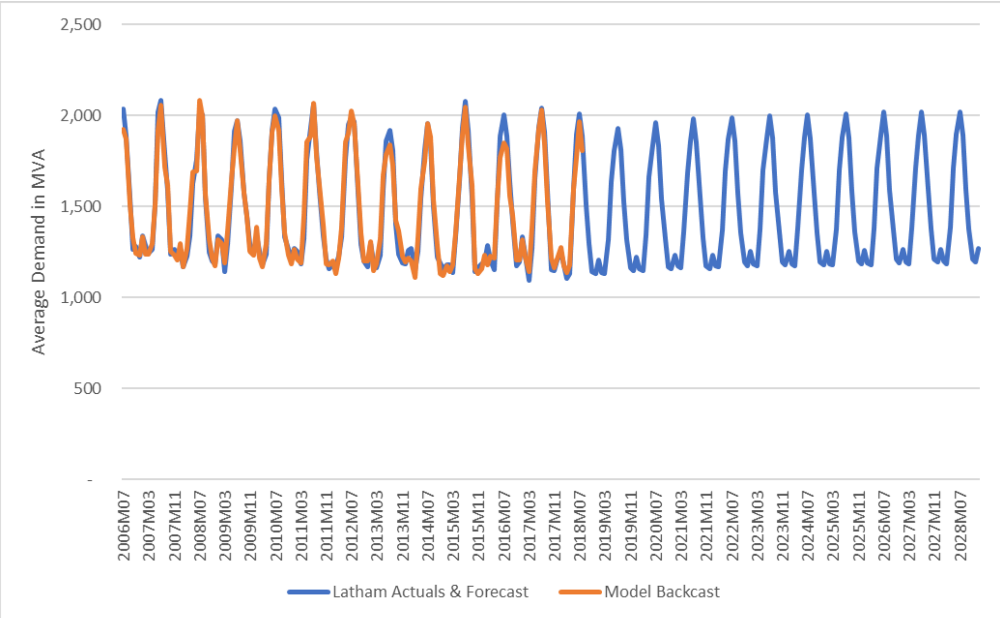
5.2.9.1 Seasonal average model

5.2.9.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Belconnen regional population, residential price and residential energy efficiency. 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: Latham ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis and assumptions:

- Figure 5.2.9.1 indicates a very slow upward trend in next ten years;
- Strathnairn Zone Substation is proposed to be constructed to supply the new Ginninderry Estate. Latham ZSS will be supplying the new estate in the next regulatory revenue cycle;
- The additional load is expected to grow at a constant rate of 0.8 MVA per year in the foreseeable future.

5.2.9.2 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.

5.2.9.3 Final summer and Winter Demand forecast

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

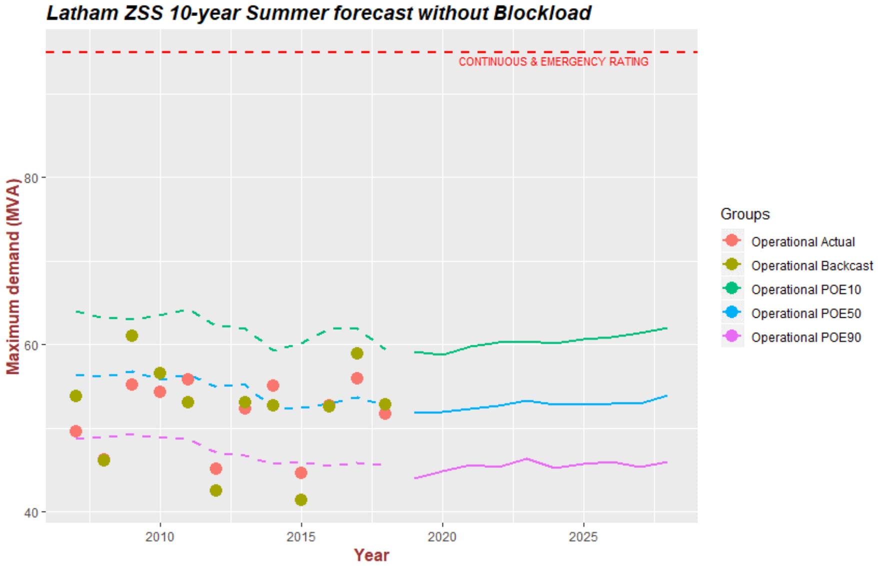
- Figure 5.2.9.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.9.3: Stack Chart by structure change impact;
- Table 5.2.9.1 to 5.2.9.4: Actual or Forecast figures for Figure 5.2.9.2 and 5.2.9.3.

Key notes from Figure 5.2.9.2:

- 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 5.2.9.3 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 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 5.2.9.2: Latham ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



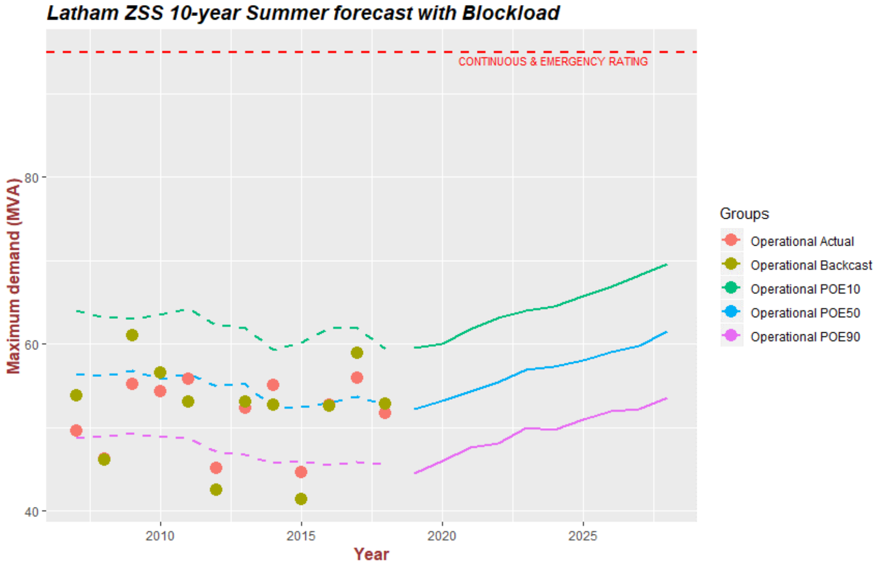
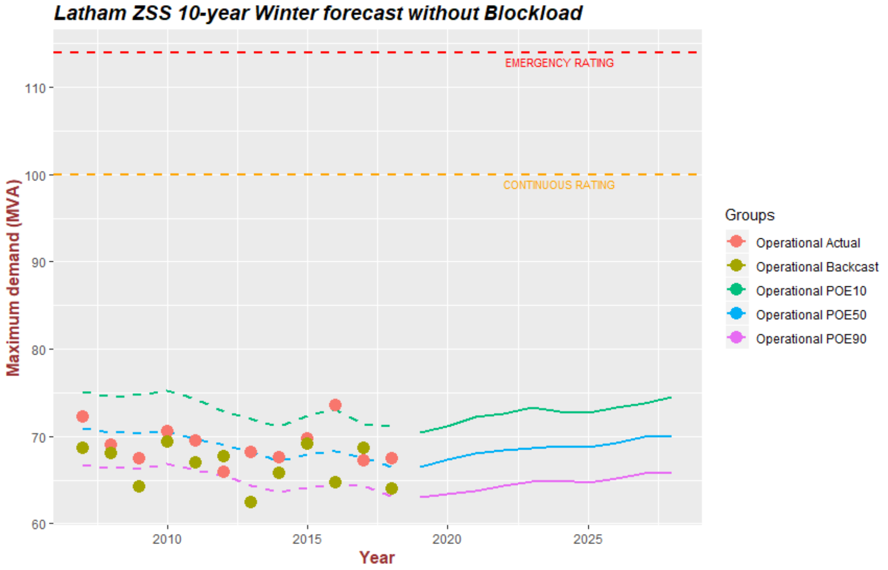


Figure 5.2.9.2: Latham ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



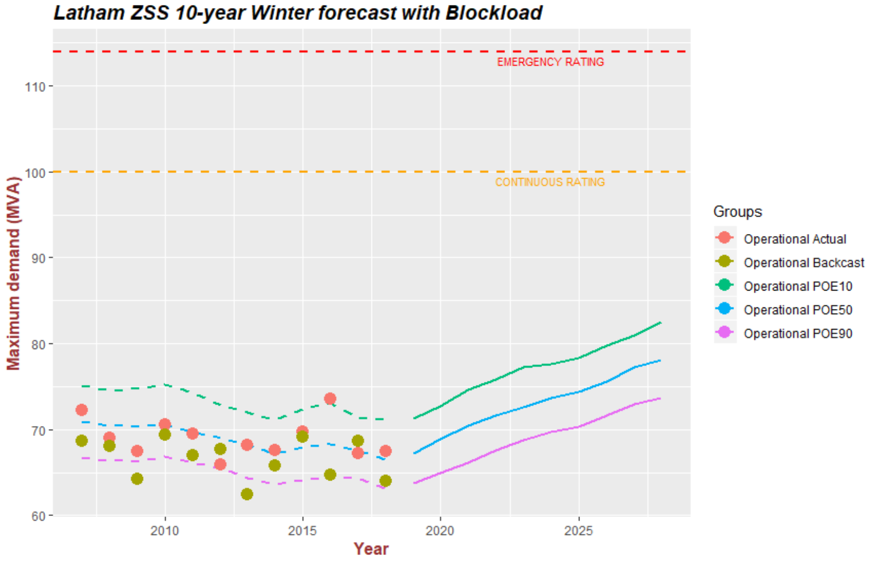
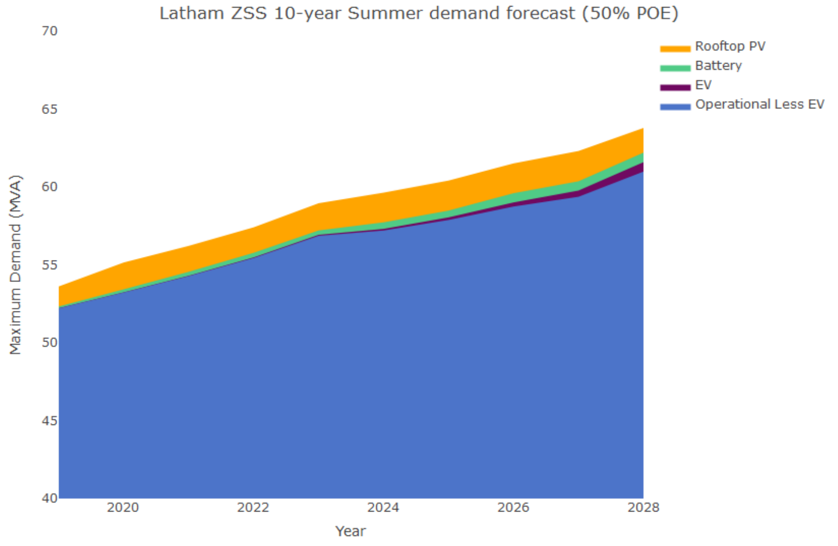


Figure 5.2.9.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	**Winter POE Forecasts**



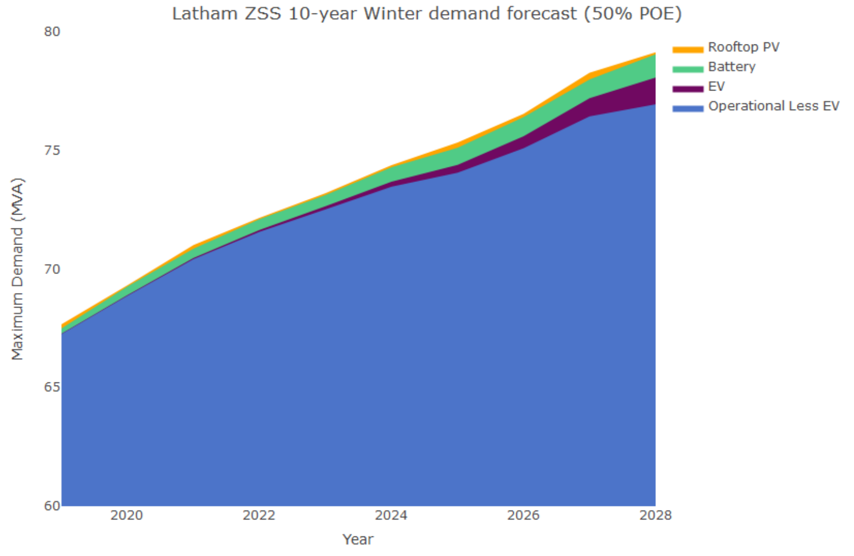
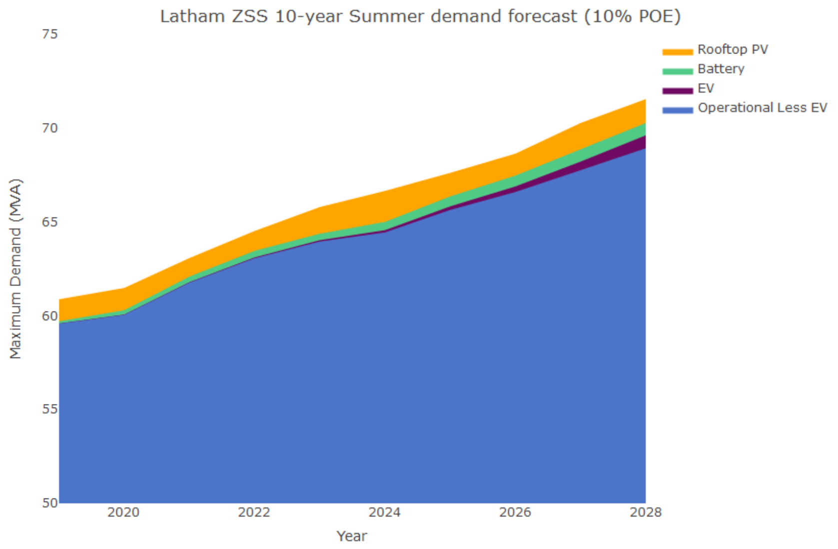


Figure 5.2.9.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	***Winter POE Forecasts***



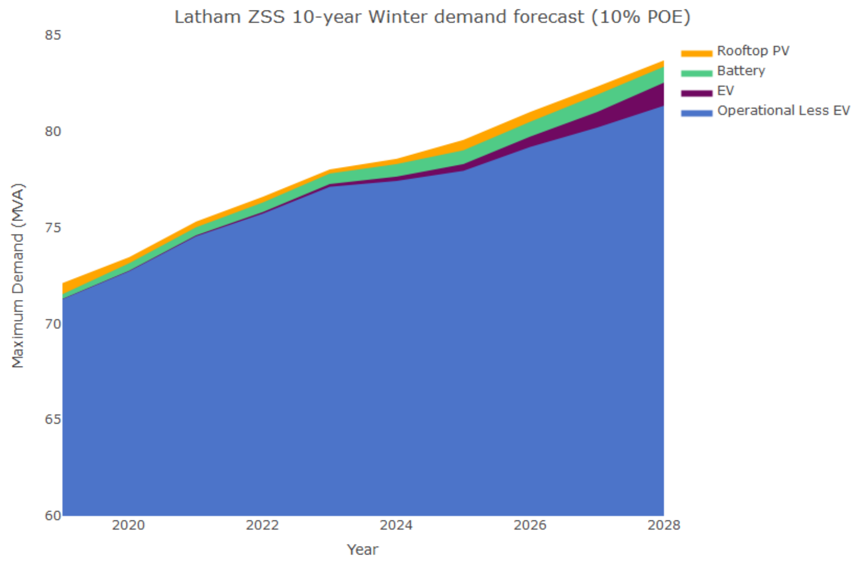


Table 5.2.9.1: Latham ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	50	54	49	56	64
2008	46	46	49	56	63
2009	55	61	49	57	63
2010	54	57	49	56	64
2011	56	53	49	56	64
2012	45	43	47	55	62
2013	52	53	47	55	62
2014	55	53	46	52	59
2015	45	41	46	52	60
2016	53	53	46	53	62
2017	56	59	46	54	62
2018	52	53	46	53	59

Table 5.2.9.2: 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
2019	52	60	52	60	52	60	54	61
2020	53	60	53	60	53	60	55	61
2021	54	62	54	62	55	62	56	63
2022	55	63	55	63	56	63	57	65
2023	57	64	57	64	57	64	59	66
2024	57	64	57	65	58	65	60	67
2025	58	66	58	66	58	66	60	68
2026	59	67	59	67	60	67	62	69
2027	59	68	60	68	60	69	62	70
2028	61	69	62	70	62	70	64	72

Table 5.2.9.3: Latham ZSS winter back-cast and weather correction in MVA

Winter			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	72	69	67	71	75
2008	69	68	66	70	74
2009	67	64	66	70	75
2010	71	69	67	71	75
2011	69	67	66	70	74
2012	66	68	66	69	73
2013	68	62	64	68	72
2014	68	66	64	67	71
2015	70	69	64	68	72
2016	74	65	64	68	73
2017	67	69	64	68	71
2018	67	64	63	66	71

Table 5.2.9.4: 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
2019	67	71	67	71	67	72	68	72
2020	69	73	69	73	69	73	69	73
2021	70	75	70	75	71	75	71	75
2022	72	76	72	76	72	76	72	77
2023	73	77	73	77	73	78	73	78
2024	73	77	74	78	74	78	74	79
2025	74	78	74	78	75	79	75	80
2026	75	79	76	80	76	81	77	81
2027	76	80	77	81	78	82	78	82
2028	77	81	78	83	79	83	79	84

5.2.10 Telopea Park Zone Substation Forecast

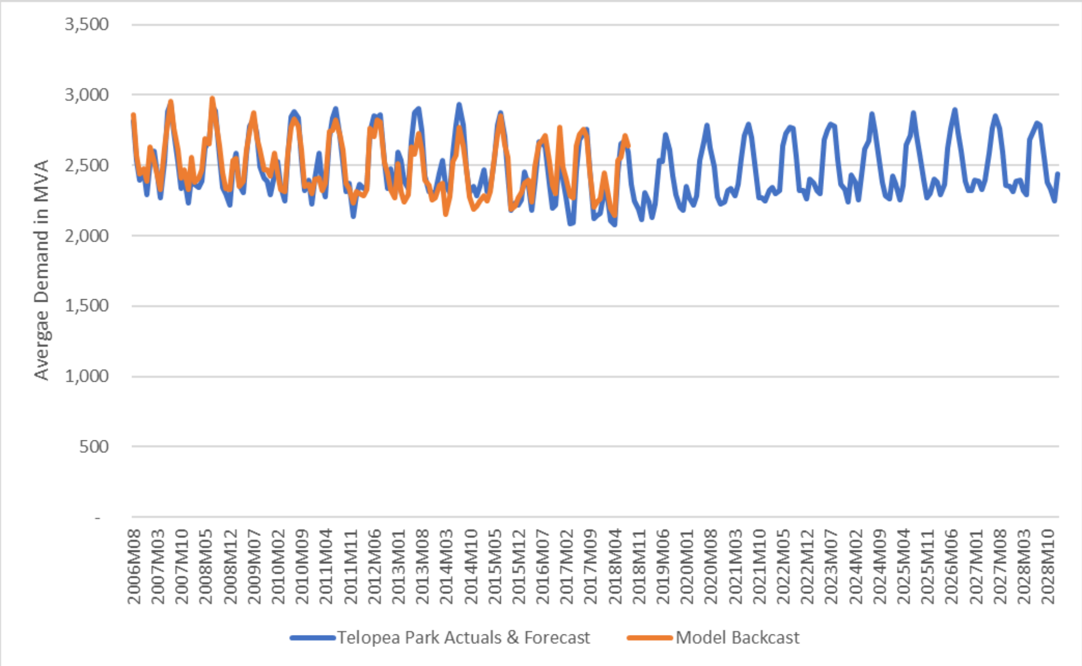
5.2.10.1 Seasonal average model

5.2.10.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, South Canberra regional population, residential price and residential energy efficiency. The model had an adjusted R-squared statistic of 92% 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: Telopea Park ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis and assumptions:

- No clear trend is indicated in Figure 5.2.10.1;
- However, three major developments initiated by ACT government are going to drive the electricity demand of Telopea Park ZSS to another level in the upcoming next regulatory period. Those three projects are: Canberra CBD expansion, City to Lake project and Kingston foreshore master plan and so on;
- More block load information can be found under in Table 5.2.10.1.

Table 5.2.10.1: Telopea Park ZSS detailed block load in MVA

Block Load Project	2019	2020	2021	2022	2023	2024	2025	2026
City to Lake development Stage 1 - Corner Commonwealth Ave & London Circuit. Residential 607 units, Commercial 107,068 m², Community 32883 m².			4.5	4.1				
City to Lake development Stage 2 - Corner Commonwealth Ave and Parkes Way. Residential 2,130 units, Commercial 37,583 m².								2
B20 S63, Corner Vernon Circle & Commonwealth Ave. Mixed use 168,000 m².				1	1			
Supply to Mixed Development		1.5						
Supply to Aged Care Development	0.8							
PN 20004264 B1&2 S14 Kingston Residential development	0.5							
PN 20005072 B2 S67 Commercial development	0.4							
PN 20005802 B50 S 19 Kingston, mixed development	1	1						
PN 20006063 B4 S 25 Griffith Residential development	0.3							
PN 20006282 B5 S1 Kingston. Aged care facility		0.8						
PN 20006396 B14 S22 Barton new commercial building		1						
Kingston Foreshore High-density residential developments, 3,850 units over 6	1.5	1.5						

years								
Kingston Foreshore Commercial development and Community development (school)			0.5	0.5	0.5	0.5		
Kingston Arts Centre Precinct S49 East Lake Parade, Commercial development			0.5	0.5	0.5			
Canberra Metro Traction Power Station TPS9						1.9		

5.2.10.2 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.

5.2.10.3 Final summer and Winter Demand forecast

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

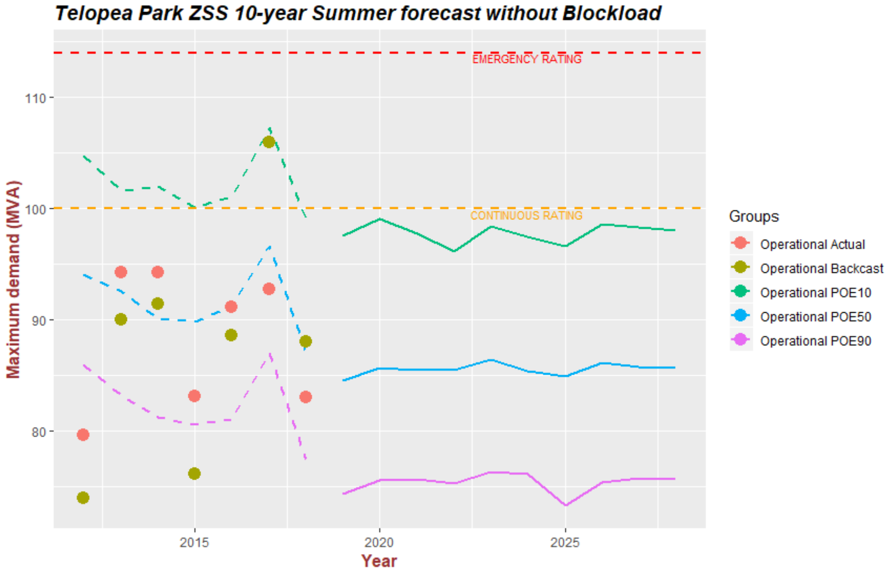
- Figure 5.2.10.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.10.3: Stack Chart by structure change impact;
- Table 5.2.10.2 to 5.2.10.5: Actual or Forecast figures for Figure 5.2.10.2 and 5.2.10.3.

Key notes from Figure 5.2.11.2:

- Telopea Park ZSS is forecast to exceed its summer continuous rating by 2022;
- The winter 50% POE forecast is expected to exceed the continuous rating by 2026;
- However, both summer and winter's 2-hour emergency rating is not going to be breached by 50% POE forecast in the foreseeable future, which implies that Telopea Park ZSS will have sufficient capacity to meet any future demand in next regulatory period at ZSS level.

Figure 5.2.10.3 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 5.2.10.2: Telopea Park ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



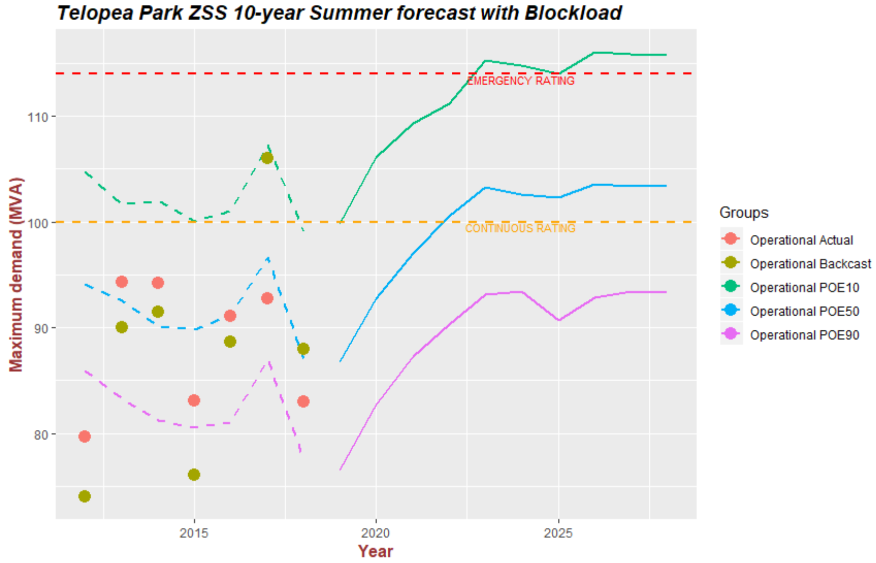
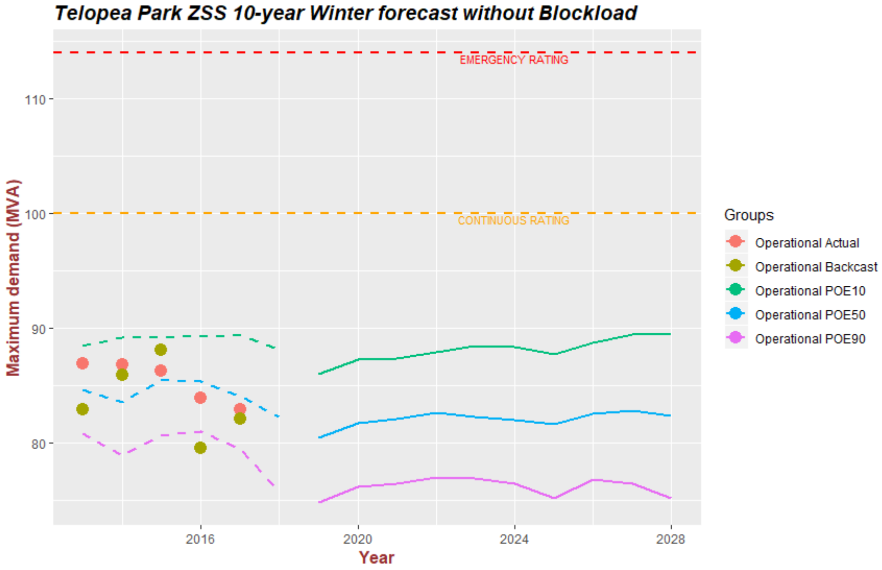


Figure 5.2.10.2: Telopea Park ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



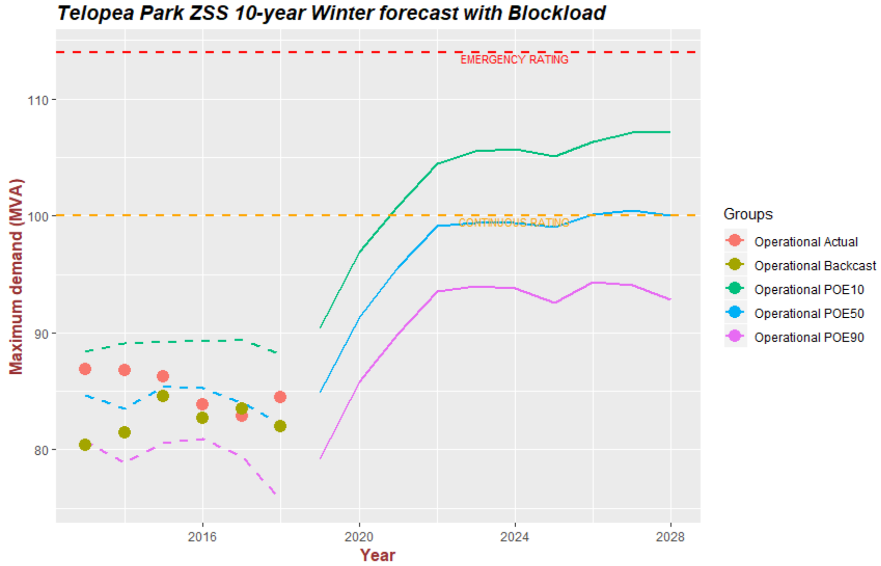


Figure 5.2.10.3: POE Forecast breakdown by structure change technology – Vertical analysis

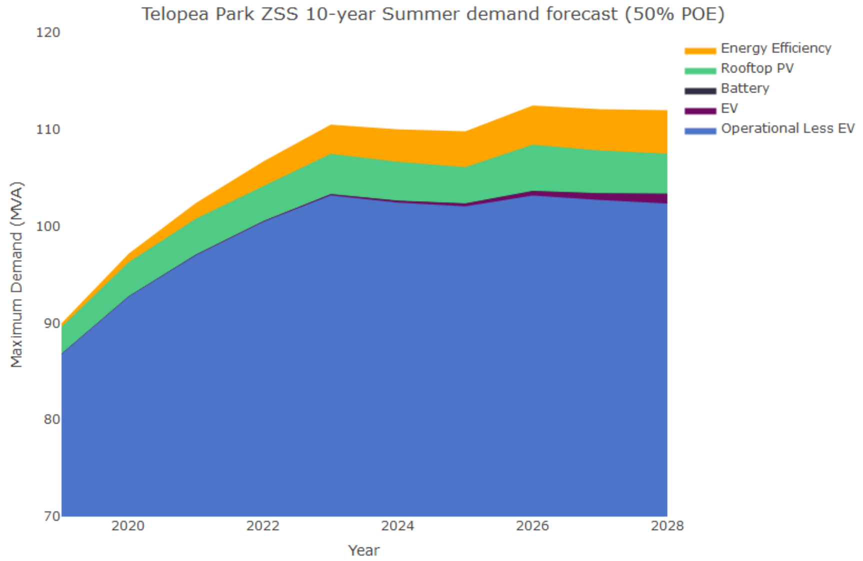
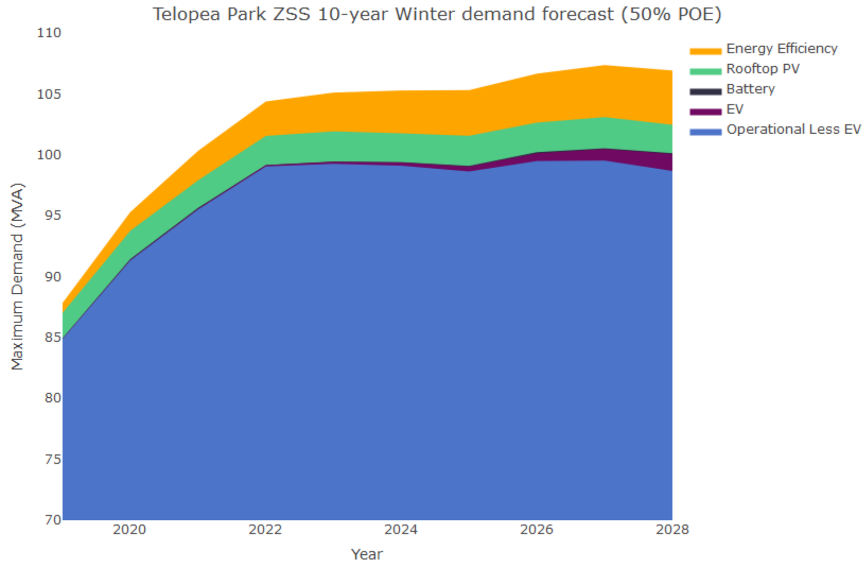
Summer POE Forecasts	***Winter POE Forecasts***
	

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

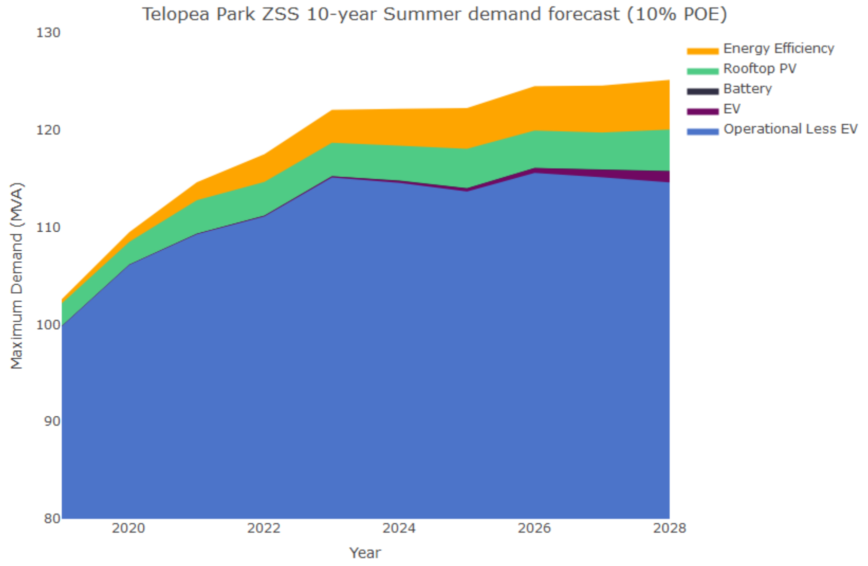
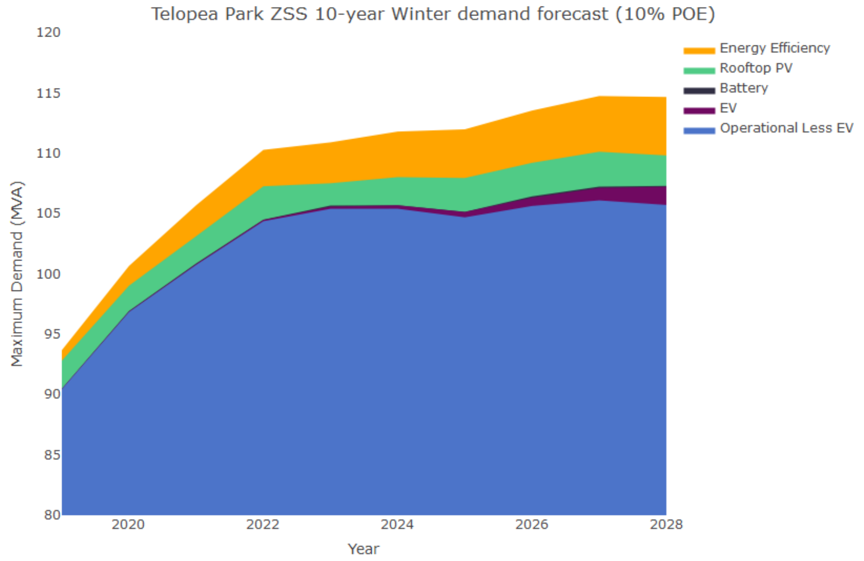
Summer POE Forecasts	Winter POE Forecasts
	

Table 5.2.10.2: Telopea Park ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2012	80	74	86	94	105
2013	94	90	83	93	102
2014	94	91	81	90	102
2015	83	76	81	90	100
2016	91	89	81	91	101
2017	93	106	87	97	107
2018	83	88	77	87	99

Table 5.2.10.3: Telopea Park ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	87	100	87	100	87	100	90	102	90	103
2020	93	106	93	106	93	106	96	108	97	109
2021	97	109	97	109	97	109	101	113	102	115
2022	100	111	101	111	101	111	104	115	107	118
2023	103	115	103	115	103	115	107	119	111	122
2024	102	115	103	115	103	115	107	118	110	122
2025	102	114	102	114	102	114	106	118	110	122
2026	103	116	104	116	104	116	108	120	112	125
2027	103	115	103	116	103	116	108	120	112	125
2028	102	115	103	116	103	116	108	120	112	125

Table 5.2.10.4: Telopea Park ZSS winter back-cast and weather correction in MVA

Winter			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2013	87	80	81	85	88
2014	87	81	79	84	89
2015	86	85	81	85	89
2016	84	83	81	85	89
2017	83	84	79	84	89
2018	85	82	76	82	88

Table 5.2.10.5: Telopea Park ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	85	90	85	90	85	90	87	93	88	94
2020	91	97	91	97	91	97	94	99	95	101
2021	96	101	96	101	96	101	98	103	100	106
2022	99	104	99	104	99	104	102	107	104	110
2023	99	105	99	106	99	106	102	108	105	111
2024	99	105	99	106	99	106	102	108	105	112
2025	99	105	99	105	99	105	102	108	105	112
2026	99	106	100	106	100	106	103	109	107	114
2027	100	106	100	107	101	107	103	110	107	115
2028	99	106	100	107	100	107	102	110	107	115

5.2.11 Theodore Zone Substation Forecast

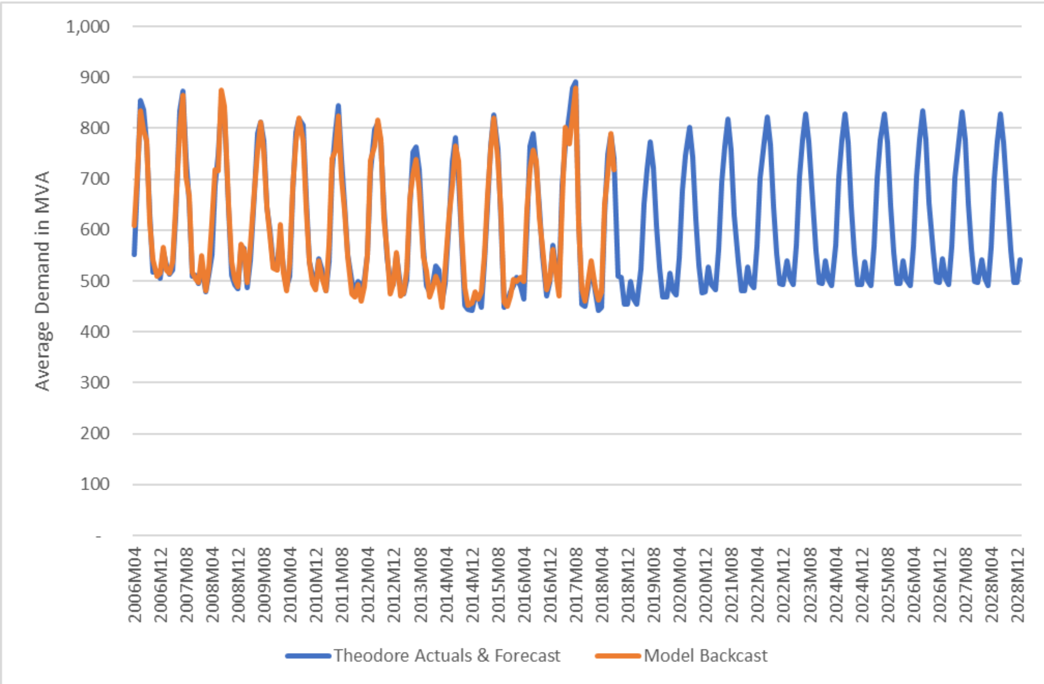
5.2.11.1 Seasonal average model

5.2.11.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Tuggeranong regional population, trend and residential price. The model had an adjusted R-squared statistic of 98% 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: Theodore 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;
- 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.

5.2.11.2 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 6.1.10.

5.2.11.3 Final summer and Winter Demand forecast

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

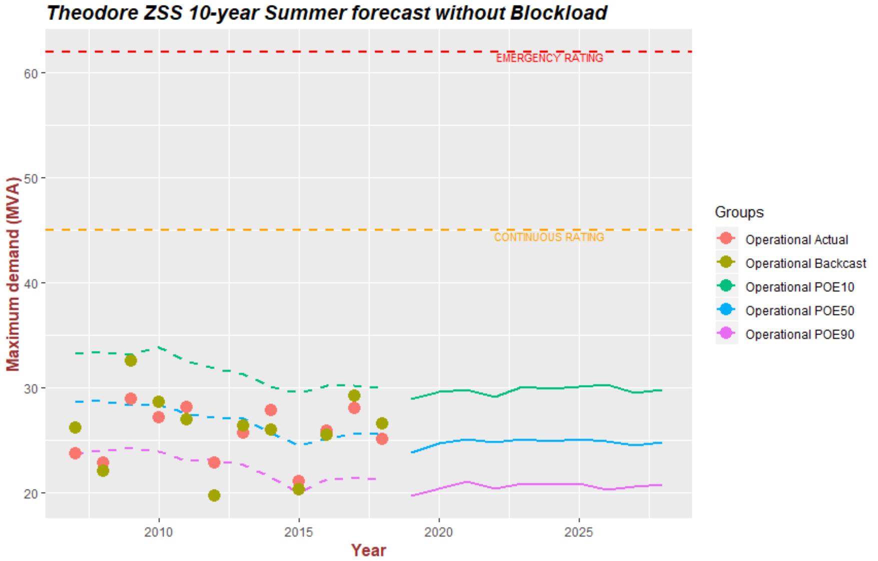
- Figure 5.2.11.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.11.3: Stack Chart by structure change impact;
- Table 5.2.11.1 to 5.2.11.4: Actual or Forecast figures for Figure 5.2.11.2 and 5.2.11.3.

Key notes from Figure 5.2.11.2 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 5.2.11.3 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 5.2.11.2: Theodore ZSS summer and winter demand forecast - Horizontal Analysis



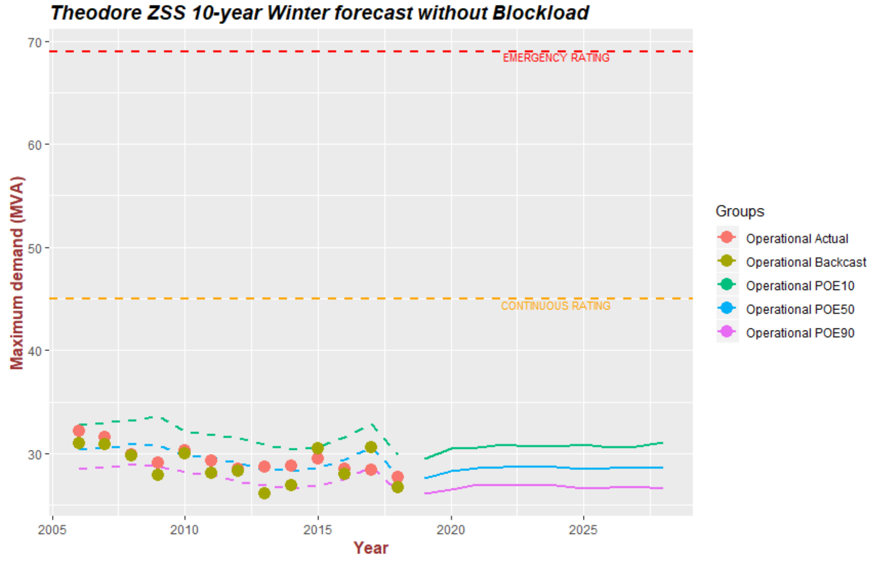


Figure 5.2.11.3: POE Forecast breakdown by structure change technology – Vertical analysis

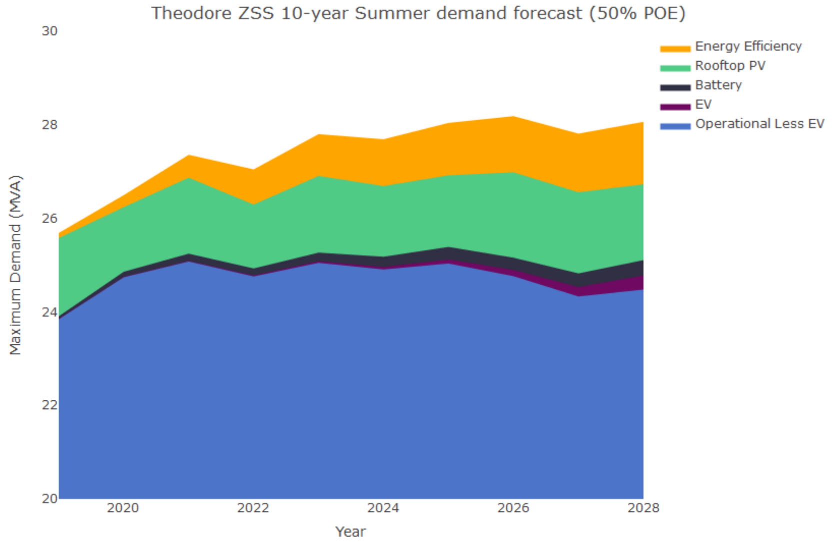
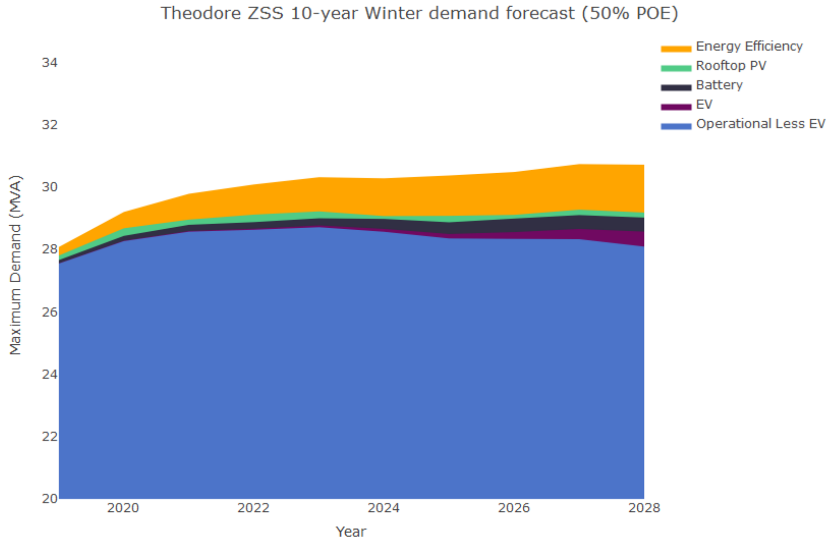
Summer POE Forecasts	***Winter POE Forecasts***
	

Figure 5.2.11.3: POE Forecast breakdown by structure change technology – Vertical analysis

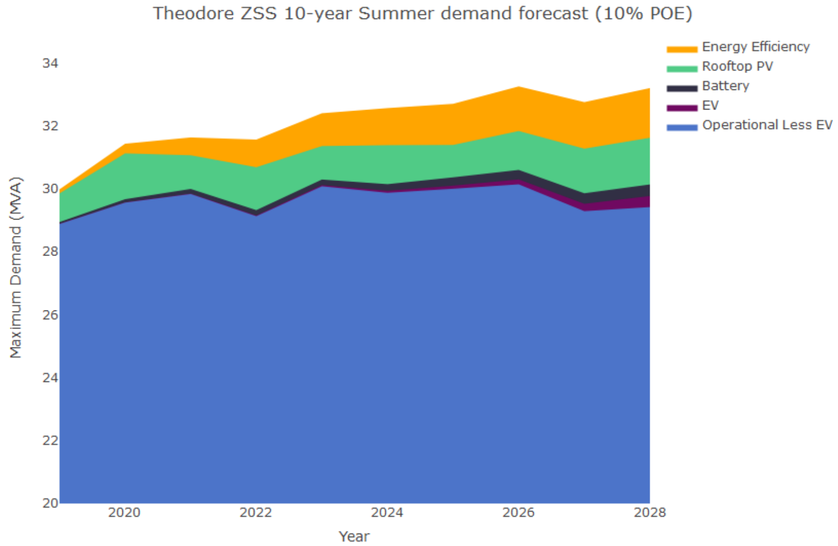
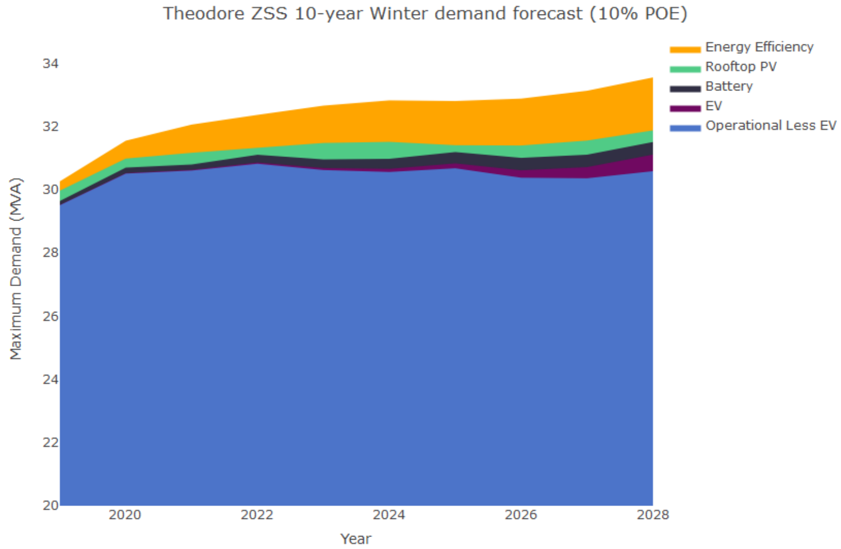
Summer POE Forecasts	Winter POE Forecasts
	

Table 5.2.11.1: Theodore ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	24	26	24	29	33
2008	23	22	24	29	33
2009	29	33	24	28	33
2010	27	29	24	28	34
2011	28	27	23	28	33
2012	23	20	23	27	32
2013	26	26	23	27	31
2014	28	26	22	26	30
2015	21	20	20	25	30
2016	26	25	21	25	30
2017	28	29	21	26	30
2018	25	27	21	26	30

Table 5.2.11.2: Theodore ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	24	29	24	29	24	29	26	30	26	30
2020	25	30	25	30	25	30	26	31	26	31
2021	25	30	25	30	25	30	27	31	27	32
2022	25	29	25	29	25	29	26	31	27	32
2023	25	30	25	30	25	30	27	31	28	32
2024	25	30	25	30	25	30	27	31	28	33
2025	25	30	25	30	25	30	27	31	28	33
2026	25	30	25	30	25	31	27	32	28	33
2027	24	29	25	30	25	30	27	31	28	33
2028	24	29	25	30	25	30	27	32	28	33

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

Winter			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2006	32	31	28	30	33
2007	32	31	29	30	33
2008	30	30	29	31	33
2009	29	28	29	31	34
2010	30	30	28	30	32
2011	29	28	28	30	32
2012	28	28	27	29	31
2013	29	26	27	28	31
2014	29	27	27	28	30
2015	30	31	27	29	31
2016	29	28	27	29	32
2017	28	31	29	31	33
2018	28	27	26	28	30

Table 5.2.11.4: Theodore ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	28	30	28	30	28	30	28	30	28	30
2020	28	31	28	31	28	31	29	31	29	32
2021	29	31	29	31	29	31	29	31	30	32
2022	29	31	29	31	29	31	29	31	30	32
2023	29	31	29	31	29	31	29	31	30	33
2024	29	31	29	31	29	31	29	32	30	33
2025	28	31	28	31	29	31	29	31	30	33
2026	28	30	29	31	29	31	29	31	30	33
2027	28	30	29	31	29	31	29	32	31	33
2028	28	31	29	31	29	32	29	32	31	34

5.2.12 Wanniassa Zone Substation Forecast

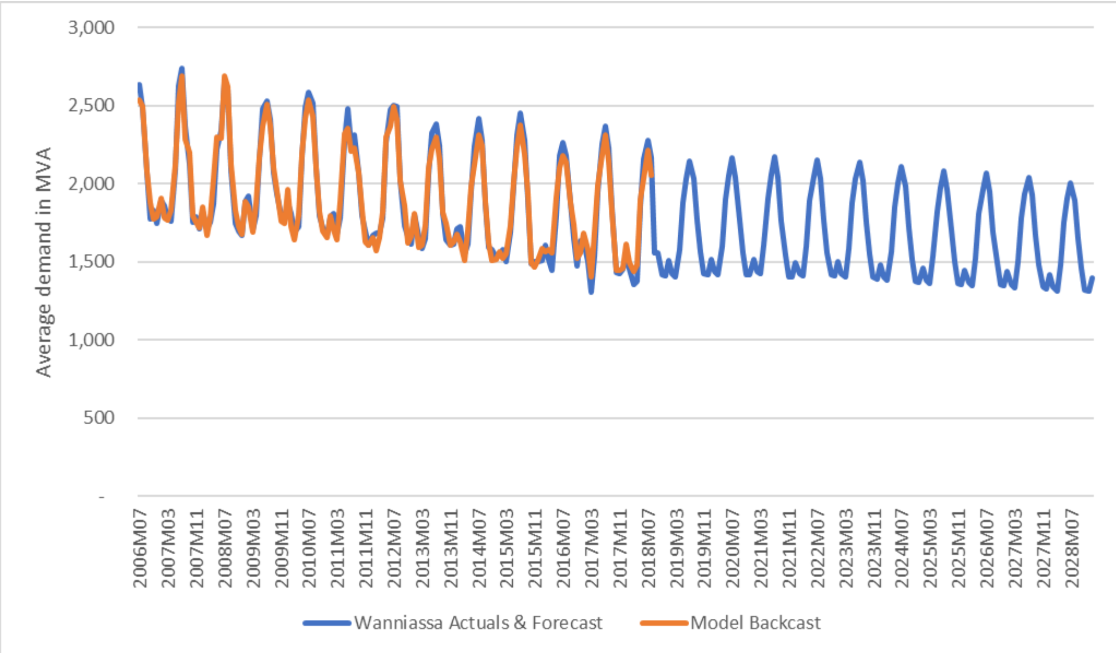
5.2.12.1 Seasonal average model

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, residential energy efficiency and residential 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: Wanniassa ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis and assumptions:

- A clear downward trend is shown in Figure 5.2.12.1. Therefore, post model block load adjustment is required if any;
- More block load information can be found in Table 5.2.12.1.

Table 5.2.12.1: Wanniassa ZSS detailed block load in MVA

Block Load Project	2019	2020	2021	2022
B1, S78 - Anketell St / Oakden St, residential apartment development (PN 20004401)		0.5	0.5	
B1 S79 – Cynthia Teague Cres – residential apartment development (PN 20003467)		1	0.5	
B4 S57 – Anketell St / Limburg Way, mixed-use development (PN 20001885)	1			
B1 S76 – Anketell St / Oakden St mixed-use development (PN 20000880)	0.6			
B2 S14 – Athllon Dr, office building development (PN 2000413)	1	1	0.9	
B5 S13 – Athllon Dr, residential townhouse development (PN 20001780)	0.4			

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 6.1.11.

5.2.12.3 Final summer and Winter Demand forecast

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

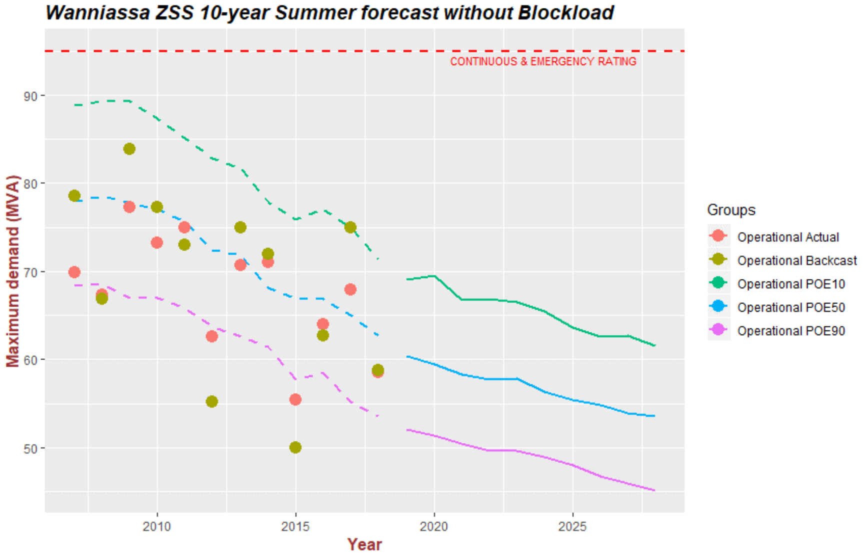
- Figure 5.2.12.2: Line diagram of historical actuals, back-cast, weather correction and POE 90, 50 and 10 forecast;
- Figure 5.2.12.3: Stack Chart by structure change impact;
- Table 5.2.12.2 to 5.2.12.5: Actual or Forecast figures for Figure 5.2.12.2 and 5.2.12.3.

Key findings from Figure 5.2.12.2:

- 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 5.2.12.3 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 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 5.2.12.2: Wanniassa ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



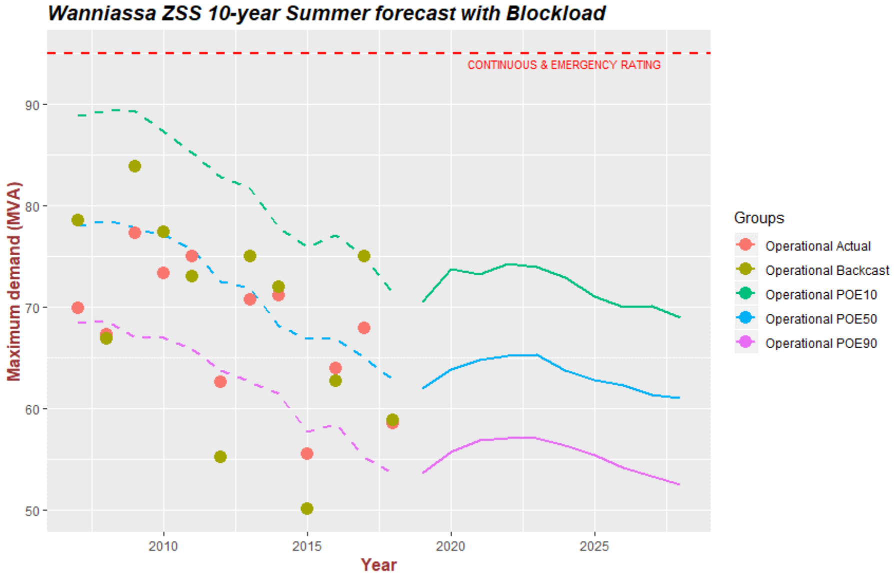
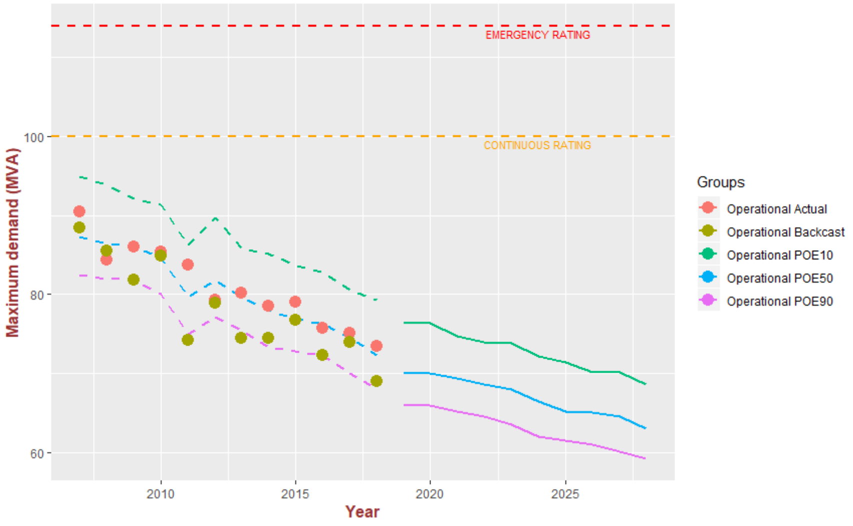


Figure 5.2.12.2: Wanniassa ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis



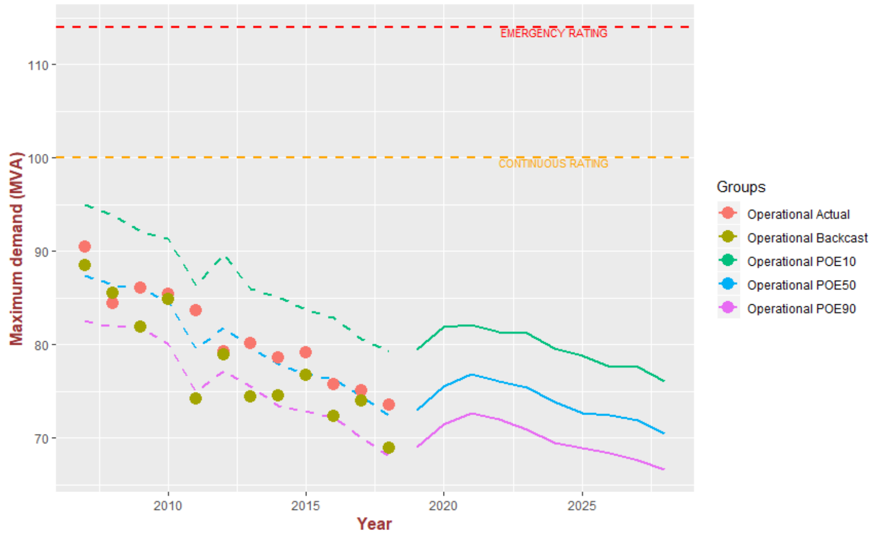


Figure 5.2.12.3: POE Forecast breakdown by structure change technology – Vertical analysis

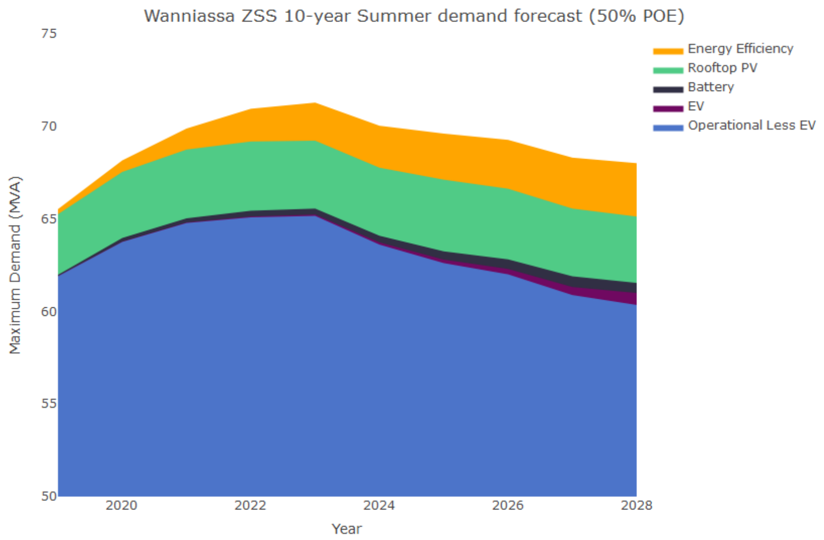
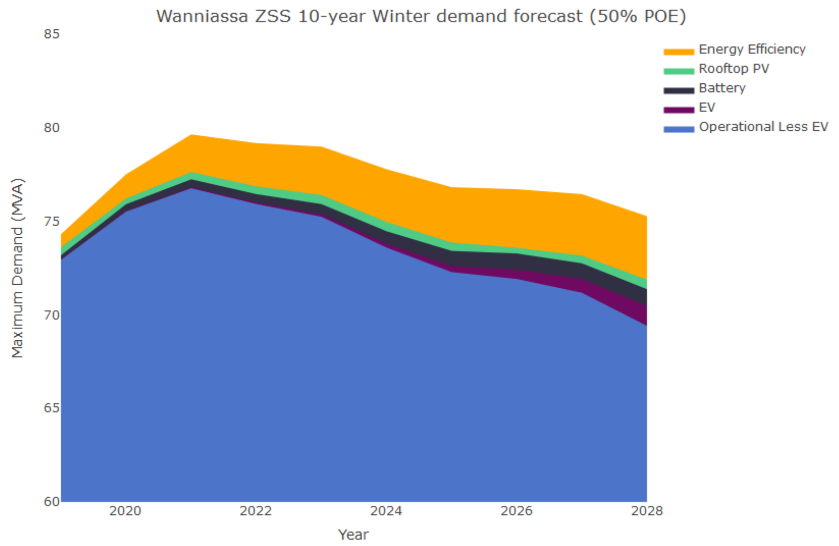
Summer POE Forecasts	*Winter POE Forecasts*
	

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

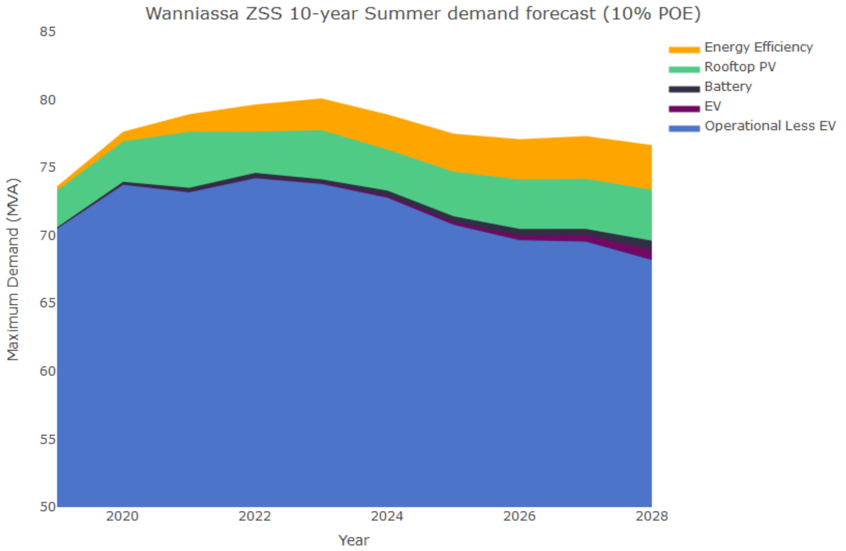
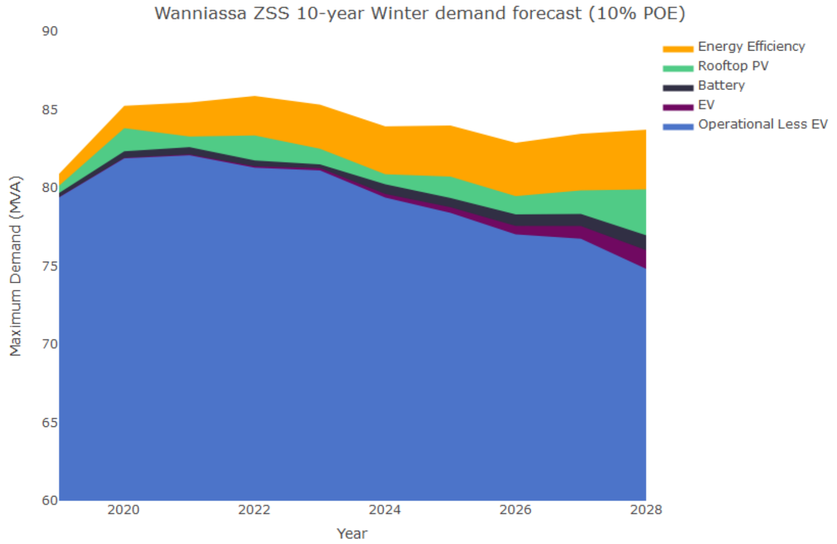
Summer POE Forecasts	***Winter POE Forecasts***
	

Table 5.2.12.2: Wanniassa ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	70	78	68	78	89
2008	67	67	69	79	89
2009	77	84	67	78	89
2010	73	77	67	77	87
2011	75	73	66	76	85
2012	63	55	64	72	83
2013	71	75	63	72	82
2014	71	72	61	68	78
2015	55	50	58	67	76
2016	64	63	58	67	77
2017	68	75	55	65	75
2018	59	59	54	63	71

Table 5.2.12.3: Wanniassa ZSS summer forecast break down in MVA

Summer	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	62	71	62	71	62	71	65	73	66	74
2020	64	74	64	74	64	74	68	77	68	78
2021	65	73	65	73	65	74	69	78	70	79
2022	65	74	65	74	65	75	69	78	71	80
2023	65	74	65	74	66	74	69	78	71	80
2024	64	73	64	73	64	73	68	76	70	79
2025	63	71	63	71	63	71	67	75	70	78
2026	62	70	62	70	63	70	67	74	69	77
2027	61	70	61	70	62	70	66	74	68	77
2028	60	68	61	69	62	70	65	73	68	77

Table 5.2.12.4: Wanniassa ZSS winter back-cast and weather correction in MVA

Winter			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	90	88	83	87	95
2008	84	85	82	86	94
2009	86	82	82	86	92
2010	85	85	80	85	91
2011	84	74	75	80	86
2012	79	79	77	82	90
2013	80	74	75	80	86
2014	79	74	73	78	85
2015	79	77	73	77	84
2016	76	72	72	76	83
2017	75	74	70	75	81
2018	73	69	68	72	79

Table 5.2.12.5: Wanniassa ZSS winter forecast breakdown in MVA

Winter	Operational Demand less EV		Plus EV (Operational Demand)		Plus Battery		Plus Rooftop Solar		Plus Energy Efficiency	
Year	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10	POE50	POE10
2019	73	79	73	79	73	80	74	80	74	81
2020	76	82	76	82	76	82	76	84	78	85
2021	77	82	77	82	77	83	78	83	80	85
2022	76	81	76	81	76	82	77	83	79	86
2023	75	81	75	81	76	82	76	82	79	85
2024	74	79	74	80	74	80	75	81	78	84
2025	72	78	73	79	73	79	74	81	77	84
2026	72	77	72	78	73	78	74	79	77	83
2027	71	77	72	78	73	78	73	80	76	83
2028	69	75	70	76	71	77	72	80	75	84

5.2.13 Woden Zone Substation Forecast

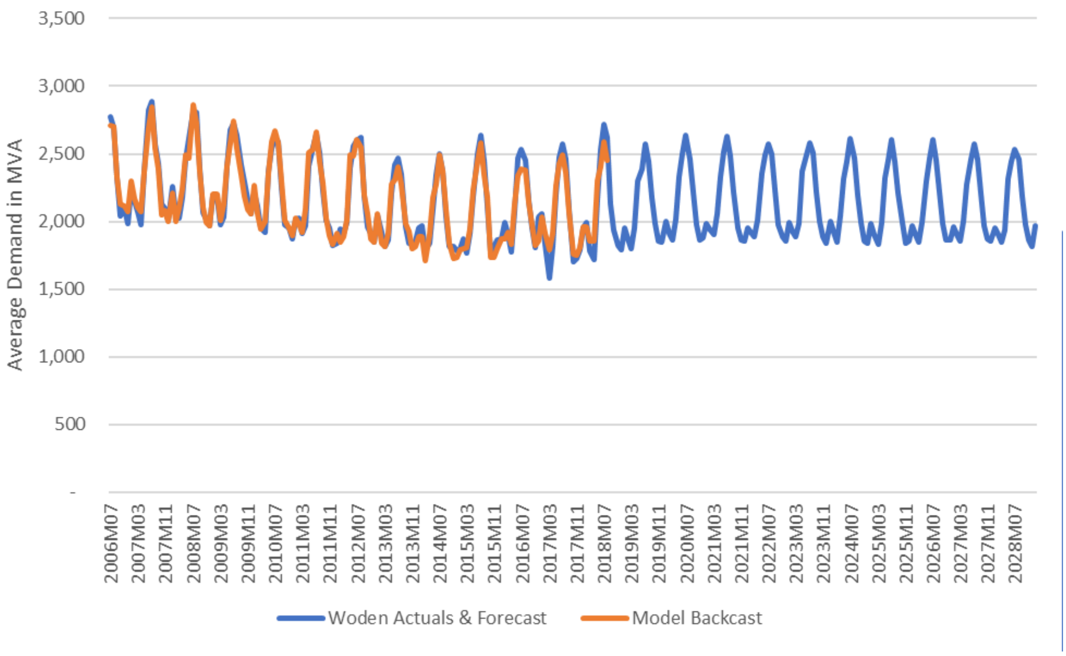
5.2.13.1 Seasonal average model

5.2.13.1.1 Model Description

Jacobs produced the seasonal average demand model and found that the key drivers were weather, Woden regional population, residential price and business energy efficiency. The model had an adjusted R-squared statistic of 96% 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: Woden ZSS seasonal average demand – Model Fit and Forecast



Block Load analysis and assumptions:

- No clear trend is shown in Figure 5.2.13.1. Therefore, post model block load adjustment is required if any;
- Woden regional population was used as independent variable and it does not include the Molonglo Valley region as a part of Woden. Therefore, Molonglo Valley load growth needs to be included as block loads towards Woden ZSS forecast;
- More detailed block load information can be found in Table 5.2.13.1.

Table 5.2.13.1: Woden ZSS detailed block loads in MVA

Molonglo Valley Development - Load Forecast @ 29.8.18									
Year	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**
Residential Loads (MVA)									
Coombs	0.5	0.4	0.2	0.2	0.2	0.1	0.1	0.1	0.1
Wright	0.4	0.7	0.5	0.5	0.2	0.1	0.1	0.1	0.1
Weston	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Denman Prospect	1.8	0.6	1.0	1.0	1.0	1.0	0.5	0.4	0.5
Whitlam		1.9	1.5	1.5	1.5	0.2	0.2	0.2	
Additional Residential Load (MVA) @ 2.5 kVA ADMD	2.9	3.7	3.3	3.3	3.0	1.5	1.0	0.9	0.8
Block Loads (MVA)									
Wright - hotel etc				0.5	0.7				
Denman Prospect Commercial centre						0.5	0.5	0.5	0.5
Stromlo Aquatic Park				0.5					
Stromlo Leisure Centre					1.0	1.0			
North Wright School				0.2					
Additional Non-residential Load (MVA) ADMD	0.0	0.0	0.0	1.2	1.7	1.5	0.5	0.5	0.5

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 6.1.12.

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 5.2.13.2 to 5.2.13.5: 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 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 summer two-hour emergency rating is forecast to be exceeded under the 10% POE forecast by 2022;
- The proposed new Molonglo ZSS will provide Woden ZSS with demand relief in the longer term after June 2022.

Figure 5.2.13.3 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 5.2.13.2: Woden ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

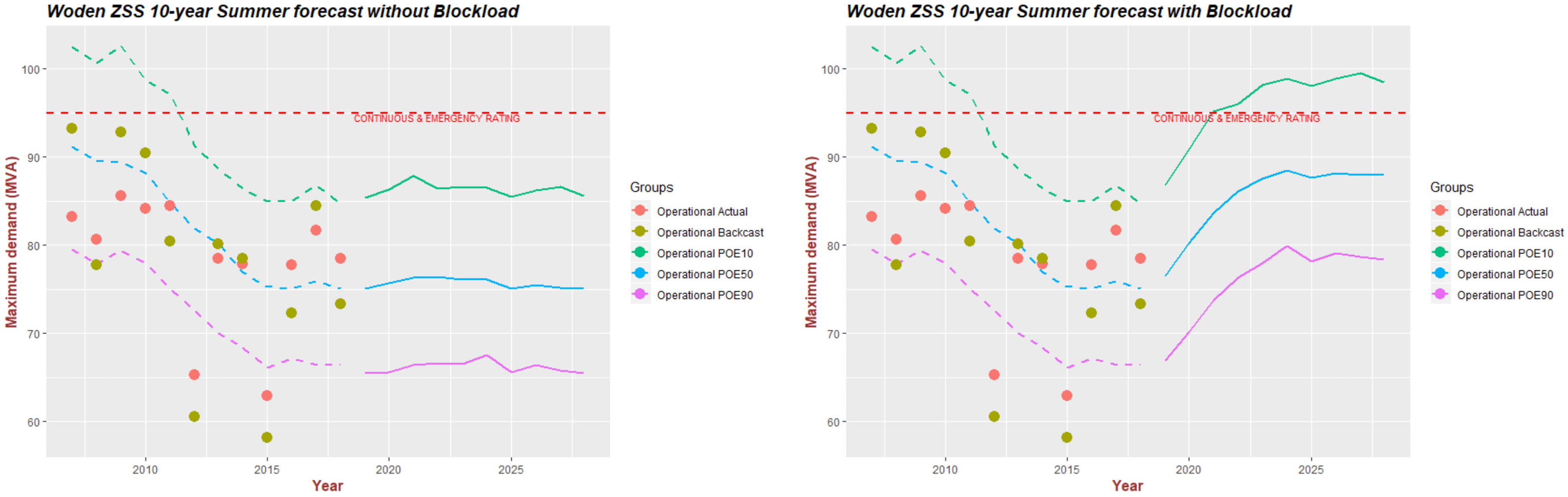


Figure 5.2.13.2: Woden ZSS summer and winter demand forecast before and after block load adjustment - Horizontal Analysis

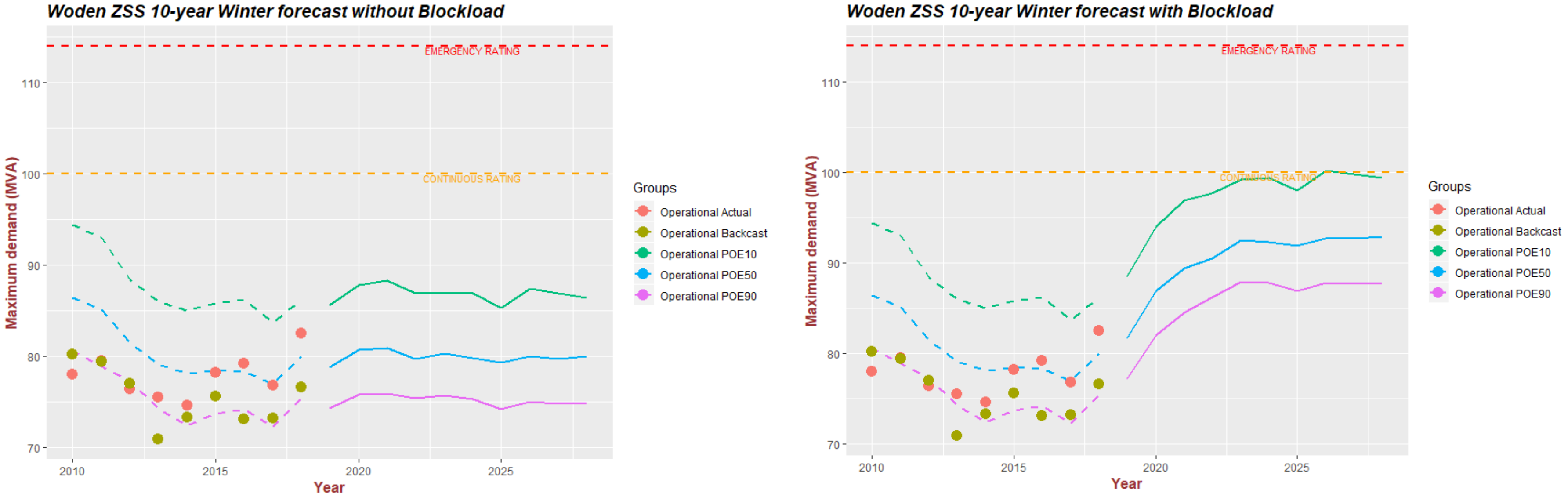


Figure 5.2.13.3: POE Forecast breakdown by structure change technology – Vertical analysis

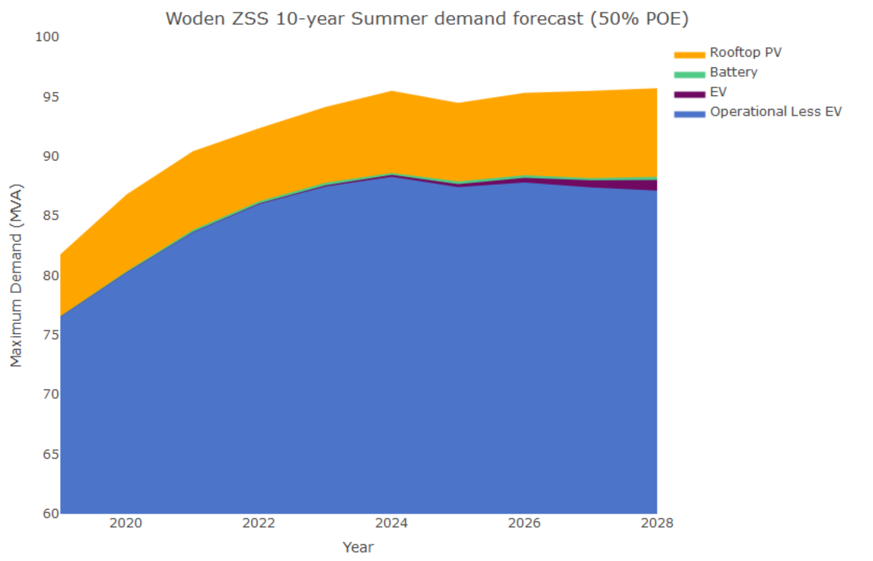
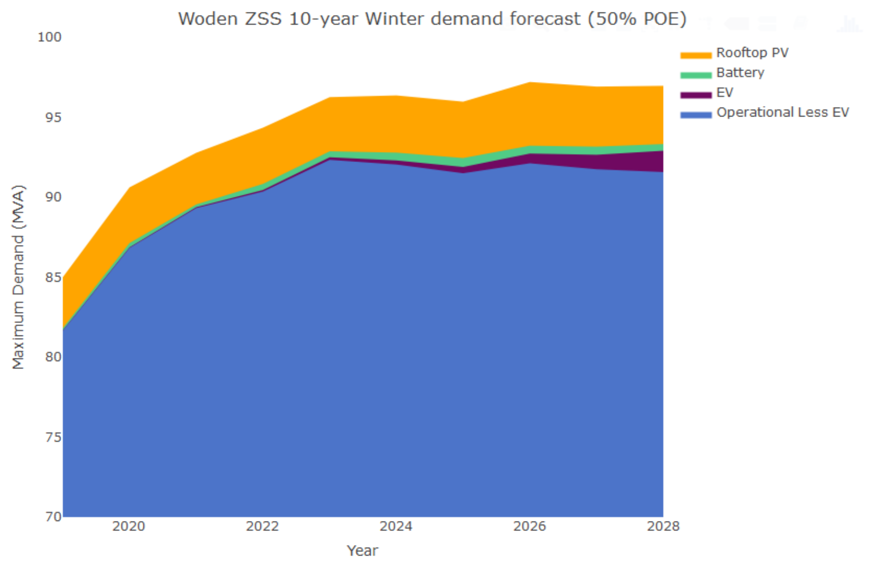
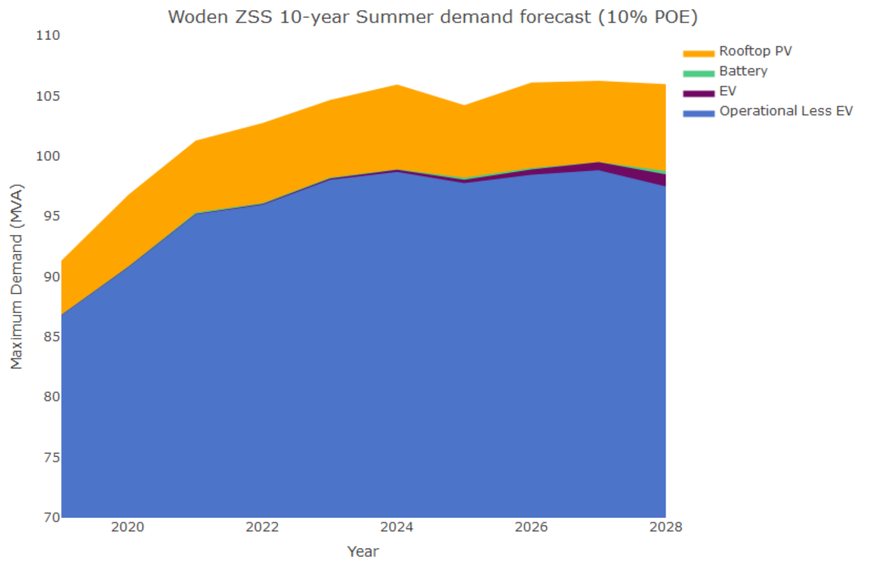
Summer POE Forecasts	***Winter POE Forecasts***
	

Figure 5.2.13.3: POE Forecast breakdown by structure change technology – Vertical analysis

Summer POE Forecasts	***Winter POE Forecasts***



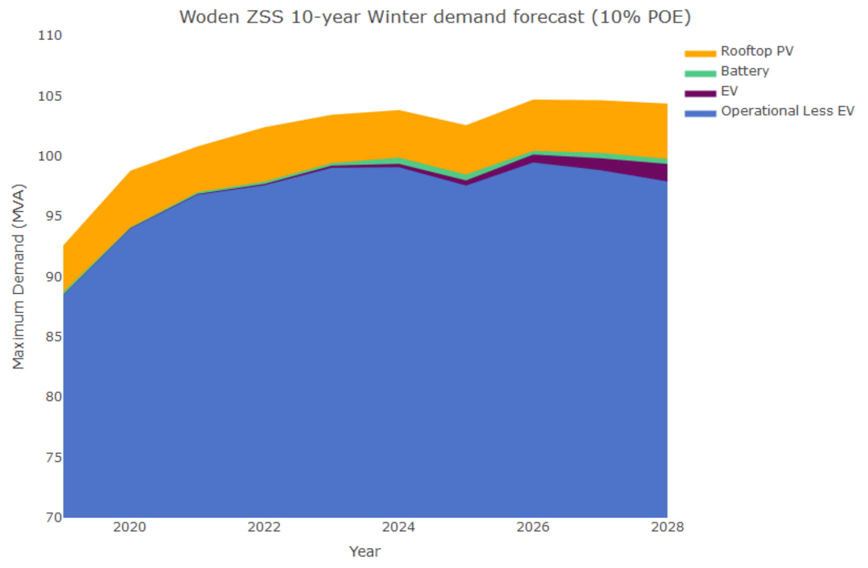


Table 5.2.13.2: Woden ZSS summer back-cast and weather correction in MVA

Summer			Weather Correction		
Year	Actual	Fitted	POE90	POE50	POE10
2007	83	93	79	91	102
2008	81	78	78	90	101
2009	86	93	79	89	103
2010	84	90	78	88	99
2011	84	80	75	85	97
2012	65	61	73	82	91
2013	78	80	70	80	89
2014	78	78	68	77	86
2015	63	58	66	75	85
2016	78	72	67	75	85
2017	82	84	66	76	87
2018	79	73	66	75	85

Table 5.2.13.3: 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
2019	77	87	77	87	77	87	82	91
2020	80	91	80	91	80	91	87	97
2021	84	95	84	95	84	95	90	101
2022	86	96	86	96	86	96	92	103
2023	87	98	88	98	88	98	94	105
2024	88	99	88	99	89	99	95	106
2025	87	98	88	98	88	98	94	104
2026	88	98	88	99	88	99	95	106
2027	87	99	88	99	88	99	95	106
2028	87	97	88	98	88	99	96	106

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	80	81	86	94
2011	79	79	79	85	93
2012	76	77	77	82	88
2013	75	71	74	79	86
2014	75	73	72	78	85
2015	78	76	74	79	86
2016	79	73	74	78	86
2017	77	73	72	77	84
2018	83	77	75	80	86

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
2019	82	88	82	88	82	89	85	93
2020	87	94	87	94	87	94	91	99
2021	89	97	89	97	90	97	93	101
2022	90	98	90	98	91	98	94	102
2023	92	99	92	99	93	99	96	103
2024	92	99	92	99	93	100	96	104
2025	92	98	92	98	92	98	96	103
2026	92	99	93	100	93	100	97	105
2027	92	99	93	100	93	100	97	105
2028	92	98	93	99	93	100	97	104

5.2.14 Tennent Zone Substation Forecast

Tennent ZSS was constructed at Angle Crossing in southern ACT to enable connection of the Williamsdale Solar Farm to Evoenergy'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.

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 
-0.315586 -0.029598  0.000976  0.030684  0.258837 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)            -0.059375   0.045281  -1.311 0.190062    
dayMon                  0.020256   0.005739   3.529 0.000435 ***
daySat                 -0.209405   0.005707 -36.693  < 2e-16 ***
daySun                 -0.223265   0.005779 -38.636  < 2e-16 ***
dayThu                  0.018826   0.005729   3.286 0.001051 ** 
dayTue                  0.021321   0.005722   3.726 0.000205 ***
dayWed                  0.018193   0.005722   3.179 0.001520 ** 
holidayDay before       0.013370   0.012510   1.069 0.285434    
holidayHoliday         -0.173010   0.011412 -15.161  < 2e-16 ***
holidayNormal           0.037219   0.009579   3.886 0.000109 ***
ns(timeofyear, 9)1      0.084930   0.011662   7.283 6.47e-13 ***
ns(timeofyear, 9)2      0.102031   0.014531   7.022 3.97e-12 ***
ns(timeofyear, 9)3      0.114977   0.014049   8.184 8.01e-16 ***
ns(timeofyear, 9)4      0.098989   0.014192   6.975 5.44e-12 ***
ns(timeofyear, 9)5      0.093002   0.013875   6.703 3.36e-11 ***
ns(timeofyear, 9)6      0.090610   0.014376   6.303 4.32e-10 ***
ns(timeofyear, 9)7      0.045864   0.011273   4.068 5.09e-05 ***
ns(timeofyear, 9)8      0.014858   0.023086   0.644 0.519985    
ns(timeofyear, 9)9     -0.166624   0.010515 -15.847  < 2e-16 ***
ns(temp, df = 2)1       0.023930   0.082015   0.292 0.770520    
ns(temp, df = 2)2      -0.002474   0.058303  -0.042 0.966157    
ns(dtemp, 3)1          -0.015418   0.013686  -1.127 0.260203    
ns(dtemp, 3)2          -0.014759   0.047106  -0.313 0.754112    
ns(dtemp, 3)3           0.061704   0.030499   2.023 0.043310 *  
ns(prevtemp1, df = 2)1  0.289444   0.123225   2.349 0.019016 *  
ns(prevtemp1, df = 2)2  0.312343   0.077221   4.045 5.63e-05 ***
ns(prevtemp2, df = 2)1 -0.049488   0.101130  -0.489 0.624701    
ns(prevtemp2, df = 2)2  0.076461   0.058067   1.317 0.188207    
ns(prevtemp5, df = 2)1  0.272715   0.054316   5.021 6.05e-07 ***
ns(prevtemp5, df = 2)2  0.151570   0.034722   4.365 1.40e-05 ***
ns(day1temp, df = 2)1   0.016616   0.026612   0.624 0.532500    
ns(day1temp, df = 2)2   0.006810   0.023385   0.291 0.770936    
ns(day5temp, df = 2)1   0.025029   0.016858   1.485 0.137931    
ns(day5temp, df = 2)2  -0.021683   0.008492  -2.553 0.010816 *  
ns(prevdtemp5, 3)1      0.017242   0.017903   0.963 0.335736    
ns(prevdtemp5, 3)2      0.055598   0.066282   0.839 0.401771    
ns(prevdtemp5, 3)3      0.070614   0.041053   1.720 0.085717 .  
ns(lastmin, 3)1         0.087356   0.015580   5.607 2.64e-08 ***
ns(lastmin, 3)2         0.153604   0.048323   3.179 0.001523 ** 
ns(lastmin, 3)3         0.072224   0.030570   2.363 0.018334 *  
```

```
ns(lastmax, 3)1        -0.025861   0.016702  -1.548 0.121842
ns(lastmax, 3)2        -0.084519   0.042778  -1.976 0.048447 *
ns(lastmax, 3)3        -0.069824   0.033693  -2.072 0.038478 *
ns(avetemp, 3)1         0.055082   0.026064   2.113 0.034811 *
ns(avetemp, 3)2        -0.069588   0.067159  -1.036 0.300369
ns(avetemp, 3)3         0.073976   0.041089   1.800 0.072090 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04956 on 1034 degrees of freedom
Multiple R-squared:  0.9335,     Adjusted R-squared:  0.9306
F-statistic: 322.5 on 45 and 1034 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
-0.06560 -0.01416 -0.00164  0.01407  0.06737

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.4636613  0.0142338  32.575  < 2e-16 ***
dayMon                  0.0512772  0.0023575  21.751  < 2e-16 ***
daySat                 -0.0727177  0.0023182 -31.368  < 2e-16 ***
daySun                 -0.0492257  0.0023653 -20.812  < 2e-16 ***
dayThu                  0.0360351  0.0023056  15.629  < 2e-16 ***
dayTue                  0.0466546  0.0023662  19.717  < 2e-16 ***
dayWed                  0.0445303  0.0023075  19.298  < 2e-16 ***
holidayDay before      -0.0756610  0.0086980  -8.699  < 2e-16 ***
holidayHoliday         -0.0616171  0.0086851  -7.095 2.26e-12 ***
holidayNormal          -0.0044525  0.0065407  -0.681 0.496171
ns(timeofyear, 9)1      0.0190017  0.0048854   3.889 0.000106 ***
ns(timeofyear, 9)2      0.0166485  0.0061136   2.723 0.006563 **
ns(timeofyear, 9)3     -0.0274756  0.0056076  -4.900 1.10e-06 ***
ns(timeofyear, 9)4      0.0136991  0.0057825   2.369 0.017999 *
ns(timeofyear, 9)5      0.0051838  0.0055862   0.928 0.353623
ns(timeofyear, 9)6     -0.0245136  0.0056185  -4.363 1.40e-05 ***
ns(timeofyear, 9)7     -0.0365212  0.0046054  -7.930 5.15e-15 ***
ns(timeofyear, 9)8     -0.0745051  0.0095441  -7.806 1.31e-14 ***
ns(timeofyear, 9)9     -0.0802708  0.0045055 -17.816  < 2e-16 ***
ns(temp, df = 2)1       0.0093447  0.0305134   0.306 0.759471
ns(temp, df = 2)2       0.0584087  0.0277452   2.105 0.035492 *
ns(prevtemp1, df = 2)1  0.0252920  0.0444265   0.569 0.569263
ns(prevtemp1, df = 2)2  0.0174260  0.0483368   0.361 0.718530
ns(prevtemp2, df = 2)1 -0.1238034  0.0383068  -3.232 0.001265 **
ns(prevtemp2, df = 2)2 -0.1983698  0.0410439  -4.833 1.53e-06 ***
ns(prevtemp4, df = 2)1 -0.1627727  0.0353481  -4.605 4.59e-06 ***
ns(prevtemp4, df = 2)2 -0.0520247  0.0304981  -1.706 0.088308 .
ns(prevtemp6, df = 2)1 -0.1354858  0.0323419  -4.189 3.01e-05 ***
ns(prevtemp6, df = 2)2 -0.0998279  0.0277970  -3.591 0.000343 ***
```

```
ns(day1temp, df = 2)1  -0.0339775  0.0106491  -3.191 0.001458 **
ns(day1temp, df = 2)2   0.0064794  0.0096982   0.668 0.504200
ns(day2temp, df = 2)1  -0.0441457  0.0084589  -5.219 2.13e-07 ***
ns(day2temp, df = 2)2  -0.0225200  0.0068444  -3.290 0.001031 **
ns(day6temp, df = 2)1  -0.0142070  0.0076993  -1.845 0.065262 .
ns(day6temp, df = 2)2  -0.0004886  0.0059283  -0.082 0.934331
ns(lastmin, 3)1         0.0045235  0.0077072   0.587 0.557370
ns(lastmin, 3)2        -0.0172588  0.0188110  -0.917 0.359080
ns(lastmin, 3)3         0.0281637  0.0116608   2.415 0.015879 *
ns(lastmax, 3)1         0.0155725  0.0110953   1.404 0.160732
ns(lastmax, 3)2         0.0303983  0.0294934   1.031 0.302907
ns(lastmax, 3)3         0.0370829  0.0220471   1.682 0.092843 .
ns(avetemp, 3)1        -0.0552151  0.0105556  -5.231 2.00e-07 ***
ns(avetemp, 3)2        -0.1106185  0.0257417  -4.297 1.88e-05 ***
ns(avetemp, 3)3        -0.1212774  0.0163162  -7.433 2.07e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02116 on 1152 degrees of freedom
Multiple R-squared:  0.9421,    Adjusted R-squared:  0.9399
F-statistic: 435.8 on 43 and 1152 DF,  p-value: < 2.2e-16
```

6.1.2 Belconnen ZSS HH Model

6.1.2.1 Belconnen summer HH model summary (Example: 16:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.40491 -0.03423  0.00235  0.03461  0.31380

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.062903   0.029980  -2.098 0.036131 *
dayMon                  0.014435   0.006751   2.138 0.032730 *
daySat                 -0.230172   0.006689 -34.411  < 2e-16 ***
daySun                 -0.271233   0.006777 -40.025  < 2e-16 ***
dayThu                  0.013558   0.006736   2.013 0.044401 *
dayTue                  0.012784   0.006688   1.911 0.056218 .
dayWed                  0.012566   0.006714   1.872 0.061545 .
holidayDay before       0.020099   0.014649   1.372 0.170340
holidayHoliday         -0.199774   0.013346 -14.969  < 2e-16 ***
holidayNormal           0.048244   0.011203   4.307 1.82e-05 ***
ns(timeofyear, 9)1      0.065556   0.013653   4.802 1.81e-06 ***
ns(timeofyear, 9)2      0.093316   0.016993   5.491 5.02e-08 ***
ns(timeofyear, 9)3      0.092456   0.016426   5.629 2.33e-08 ***
ns(timeofyear, 9)4      0.100995   0.016565   6.097 1.52e-09 ***
```

```
ns(timeofyear, 9)5       0.074723   0.016215   4.608 4.56e-06 ***
ns(timeofyear, 9)6       0.069168   0.016773   4.124 4.03e-05 ***
ns(timeofyear, 9)7       0.047013   0.013118   3.584 0.000354 ***
ns(timeofyear, 9)8      -0.010667   0.027003  -0.395 0.692905
ns(timeofyear, 9)9      -0.174609   0.012283 -14.215  < 2e-16 ***
ns(temp, df = 2)1        0.085609   0.069980   1.223 0.221480
ns(temp, df = 2)2        0.011129   0.049052   0.227 0.820567
ns(prevtemp1, df = 2)1  0.221700   0.086279   2.570 0.010320 *
ns(prevtemp1, df = 2)2  0.285972   0.056921   5.024 5.95e-07 ***
ns(prevtemp3, df = 2)1  0.232631   0.069435   3.350 0.000836 ***
ns(prevtemp3, df = 2)2  0.180707   0.045459   3.975 7.52e-05 ***
ns(prevtemp6, df = 2)1  0.070184   0.053189   1.320 0.187284
ns(prevtemp6, df = 2)2  0.086047   0.041753   2.061 0.039564 *
ns(day1temp, df = 2)1   0.024564   0.029230   0.840 0.400898
ns(day1temp, df = 2)2   0.019539   0.024343   0.803 0.422374
ns(day5temp, df = 2)1   0.029391   0.019401   1.515 0.130112
ns(day5temp, df = 2)2  -0.019717   0.009686  -2.036 0.042045 *
ns(lastmin, 3)1          0.068155   0.018932   3.600 0.000333 ***
ns(lastmin, 3)2          0.118823   0.059983   1.981 0.047862 *
ns(lastmin, 3)3          0.076056   0.041164   1.848 0.064942 .
ns(lastmax, 3)1         -0.028987   0.018894  -1.534 0.125295
ns(lastmax, 3)2         -0.076147   0.047634  -1.599 0.110213
ns(lastmax, 3)3         -0.053225   0.037054  -1.436 0.151183
ns(avetemp, 3)1          0.077213   0.031169   2.477 0.013399 *
ns(avetemp, 3)2         -0.029274   0.079253  -0.369 0.711924
ns(avetemp, 3)3          0.049348   0.048236   1.023 0.306523
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05813 on 1040 degrees of freedom
Multiple R-squared:  0.9209,    Adjusted R-squared:  0.9179
F-statistic: 310.3 on 39 and 1040 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

-0.279248 -0.019688 -0.001181  0.018042  0.082786


Coefficients:

                        Estimate Std. Error t value Pr(>|t|)

(Intercept)              0.495121   0.014573  33.976  < 2e-16 ***
```

```
dayMon                0.032647   0.003383   9.650  < 2e-16 ***
daySat               -0.103485   0.003334 -31.035  < 2e-16 ***
daySun               -0.092260   0.003405 -27.098  < 2e-16 ***
dayThu                0.018437   0.003321   5.551 3.59e-08 ***
dayTue                0.024931   0.003377   7.382 3.13e-13 ***
dayWed                0.024968   0.003320   7.521 1.15e-13 ***
holidayDay before    -0.090899   0.011460  -7.932 5.46e-15 ***
holidayHoliday       -0.087453   0.011453  -7.636 5.00e-14 ***
holidayNormal        -0.012086   0.007445  -1.623 0.104796
ns(timeofyear, 9)1    0.011893   0.006920   1.719 0.085946 .
ns(timeofyear, 9)2    0.013544   0.008639   1.568 0.117215
ns(timeofyear, 9)3   -0.024947   0.007984  -3.124 0.001830 **
ns(timeofyear, 9)4    0.021460   0.008213   2.613 0.009103 **
ns(timeofyear, 9)5    0.005553   0.007953   0.698 0.485184
ns(timeofyear, 9)6   -0.022513   0.008006  -2.812 0.005015 **
ns(timeofyear, 9)7   -0.029528   0.006685  -4.417 1.10e-05 ***
ns(timeofyear, 9)8   -0.070092   0.013471  -5.203 2.35e-07 ***
ns(timeofyear, 9)9   -0.067667   0.006339 -10.674  < 2e-16 ***
ns(temp, df = 2)1    -0.007756   0.025865  -0.300 0.764337
ns(temp, df = 2)2     0.066665   0.029015   2.298 0.021780 *
ns(prevtemp1, df = 2)1  0.013296   0.035775   0.372 0.710227
ns(prevtemp1, df = 2)2  0.039448   0.045612   0.865 0.387314
ns(prevtemp2, df = 2)1 -0.100408   0.046023  -2.182 0.029353 *
ns(prevtemp2, df = 2)2 -0.240784   0.056255  -4.280 2.04e-05 ***
ns(prevtemp3, df = 2)1 -0.059582   0.060536  -0.984 0.325216
ns(prevtemp3, df = 2)2  0.004003   0.051994   0.077 0.938651
ns(prevtemp4, df = 2)1 -0.057994   0.060692  -0.956 0.339520
ns(prevtemp4, df = 2)2  0.030214   0.045319   0.667 0.505112
ns(prevtemp5, df = 2)1 -0.118832   0.057513  -2.066 0.039052 *
ns(prevtemp5, df = 2)2 -0.147156   0.041332  -3.560 0.000387 ***
ns(prevtemp6, df = 2)1 -0.045122   0.039992  -1.128 0.259454
ns(prevtemp6, df = 2)2  0.004266   0.032637   0.131 0.896030
ns(day1temp, df = 2)1  -0.052898   0.012374  -4.275 2.08e-05 ***
ns(day1temp, df = 2)2  -0.001139   0.012371  -0.092 0.926643
```

```
ns(day2temp, df = 2)1  -0.035310   0.010406  -3.393 0.000716 ***
ns(day2temp, df = 2)2  -0.015914   0.009462  -1.682 0.092871 .
ns(day6temp, df = 2)1  -0.011716   0.009511  -1.232 0.218288
ns(day6temp, df = 2)2   0.006808   0.008332   0.817 0.414029
ns(avetemp, 3)1        -0.032856   0.005298  -6.201 8.00e-10 ***
ns(avetemp, 3)2        -0.085663   0.015209  -5.632 2.28e-08 ***
ns(avetemp, 3)3        -0.069295   0.010369  -6.683 3.78e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02925 on 1062 degrees of freedom
Multiple R-squared:  0.9007,    Adjusted R-squared:  0.8969
F-statistic: 235.1 on 41 and 1062 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: 16:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.279248 -0.019688 -0.001181  0.018042  0.082786

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.495121   0.014573  33.976  < 2e-16 ***
dayMon                  0.032647   0.003383   9.650  < 2e-16 ***
daySat                 -0.103485   0.003334 -31.035  < 2e-16 ***
daySun                 -0.092260   0.003405 -27.098  < 2e-16 ***
dayThu                  0.018437   0.003321   5.551 3.59e-08 ***
dayTue                  0.024931   0.003377   7.382 3.13e-13 ***
dayWed                  0.024968   0.003320   7.521 1.15e-13 ***
holidayDay before      -0.090899   0.011460  -7.932 5.46e-15 ***
holidayHoliday         -0.087453   0.011453  -7.636 5.00e-14 ***
holidayNormal          -0.012086   0.007445  -1.623 0.104796
ns(timeofyear, 9)1      0.011893   0.006920   1.719 0.085946 .
ns(timeofyear, 9)2      0.013544   0.008639   1.568 0.117215
ns(timeofyear, 9)3     -0.024947   0.007984  -3.124 0.001830 **
ns(timeofyear, 9)4      0.021460   0.008213   2.613 0.009103 **
ns(timeofyear, 9)5      0.005553   0.007953   0.698 0.485184
ns(timeofyear, 9)6     -0.022513   0.008006  -2.812 0.005015 **
ns(timeofyear, 9)7     -0.029528   0.006685  -4.417 1.10e-05 ***
```

```
ns(timeofyear, 9)8     -0.070092   0.013471  -5.203 2.35e-07 ***
ns(timeofyear, 9)9     -0.067667   0.006339 -10.674  < 2e-16 ***
ns(temp, df = 2)1      -0.007756   0.025865  -0.300 0.764337
ns(temp, df = 2)2       0.066665   0.029015   2.298 0.021780 *
ns(prevtemp1, df = 2)1  0.013296   0.035775   0.372 0.710227
ns(prevtemp1, df = 2)2  0.039448   0.045612   0.865 0.387314
ns(prevtemp2, df = 2)1 -0.100408   0.046023  -2.182 0.029353 *
ns(prevtemp2, df = 2)2 -0.240784   0.056255  -4.280 2.04e-05 ***
ns(prevtemp3, df = 2)1 -0.059582   0.060536  -0.984 0.325216
ns(prevtemp3, df = 2)2  0.004003   0.051994   0.077 0.938651
ns(prevtemp4, df = 2)1 -0.057994   0.060692  -0.956 0.339520
ns(prevtemp4, df = 2)2  0.030214   0.045319   0.667 0.505112
ns(prevtemp5, df = 2)1 -0.118832   0.057513  -2.066 0.039052 *
ns(prevtemp5, df = 2)2 -0.147156   0.041332  -3.560 0.000387 ***
ns(prevtemp6, df = 2)1 -0.045122   0.039992  -1.128 0.259454
ns(prevtemp6, df = 2)2  0.004266   0.032637   0.131 0.896030
ns(day1temp, df = 2)1  -0.052898   0.012374  -4.275 2.08e-05 ***
ns(day1temp, df = 2)2  -0.001139   0.012371  -0.092 0.926643
ns(day2temp, df = 2)1  -0.035310   0.010406  -3.393 0.000716 ***
ns(day2temp, df = 2)2  -0.015914   0.009462  -1.682 0.092871 .
ns(day6temp, df = 2)1  -0.011716   0.009511  -1.232 0.218288
ns(day6temp, df = 2)2   0.006808   0.008332   0.817 0.414029
ns(avetemp, 3)1        -0.032856   0.005298  -6.201 8.00e-10 ***
ns(avetemp, 3)2        -0.085663   0.015209  -5.632 2.28e-08 ***
ns(avetemp, 3)3        -0.069295   0.010369  -6.683 3.78e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02925 on 1062 degrees of freedom
Multiple R-squared:  0.9007,    Adjusted R-squared:  0.8969
F-statistic: 235.1 on 41 and 1062 DF,  p-value: < 2.2e-16
```

6.1.3.2 City East winter HH model summary (Example: 18:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.122853 -0.017124  0.000968  0.018463  0.168494

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.4563428  0.0166693  27.376  < 2e-16 ***
dayMon                  0.0248582  0.0036480   6.814 1.66e-11 ***
daySat                 -0.1416764  0.0035797 -39.578  < 2e-16 ***
daySun                 -0.1536395  0.0036555 -42.029  < 2e-16 ***
```

```
dayThu                    0.0158660  0.0035681   4.447 9.73e-06 ***
dayTue                    0.0211690  0.0036221   5.844 6.94e-09 ***
dayWed                    0.0237560  0.0035766   6.642 5.15e-11 ***
holidayDay before        -0.0650318  0.0122849  -5.294 1.48e-07 ***
holidayHoliday           -0.1264710  0.0122410 -10.332  < 2e-16 ***
holidayNormal            -0.0106285  0.0078598  -1.352  0.17661
ns(timeofyear, 9)1        0.0102844  0.0074853   1.374  0.16977
ns(timeofyear, 9)2        0.0125111  0.0093448   1.339  0.18094
ns(timeofyear, 9)3       -0.0196628  0.0086310  -2.278  0.02293 *
ns(timeofyear, 9)4        0.0014965  0.0088009   0.170  0.86502
ns(timeofyear, 9)5        0.0017150  0.0085736   0.200  0.84150
ns(timeofyear, 9)6       -0.0376527  0.0086301  -4.363 1.42e-05 ***
ns(timeofyear, 9)7       -0.0395530  0.0071006  -5.570 3.29e-08 ***
ns(timeofyear, 9)8       -0.0815216  0.0144591  -5.638 2.25e-08 ***
ns(timeofyear, 9)9       -0.0871008  0.0065864 -13.224  < 2e-16 ***
ns(temp, df = 2)1         0.0018396  0.0264434   0.070  0.94455
ns(temp, df = 2)2         0.0250784  0.0217246   1.154  0.24863
ns(prevtemp1, df = 2)1 -0.0182608  0.0313407  -0.583  0.56026
ns(prevtemp1, df = 2)2 -0.0275495  0.0303600  -0.907  0.36441
ns(prevtemp4, df = 2)1 -0.1544755  0.0312228  -4.948 8.86e-07 ***
ns(prevtemp4, df = 2)2 -0.0698563  0.0252885  -2.762  0.00585 **
ns(prevtemp6, df = 2)1 -0.0687004  0.0305102  -2.252  0.02456 *
ns(prevtemp6, df = 2)2 -0.0584901  0.0236538  -2.473  0.01358 *
ns(day1temp, df = 2)1  -0.0194572  0.0139601  -1.394  0.16370
ns(day1temp, df = 2)2   0.0076052  0.0101321   0.751  0.45307
ns(day2temp, df = 2)1  -0.0241732  0.0121079  -1.996  0.04616 *
ns(day2temp, df = 2)2  -0.0116663  0.0080559  -1.448  0.14789
ns(day3temp, df = 2)1  -0.0173845  0.0114534  -1.518  0.12938
ns(day3temp, df = 2)2  -0.0133069  0.0074023  -1.798  0.07254 .
ns(day6temp, df = 2)1  -0.0088858  0.0107482  -0.827  0.40860
ns(day6temp, df = 2)2  -0.0125400  0.0066833  -1.876  0.06091 .
ns(lastmin, 3)1           0.0204544  0.0110337   1.854  0.06407 .
ns(lastmin, 3)2          -0.0006376  0.0282745  -0.023  0.98201
ns(lastmin, 3)3           0.0332365  0.0181415   1.832  0.06725 .
ns(avetemp, 3)1          -0.0666915  0.0130338  -5.117 3.74e-07 ***
ns(avetemp, 3)2          -0.1406248  0.0309045  -4.550 6.04e-06 ***
ns(avetemp, 3)3          -0.1322745  0.0242070  -5.464 5.91e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0301 on 971 degrees of freedom
Multiple R-squared:  0.9101,    Adjusted R-squared:  0.9064
F-statistic: 245.7 on 40 and 971 DF,  p-value: < 2.2e-16
```

6.1.4 Civic ZSS HH Model

6.1.4.1 Civic summer HH model summary (Example: 16:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max 
-0.34516 -0.03330  0.00061  0.03340  0.30677 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)            -0.060299   0.026714  -2.257 0.024218 *  
dayMon                  0.021505   0.006863   3.134 0.001779 ** 
daySat                 -0.365572   0.006804 -53.726  < 2e-16 ***
daySun                 -0.382423   0.006901 -55.412  < 2e-16 ***
dayThu                  0.024891   0.006835   3.641 0.000286 ***
dayTue                  0.027278   0.006801   4.011 6.53e-05 ***
dayWed                  0.024285   0.006849   3.546 0.000410 ***
holidayDay before       0.023500   0.015000   1.567 0.117539    
holidayHoliday         -0.231507   0.013627 -16.989  < 2e-16 ***
holidayNormal           0.045756   0.011427   4.004 6.70e-05 ***
ns(timeofyear, 9)1      0.130417   0.013892   9.388  < 2e-16 ***
ns(timeofyear, 9)2      0.172509   0.017403   9.913  < 2e-16 ***
ns(timeofyear, 9)3      0.170337   0.016653  10.229  < 2e-16 ***
ns(timeofyear, 9)4      0.196263   0.016861  11.640  < 2e-16 ***
ns(timeofyear, 9)5      0.147473   0.016477   8.950  < 2e-16 ***
ns(timeofyear, 9)6      0.163158   0.017060   9.564  < 2e-16 ***
ns(timeofyear, 9)7      0.072363   0.013337   5.426 7.31e-08 ***
ns(timeofyear, 9)8      0.082051   0.027486   2.985 0.002906 ** 
ns(timeofyear, 9)9     -0.241656   0.012448 -19.413  < 2e-16 ***
ns(temp, df = 2)1       0.141236   0.069981   2.018 0.043847 *  
ns(temp, df = 2)2       0.050294   0.048999   1.026 0.304946    
ns(prevtemp1, df = 2)1  0.120080   0.086086   1.395 0.163377    
ns(prevtemp1, df = 2)2  0.242986   0.058688   4.140 3.78e-05 ***
ns(prevtemp3, df = 2)1  0.102158   0.069431   1.471 0.141526    
ns(prevtemp3, df = 2)2  0.049333   0.045611   1.082 0.279701    
ns(prevtemp6, df = 2)1  0.076197   0.051012   1.494 0.135586    
ns(prevtemp6, df = 2)2  0.022641   0.041463   0.546 0.585160    
ns(day6temp, df = 2)1  -0.012966   0.019731  -0.657 0.511250    
ns(day6temp, df = 2)2  -0.027541   0.009624  -2.862 0.004307 ** 
ns(lastmin, 3)1         0.058391   0.015454   3.778 0.000168 ***
ns(lastmin, 3)2         0.057011   0.046090   1.237 0.216411    
ns(lastmin, 3)3         0.048369   0.038135   1.268 0.204972    
ns(avetemp, 3)1         0.056547   0.021941   2.577 0.010107 *  
ns(avetemp, 3)2         0.026528   0.057919   0.458 0.647042    
```

```
ns(avetemp, 3)3         0.073987   0.037489   1.974 0.048723 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05686 on 955 degrees of freedom
Multiple R-squared:  0.942,     Adjusted R-squared:   0.94
F-statistic: 456.5 on 34 and 955 DF,  p-value: < 2.2e-16
```

6.1.4.2 Civic winter HH model summary (Example: 18:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.120366 -0.013351  0.000005  0.013826  0.120880

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.3291129  0.0144261  22.814  < 2e-16 ***
dayMon                  0.0450044  0.0026583  16.930  < 2e-16 ***
daySat                 -0.1420679  0.0026080 -54.474  < 2e-16 ***
daySun                 -0.1467628  0.0026689 -54.989  < 2e-16 ***
dayThu                  0.0422322  0.0026038  16.220  < 2e-16 ***
dayTue                  0.0452771  0.0026363  17.174  < 2e-16 ***
dayWed                  0.0476031  0.0026085  18.249  < 2e-16 ***
holidayDay before      -0.0446919  0.0089569  -4.990 7.17e-07 ***
holidayHoliday         -0.1350203  0.0089261 -15.127  < 2e-16 ***
holidayNormal          -0.0005861  0.0057344  -0.102 0.918615
ns(timeofyear, 9)1      0.0056083  0.0054324   1.032 0.302157
ns(timeofyear, 9)2     -0.0100317  0.0067983  -1.476 0.140370
ns(timeofyear, 9)3     -0.0342356  0.0062811  -5.451 6.37e-08 ***
ns(timeofyear, 9)4      0.0121084  0.0064110   1.889 0.059233 .
ns(timeofyear, 9)5      0.0108936  0.0062426   1.745 0.081297 .
ns(timeofyear, 9)6     -0.0148819  0.0062845  -2.368 0.018078 *
ns(timeofyear, 9)7     -0.0236420  0.0052125  -4.536 6.46e-06 ***
ns(timeofyear, 9)8     -0.0460145  0.0105368  -4.367 1.39e-05 ***
ns(timeofyear, 9)9     -0.0602281  0.0048322 -12.464  < 2e-16 ***
ns(temp, df = 2)1       0.0046684  0.0193295   0.242 0.809208
ns(temp, df = 2)2       0.0256161  0.0160274   1.598 0.110309
ns(prevtemp1, df = 2)1 -0.0082418  0.0265339  -0.311 0.756160
ns(prevtemp1, df = 2)2  0.0191110  0.0288620   0.662 0.508032
ns(prevtemp2, df = 2)1 -0.0112475  0.0272772  -0.412 0.680180
ns(prevtemp2, df = 2)2 -0.0952105  0.0263530  -3.613 0.000318 ***
ns(prevtemp4, df = 2)1 -0.1154603  0.0281479  -4.102 4.44e-05 ***
ns(prevtemp4, df = 2)2 -0.0076481  0.0231795  -0.330 0.741508
ns(prevtemp6, df = 2)1 -0.0895669  0.0253700  -3.530 0.000434 ***
```

```
ns(prevtemp6, df = 2)2 -0.0837236  0.0209664  -3.993 7.01e-05 ***
ns(day2temp, df = 2)1  -0.0296376  0.0081556  -3.634 0.000294 ***
ns(day2temp, df = 2)2  -0.0133708  0.0051956  -2.573 0.010215 *
ns(day6temp, df = 2)1   0.0022048  0.0078196   0.282 0.778036
ns(day6temp, df = 2)2  -0.0024832  0.0048619  -0.511 0.609647
ns(lastmin, 3)1         0.0259849  0.0079951   3.250 0.001193 **
ns(lastmin, 3)2         0.0474602  0.0215528   2.202 0.027897 *
ns(lastmin, 3)3         0.0361450  0.0135994   2.658 0.007994 **
ns(lastmax, 3)1        -0.0010851  0.0104835  -0.104 0.917581
ns(lastmax, 3)2         0.0024824  0.0289450   0.086 0.931672
ns(lastmax, 3)3         0.0226515  0.0174587   1.297 0.194793
ns(avetemp, 3)1        -0.0634670  0.0092051  -6.895 9.71e-12 ***
ns(avetemp, 3)2        -0.1275841  0.0229985  -5.548 3.74e-08 ***
ns(avetemp, 3)3        -0.1088955  0.0171179  -6.362 3.07e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02194 on 970 degrees of freedom
Multiple R-squared:  0.9505,    Adjusted R-squared:  0.9484
F-statistic: 454.2 on 41 and 970 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: 16:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.52631 -0.06041  0.00702  0.06416  0.51007

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.315333   0.076626  -4.115 4.51e-05 ***
dayMon                  0.046939   0.018870   2.488 0.013183 *
daySat                 -0.521939   0.018773 -27.802  < 2e-16 ***
daySun                 -0.559861   0.018867 -29.675  < 2e-16 ***
dayThu                  0.063845   0.018857   3.386 0.000765 ***
dayTue                  0.053048   0.018736   2.831 0.004819 **
dayWed                  0.058277   0.018798   3.100 0.002042 **
holidayDay before      -0.103747   0.043356  -2.393 0.017080 *
holidayHoliday         -0.374317   0.038428  -9.741  < 2e-16 ***
holidayNormal           0.036566   0.032686   1.119 0.263800
ns(timeofyear, 9)1      0.207467   0.037773   5.492 6.28e-08 ***
ns(timeofyear, 9)2      0.258467   0.047897   5.396 1.05e-07 ***
ns(timeofyear, 9)3      0.299300   0.044158   6.778 3.40e-11 ***
```

```
ns(timeofyear, 9)4       0.256510   0.046149   5.558 4.41e-08 ***
ns(timeofyear, 9)5       0.218092   0.044802   4.868 1.51e-06 ***
ns(timeofyear, 9)6       0.257035   0.047017   5.467 7.20e-08 ***
ns(timeofyear, 9)7       0.085392   0.036259   2.355 0.018900 *
ns(timeofyear, 9)8       0.285819   0.075165   3.803 0.000161 ***
ns(timeofyear, 9)9      -0.264381   0.034214  -7.727 5.93e-14 ***
ns(prevtemp1, df = 2)1  0.399985   0.135945   2.942 0.003408 **
ns(prevtemp1, df = 2)2  0.389653   0.072329   5.387 1.10e-07 ***
ns(prevtemp4, df = 2)1  0.097596   0.192464   0.507 0.612314
ns(prevtemp4, df = 2)2  0.015238   0.117712   0.129 0.897053
ns(prevtemp6, df = 2)1  0.140143   0.166582   0.841 0.400585
ns(prevtemp6, df = 2)2 -0.139278   0.125940  -1.106 0.269288
ns(day1temp, df = 2)1  -0.059531   0.077793  -0.765 0.444477
ns(day1temp, df = 2)2   0.040002   0.046732   0.856 0.392404
ns(lastmin, 3)1         0.003091   0.045695   0.068 0.946095
ns(lastmin, 3)2         0.006571   0.137566   0.048 0.961921
ns(lastmin, 3)3        -0.106587   0.065063  -1.638 0.101996
ns(avetemp, 3)1         0.170209   0.074735   2.277 0.023172 *
ns(avetemp, 3)2         0.309466   0.177950   1.739 0.082630 .
ns(avetemp, 3)3         0.193781   0.104335   1.857 0.063849 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1144 on 507 degrees of freedom
Multiple R-squared:  0.8912,    Adjusted R-squared:  0.8843
F-statistic: 129.8 on 32 and 507 DF,  p-value: < 2.2e-16
```

6.1.5.2 East Lake winter HH model summary (Example: 8:30 AM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.306016 -0.038646  0.002181  0.040225  0.242373

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.475597   0.033751  14.091  < 2e-16 ***
dayMon                  0.018426   0.012322   1.495 0.135531
daySat                 -0.554274   0.012046 -46.013  < 2e-16 ***
daySun                 -0.780621   0.012289 -63.521  < 2e-16 ***
dayThu                  0.012928   0.012048   1.073 0.283836
dayTue                  0.030479   0.012136   2.512 0.012381 *
dayWed                  0.015620   0.012086   1.292 0.196913
holidayDay before      -0.137513   0.038345  -3.586 0.000373 ***
holidayHoliday         -0.631692   0.038457 -16.426  < 2e-16 ***
```

```
holidayNormal           -0.022725   0.021343  -1.065 0.287577
ns(prevtemp1, df = 2)1   0.049026   0.061191   0.801 0.423456
ns(prevtemp1, df = 2)2  -0.069526   0.033769  -2.059 0.040100 *
ns(day2temp, df = 2)1   -0.040286   0.025544  -1.577 0.115485
ns(day2temp, df = 2)2   -0.028024   0.017357  -1.615 0.107125
ns(day6temp, df = 2)1   -0.004237   0.024730  -0.171 0.864044
ns(day6temp, df = 2)2   -0.014446   0.016195  -0.892 0.372869
ns(lastmin, 3)1         -0.052800   0.037259  -1.417 0.157155
ns(lastmin, 3)2         -0.037977   0.091650  -0.414 0.678803
ns(lastmin, 3)3          0.047111   0.041825   1.126 0.260618
ns(avetemp, 3)1         -0.080298   0.026124  -3.074 0.002246 **
ns(avetemp, 3)2         -0.223097   0.072503  -3.077 0.002222 **
ns(avetemp, 3)3         -0.203531   0.044421  -4.582 6.02e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06814 on 438 degrees of freedom
Multiple R-squared:  0.9592,    Adjusted R-squared:  0.9573
F-statistic: 490.9 on 21 and 438 DF,  p-value: < 2.2e-16
```

6.1.6 Gilmore ZSS HH Model

6.1.6.1 Gilmore summer HH model summary (Example: 16:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.52221 -0.04919  0.00025  0.05097  0.34625

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             -0.136484   0.034457  -3.961 7.97e-05 ***
dayMon                   0.049556   0.010131   4.892 1.16e-06 ***
daySat                  -0.062679   0.010052  -6.235 6.52e-10 ***
daySun                  -0.041085   0.010135  -4.054 5.41e-05 ***
dayThu                   0.034354   0.010063   3.414 0.000665 ***
dayTue                   0.039650   0.010074   3.936 8.83e-05 ***
dayWed                   0.040788   0.010083   4.045 5.61e-05 ***
holidayDay before        0.009357   0.022006   0.425 0.670769
holidayHoliday          -0.081076   0.020023  -4.049 5.52e-05 ***
holidayNormal            0.014009   0.016797   0.834 0.404444
ns(timeofyear, 9)1       0.080025   0.020274   3.947 8.43e-05 ***
ns(timeofyear, 9)2       0.164623   0.025476   6.462 1.58e-10 ***
ns(timeofyear, 9)3       0.060155   0.024309   2.475 0.013493 *
```

```
ns(timeofyear, 9)4      0.116308   0.024918   4.668 3.44e-06 ***
ns(timeofyear, 9)5      0.083790   0.024262   3.454 0.000575 ***
ns(timeofyear, 9)6      0.078481   0.025160   3.119 0.001862 **
ns(timeofyear, 9)7      0.041596   0.019633   2.119 0.034353 *
ns(timeofyear, 9)8      0.033497   0.040271   0.832 0.405713
ns(timeofyear, 9)9     -0.114180   0.018322  -6.232 6.66e-10 ***
ns(prevtemp1, df = 2)1  0.169915   0.082773   2.053 0.040340 *
ns(prevtemp1, df = 2)2  0.400320   0.055812   7.173 1.39e-12 ***
ns(prevtemp3, df = 2)1  0.080451   0.119763   0.672 0.501890
ns(prevtemp3, df = 2)2  0.303914   0.068168   4.458 9.15e-06 ***
ns(prevtemp6, df = 2)1  0.216245   0.079613   2.716 0.006712 **
ns(prevtemp6, df = 2)2 -0.054872   0.057472  -0.955 0.339918
ns(day1temp, df = 2)1  -0.044016   0.041176  -1.069 0.285333
ns(day1temp, df = 2)2  -0.097704   0.026850  -3.639 0.000287 ***
ns(avetemp, 3)1         0.166939   0.025775   6.477 1.44e-10 ***
ns(avetemp, 3)2         0.127714   0.067365   1.896 0.058254 .
ns(avetemp, 3)3         0.256353   0.043593   5.881 5.49e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.08778 on 1050 degrees of freedom
Multiple R-squared:  0.8271,    Adjusted R-squared:  0.8223
F-statistic: 173.2 on 29 and 1050 DF,  p-value: < 2.2e-16
```

6.1.6.2 Gilmore winter HH model summary (Example: 8:30 AM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.76981 -0.04485 -0.00371  0.04732  0.44796

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.2817721  0.0337866   8.340 2.51e-16 ***
dayMon                 -0.0038042  0.0091193  -0.417 0.676656
daySat                 -0.2947471  0.0089319 -32.999  < 2e-16 ***
daySun                 -0.4255902  0.0091306 -46.611  < 2e-16 ***
dayThu                 -0.0037484  0.0089340  -0.420 0.674899
dayTue                  0.0055849  0.0090610   0.616 0.537797
dayWed                  0.0067664  0.0089070   0.760 0.447635
holidayDay before      -0.0370274  0.0307330  -1.205 0.228569
holidayHoliday         -0.4212922  0.0307745 -13.690  < 2e-16 ***
holidayNormal           0.0062737  0.0197363   0.318 0.750647
ns(timeofyear, 9)1      0.0580731  0.0180679   3.214 0.001351 **
ns(timeofyear, 9)2      0.0946536  0.0231584   4.087 4.72e-05 ***
```

```
ns(timeofyear, 9)3     -0.0263817  0.0207878  -1.269 0.204709
ns(timeofyear, 9)4      0.0823677  0.0218469   3.770 0.000173 ***
ns(timeofyear, 9)5      0.0917244  0.0207063   4.430 1.05e-05 ***
ns(timeofyear, 9)6      0.0822788  0.0214846   3.830 0.000137 ***
ns(timeofyear, 9)7      0.0862890  0.0177657   4.857 1.39e-06 ***
ns(timeofyear, 9)8      0.0908667  0.0358368   2.536 0.011382 *
ns(timeofyear, 9)9      0.0108230  0.0168269   0.643 0.520250
ns(temp, df = 2)1       0.2291549  0.1050234   2.182 0.029352 *
ns(temp, df = 2)2       0.1363762  0.0700040   1.948 0.051687 .
ns(prevtemp1, df = 2)1 -0.2593402  0.1376684  -1.884 0.059889 .
ns(prevtemp1, df = 2)2 -0.0996386  0.0886869  -1.123 0.261507
ns(prevtemp3, df = 2)1  0.0899883  0.1093206   0.823 0.410618
ns(prevtemp3, df = 2)2 -0.0004916  0.0758214  -0.006 0.994828
ns(prevtemp6, df = 2)1 -0.0955042  0.0755582  -1.264 0.206538
ns(prevtemp6, df = 2)2 -0.0706171  0.0525024  -1.345 0.178929
ns(day1temp, df = 2)1   0.0064413  0.0259445   0.248 0.803977
ns(day1temp, df = 2)2   0.0574112  0.0163319   3.515 0.000459 ***
ns(day2temp, df = 2)1  -0.0061849  0.0231535  -0.267 0.789429
ns(day2temp, df = 2)2  -0.0191692  0.0140187  -1.367 0.171814
ns(day4temp, df = 2)1  -0.0049666  0.0215225  -0.231 0.817545
ns(day4temp, df = 2)2  -0.0061349  0.0133639  -0.459 0.646293
ns(avetemp, 3)1        -0.1413055  0.0219186  -6.447 1.79e-10 ***
ns(avetemp, 3)2        -0.1942405  0.0501329  -3.875 0.000114 ***
ns(avetemp, 3)3        -0.2425517  0.0377238  -6.430 2.00e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07554 on 976 degrees of freedom
Multiple R-squared:  0.8592,    Adjusted R-squared:  0.8541
F-statistic: 170.1 on 35 and 976 DF,  p-value: < 2.2e-16
```

6.1.7 Gold Creek ZSS HH Model

6.1.7.1 Gold Creek summer HH model summary (Example: 16:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.26325 -0.04715  0.00075  0.05003  0.34576

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.1193142  0.0389865  -3.060 0.002267 **
dayMon                  0.0143795  0.0090592   1.587 0.112754
daySat                 -0.0080607  0.0089900  -0.897 0.370122
```

```
daySun                  0.0165606  0.0091052   1.819 0.069229 .
dayThu                  0.0060904  0.0090464   0.673 0.500946
dayTue                  0.0001565  0.0089886   0.017 0.986116
dayWed                  0.0022477  0.0090238   0.249 0.803345
holidayDay before       0.0090565  0.0197242   0.459 0.646218
holidayHoliday         -0.0677282  0.0179356  -3.776 0.000168 ***
holidayNormal           0.0259251  0.0150352   1.724 0.084951 .
ns(timeofyear, 9)1      0.0552549  0.0183698   3.008 0.002694 **
ns(timeofyear, 9)2      0.1013730  0.0228736   4.432 1.03e-05 ***
ns(timeofyear, 9)3      0.0951347  0.0220610   4.312 1.77e-05 ***
ns(timeofyear, 9)4      0.1033694  0.0222415   4.648 3.79e-06 ***
ns(timeofyear, 9)5      0.0459686  0.0217797   2.111 0.035043 *
ns(timeofyear, 9)6      0.0142679  0.0225234   0.633 0.526566
ns(timeofyear, 9)7      0.0343617  0.0176109   1.951 0.051306 .
ns(timeofyear, 9)8     -0.0056324  0.0362947  -0.155 0.876706
ns(timeofyear, 9)9     -0.1094977  0.0164311  -6.664 4.31e-11 ***
ns(temp, df = 2)1       0.0825381  0.0940165   0.878 0.380195
ns(temp, df = 2)2       0.0932918  0.0659212   1.415 0.157309
ns(prevtemp1, df = 2)1  0.2376844  0.1158745   2.051 0.040495 *
ns(prevtemp1, df = 2)2  0.3239360  0.0765092   4.234 2.50e-05 ***
ns(prevtemp3, df = 2)1  0.1848696  0.0934612   1.978 0.048188 *
ns(prevtemp3, df = 2)2  0.4239803  0.0610769   6.942 6.81e-12 ***
ns(prevtemp6, df = 2)1  0.2934601  0.0714938   4.105 4.37e-05 ***
ns(prevtemp6, df = 2)2  0.1328216  0.0560656   2.369 0.018016 *
ns(day1temp, df = 2)1   0.0442810  0.0392938   1.127 0.260035
ns(day1temp, df = 2)2   0.0149428  0.0327022   0.457 0.647813
ns(day6temp, df = 2)1  -0.0010989  0.0259325  -0.042 0.966206
ns(day6temp, df = 2)2  -0.0486148  0.0130673  -3.720 0.000210 ***
ns(lastmin, 3)1         0.1431926  0.0254220   5.633 2.28e-08 ***
ns(lastmin, 3)2         0.2501993  0.0806356   3.103 0.001968 **
ns(lastmin, 3)3         0.1113740  0.0554212   2.010 0.044732 *
ns(lastmax, 3)1         0.0097499  0.0253267   0.385 0.700343
ns(lastmax, 3)2        -0.2353356  0.0639934  -3.677 0.000248 ***
ns(lastmax, 3)3        -0.1836760  0.0496687  -3.698 0.000229 ***
ns(avetemp, 3)1         0.0436872  0.0418547   1.044 0.296829
ns(avetemp, 3)2        -0.1731458  0.1065341  -1.625 0.104410
ns(avetemp, 3)3         0.0950232  0.0648903   1.464 0.143396
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07809 on 1040 degrees of freedom
Multiple R-squared:  0.9016,    Adjusted R-squared:  0.898
F-statistic: 244.5 on 39 and 1040 DF,  p-value: < 2.2e-16
```

6.1.7.2 Gold Creek winter HH model summary (Example: 18:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max 
-0.169889 -0.028889 -0.000927  0.028069  0.143057 

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)             0.5721649  0.0202668  28.232  < 2e-16 ***
dayMon                  0.0643607  0.0048815  13.185  < 2e-16 ***
daySat                  0.0129523  0.0047887   2.705 0.006945 ** 
daySun                  0.0720165  0.0049007  14.695  < 2e-16 ***
dayThu                  0.0409848  0.0047817   8.571  < 2e-16 ***
dayTue                  0.0493373  0.0048567  10.159  < 2e-16 ***
dayWed                  0.0508223  0.0047873  10.616  < 2e-16 ***
holidayDay before      -0.1410435  0.0165205  -8.537  < 2e-16 ***
holidayHoliday         -0.0060032  0.0165199  -0.363 0.716385    
holidayNormal          -0.0366185  0.0107357  -3.411 0.000672 ***
ns(timeofyear, 9)1      0.0270233  0.0096460   2.801 0.005179 ** 
ns(timeofyear, 9)2      0.0230258  0.0122117   1.886 0.059627 .  
ns(timeofyear, 9)3     -0.0173868  0.0111086  -1.565 0.117842    
ns(timeofyear, 9)4      0.0210969  0.0116257   1.815 0.069854 .  
ns(timeofyear, 9)5      0.0231674  0.0112005   2.068 0.038841 *  
ns(timeofyear, 9)6     -0.0137316  0.0113321  -1.212 0.225879    
ns(timeofyear, 9)7     -0.0229892  0.0094972  -2.421 0.015660 *  
ns(timeofyear, 9)8     -0.0752392  0.0192177  -3.915 9.61e-05 ***
ns(timeofyear, 9)9     -0.0773558  0.0091282  -8.474  < 2e-16 ***
ns(temp, df = 2)1       0.0377437  0.0371340   1.016 0.309660    
ns(temp, df = 2)2       0.1609866  0.0415048   3.879 0.000111 ***
ns(prevtemp1, df = 2)1  0.0112131  0.0513403   0.218 0.827154    
ns(prevtemp1, df = 2)2 -0.0615934  0.0658063  -0.936 0.349494    
ns(prevtemp2, df = 2)1 -0.2753731  0.0526400  -5.231 2.03e-07 ***
ns(prevtemp2, df = 2)2 -0.3555310  0.0659143  -5.394 8.49e-08 ***
ns(prevtemp4, df = 2)1 -0.2632847  0.0529803  -4.969 7.82e-07 ***
ns(prevtemp4, df = 2)2 -0.1394382  0.0485618  -2.871 0.004168 ** 
ns(prevtemp6, df = 2)1 -0.1258414  0.0415524  -3.029 0.002517 ** 
ns(prevtemp6, df = 2)2 -0.0341783  0.0356960  -0.957 0.338541    
ns(day1temp, df = 2)1  -0.1135381  0.0183276  -6.195 8.31e-10 ***
ns(day1temp, df = 2)2  -0.0389523  0.0174948  -2.227 0.026189 *  
ns(lastmin, 3)1        -0.0572737  0.0146746  -3.903 0.000101 ***
ns(lastmin, 3)2        -0.1113063  0.0370528  -3.004 0.002727 ** 
ns(lastmin, 3)3         0.0377755  0.0235750   1.602 0.109373    
ns(avetemp, 3)1         0.0258282  0.0173774   1.486 0.137493    
ns(avetemp, 3)2         0.0004699  0.0403296   0.012 0.990707    
ns(avetemp, 3)3        -0.0828450  0.0317365  -2.610 0.009170 ** 
```

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

Residual standard error: 0.04223 on 1067 degrees of freedom
Multiple R-squared:  0.8583,    Adjusted R-squared:  0.8535
F-statistic: 179.5 on 36 and 1067 DF,  p-value: < 2.2e-16
```

6.1.8 Latham ZSS HH Model

6.1.8.1 Latham summer HH model summary (Example: 16:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.264473 -0.042278  0.000658  0.043221  0.226631

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.085349   0.034655  -2.463 0.013946 *
dayMon                  0.018554   0.007575   2.449 0.014476 *
daySat                  0.002907   0.007513   0.387 0.698900
daySun                  0.026366   0.007604   3.467 0.000547 ***
dayThu                  0.010454   0.007560   1.383 0.167028
dayTue                  0.009097   0.007505   1.212 0.225742
dayWed                  0.006969   0.007568   0.921 0.357374
holidayDay before       0.016140   0.016476   0.980 0.327528
holidayHoliday         -0.041212   0.015032  -2.742 0.006218 **
holidayNormal           0.024241   0.012594   1.925 0.054527 .
ns(timeofyear, 9)1      0.030590   0.015370   1.990 0.046828 *
ns(timeofyear, 9)2      0.051231   0.019125   2.679 0.007507 **
ns(timeofyear, 9)3      0.064157   0.018471   3.473 0.000535 ***
ns(timeofyear, 9)4      0.003819   0.018599   0.205 0.837349
ns(timeofyear, 9)5      0.039409   0.018197   2.166 0.030561 *
ns(timeofyear, 9)6      0.007042   0.018806   0.374 0.708142
ns(timeofyear, 9)7      0.037204   0.014718   2.528 0.011628 *
ns(timeofyear, 9)8     -0.019882   0.030329  -0.656 0.512262
ns(timeofyear, 9)9     -0.072015   0.013775  -5.228 2.07e-07 ***
ns(temp, df = 2)1      -0.052946   0.078555  -0.674 0.500459
ns(temp, df = 2)2       0.028340   0.055048   0.515 0.606787
ns(prevtemp1, df = 2)1  0.293075   0.110734   2.647 0.008252 **
ns(prevtemp1, df = 2)2  0.355718   0.071358   4.985 7.26e-07 ***
ns(prevtemp2, df = 2)1 -0.049831   0.129432  -0.385 0.700315
ns(prevtemp2, df = 2)2  0.021255   0.070977   0.299 0.764649
ns(prevtemp3, df = 2)1  0.120255   0.099639   1.207 0.227744
ns(prevtemp3, df = 2)2  0.287449   0.063701   4.512 7.14e-06 ***
```

```
ns(prevtemp6, df = 2)1  0.267668   0.059858   4.472 8.62e-06 ***
ns(prevtemp6, df = 2)2  0.089029   0.047062   1.892 0.058804 .
ns(day1temp, df = 2)1   0.046491   0.032791   1.418 0.156557
ns(day1temp, df = 2)2   0.043659   0.027431   1.592 0.111780
ns(day5temp, df = 2)1   0.030055   0.023547   1.276 0.202108
ns(day5temp, df = 2)2   0.017603   0.013032   1.351 0.177059
ns(day6temp, df = 2)1  -0.008467   0.023561  -0.359 0.719377
ns(day6temp, df = 2)2  -0.046129   0.013044  -3.536 0.000423 ***
ns(lastmin, 3)1         0.091571   0.021236   4.312 1.77e-05 ***
ns(lastmin, 3)2         0.192040   0.067356   2.851 0.004443 **
ns(lastmin, 3)3         0.056419   0.046298   1.219 0.223264
ns(lastmax, 3)1        -0.000651   0.021206  -0.031 0.975515
ns(lastmax, 3)2        -0.232915   0.053548  -4.350 1.50e-05 ***
ns(lastmax, 3)3        -0.190365   0.041806  -4.554 5.90e-06 ***
ns(avetemp, 3)1         0.069222   0.034994   1.978 0.048183 *
ns(avetemp, 3)2        -0.081475   0.088977  -0.916 0.360048
ns(avetemp, 3)3         0.124179   0.054154   2.293 0.022044 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06515 on 1036 degrees of freedom
Multiple R-squared:  0.8965,    Adjusted R-squared:  0.8922
F-statistic: 208.7 on 43 and 1036 DF,  p-value: < 2.2e-16
```

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

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.33684 -0.03952 -0.00371  0.03759  0.26726

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.292263   0.031759   9.203  < 2e-16 ***
dayMon                  0.020766   0.007044   2.948 0.003267 **
daySat                  0.060261   0.006932   8.693  < 2e-16 ***
daySun                  0.100070   0.007074  14.146  < 2e-16 ***
dayThu                  0.008706   0.006925   1.257 0.208958
dayTue                  0.014622   0.006999   2.089 0.036937 *
dayWed                  0.011149   0.006891   1.618 0.105954
holidayDay before      -0.098791   0.023835  -4.145 3.67e-05 ***
holidayHoliday          0.084911   0.023819   3.565 0.000380 ***
holidayNormal          -0.033492   0.015484  -2.163 0.030762 *
ns(timeofyear, 9)1      0.023469   0.013877   1.691 0.091088 .
ns(timeofyear, 9)2      0.028701   0.017568   1.634 0.102610
```

```
ns(timeofyear, 9)3       0.008068   0.015965   0.505 0.613412
ns(timeofyear, 9)4       0.001330   0.016715   0.080 0.936602
ns(timeofyear, 9)5       0.015081   0.016054   0.939 0.347714
ns(timeofyear, 9)6      -0.027985   0.016246  -1.723 0.085250 .
ns(timeofyear, 9)7      -0.041879   0.013642  -3.070 0.002196 **
ns(timeofyear, 9)8      -0.087736   0.027700  -3.167 0.001582 **
ns(timeofyear, 9)9      -0.060404   0.012926  -4.673 3.35e-06 ***
ns(temp, df = 2)1        0.317059   0.090740   3.494 0.000495 ***
ns(temp, df = 2)2        0.167072   0.074843   2.232 0.025801 *
ns(prevtemp1, df = 2)1 -0.623049   0.105291  -5.917 4.40e-09 ***
ns(prevtemp1, df = 2)2 -0.479024   0.084060  -5.699 1.56e-08 ***
ns(prevtemp3, df = 2)1 -0.416140   0.073359  -5.673 1.81e-08 ***
ns(prevtemp3, df = 2)2 -0.197815   0.062263  -3.177 0.001530 **
ns(prevtemp6, df = 2)1 -0.069514   0.059789  -1.163 0.245230
ns(prevtemp6, df = 2)2 -0.119466   0.045315  -2.636 0.008502 **
ns(day1temp, df = 2)1    0.026595   0.025073   1.061 0.289076
ns(day1temp, df = 2)2    0.051432   0.024686   2.083 0.037448 *
ns(lastmin, 3)1          0.017131   0.021306   0.804 0.421558
ns(lastmin, 3)2          0.121421   0.055589   2.184 0.029160 *
ns(lastmin, 3)3          0.182192   0.035650   5.111 3.81e-07 ***
ns(lastmax, 3)1          0.033037   0.021684   1.524 0.127904
ns(lastmax, 3)2          0.094180   0.053882   1.748 0.080771 .
ns(lastmax, 3)3          0.193390   0.061028   3.169 0.001574 **
ns(avetemp, 3)1         -0.079471   0.023941  -3.320 0.000932 ***
ns(avetemp, 3)2         -0.223657   0.058976  -3.792 0.000158 ***
ns(avetemp, 3)3         -0.244035   0.043646  -5.591 2.86e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06087 on 1066 degrees of freedom
Multiple R-squared:  0.7885,    Adjusted R-squared:  0.7812
F-statistic: 107.4 on 37 and 1066 DF,  p-value: < 2.2e-16
```

6.1.9 Telopea Park ZSS HH Model

6.1.9.1 Telopea Park summer HH model summary (Example: 16:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.33015 -0.03171  0.00207  0.03039  0.32974

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.087777   0.035907  -2.445  0.01479 *
```

```
dayMon                  0.021603   0.008937   2.417  0.01593 *
daySat                 -0.336902   0.008852 -38.061  < 2e-16 ***
daySun                 -0.341767   0.008903 -38.390  < 2e-16 ***
dayThu                  0.026070   0.008830   2.952  0.00328 **
dayTue                  0.026255   0.008848   2.967  0.00312 **
dayWed                  0.025003   0.008951   2.793  0.00539 **
holidayDay before       0.022487   0.020246   1.111  0.26715
holidayHoliday         -0.198174   0.018161 -10.912  < 2e-16 ***
holidayNormal           0.040095   0.015367   2.609  0.00931 **
ns(timeofyear, 9)1      0.137636   0.018051   7.625 9.68e-14 ***
ns(timeofyear, 9)2      0.130263   0.022785   5.717 1.71e-08 ***
ns(timeofyear, 9)3      0.186061   0.021322   8.726  < 2e-16 ***
ns(timeofyear, 9)4      0.150163   0.021965   6.836 2.01e-11 ***
ns(timeofyear, 9)5      0.155557   0.021529   7.225 1.53e-12 ***
ns(timeofyear, 9)6      0.140558   0.022491   6.250 7.83e-10 ***
ns(timeofyear, 9)7      0.064363   0.017311   3.718  0.00022 ***
ns(timeofyear, 9)8      0.029991   0.035787   0.838  0.40235
ns(timeofyear, 9)9     -0.245171   0.016099 -15.229  < 2e-16 ***
ns(temp, df = 2)1       0.157590   0.054434   2.895  0.00393 **
ns(temp, df = 2)2       0.184630   0.038163   4.838 1.67e-06 ***
ns(prevtemp3, df = 2)1  0.174004   0.089599   1.942  0.05260 .
ns(prevtemp3, df = 2)2  0.185017   0.059004   3.136  0.00180 **
ns(prevtemp6, df = 2)1  0.099136   0.071758   1.382  0.16763
ns(prevtemp6, df = 2)2 -0.043685   0.055553  -0.786  0.43196
ns(day6temp, df = 2)1  -0.039877   0.022784  -1.750  0.08059 .
ns(day6temp, df = 2)2  -0.040930   0.012933  -3.165  0.00163 **
ns(lastmin, 3)1         0.061246   0.020136   3.042  0.00246 **
ns(lastmin, 3)2         0.114428   0.062236   1.839  0.06647 .
ns(lastmin, 3)3         0.071669   0.029870   2.399  0.01673 *
ns(avetemp, 3)1         0.058050   0.025567   2.271  0.02353 *
ns(avetemp, 3)2         0.047533   0.065590   0.725  0.46892
ns(avetemp, 3)3         0.122924   0.040826   3.011  0.00271 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05872 on 597 degrees of freedom
Multiple R-squared:  0.9314,    Adjusted R-squared:  0.9277
F-statistic: 253.4 on 32 and 597 DF,  p-value: < 2.2e-16
```

6.1.9.2 Telopea Park winter HH model summary (Example: 18:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.172637 -0.017145  0.000315  0.019182  0.253311
```

```
Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)             0.402419   0.018723  21.494  < 2e-16 ***
dayMon                  0.048333   0.005111   9.456  < 2e-16 ***
daySat                 -0.146897   0.005006 -29.343  < 2e-16 ***
daySun                 -0.136468   0.005140 -26.550  < 2e-16 ***
dayThu                  0.040561   0.004983   8.140 2.94e-15 ***
dayTue                  0.050556   0.005058   9.996  < 2e-16 ***
dayWed                  0.048620   0.004996   9.732  < 2e-16 ***
holidayDay before      -0.063331   0.016514  -3.835 0.000141 ***
holidayHoliday         -0.144187   0.016511  -8.733  < 2e-16 ***
holidayNormal          -0.015686   0.009630  -1.629 0.103951    
ns(timeofyear, 9)1      0.015163   0.010226   1.483 0.138742    
ns(timeofyear, 9)2     -0.023725   0.012745  -1.862 0.063236 .  
ns(timeofyear, 9)3     -0.056842   0.011734  -4.844 1.68e-06 ***
ns(timeofyear, 9)4      0.001325   0.012130   0.109 0.913040    
ns(timeofyear, 9)5     -0.043356   0.011782  -3.680 0.000258 ***
ns(timeofyear, 9)6     -0.040450   0.011940  -3.388 0.000758 ***
ns(timeofyear, 9)7     -0.044239   0.009813  -4.508 8.08e-06 ***
ns(timeofyear, 9)8     -0.125137   0.020068  -6.235 9.33e-10 ***
ns(timeofyear, 9)9     -0.070229   0.009324  -7.532 2.22e-13 ***
ns(temp, df = 2)1      -0.005631   0.034507  -0.163 0.870444    
ns(temp, df = 2)2       0.044620   0.029903   1.492 0.136259    
ns(prevtemp1, df = 2)1  0.018775   0.043493   0.432 0.666150    
ns(prevtemp1, df = 2)2 -0.045374   0.045367  -1.000 0.317701    
ns(prevtemp3, df = 2)1 -0.134387   0.042763  -3.143 0.001770 ** 
ns(prevtemp3, df = 2)2 -0.098293   0.031914  -3.080 0.002180 ** 
ns(prevtemp6, df = 2)1 -0.127123   0.034250  -3.712 0.000228 ***
ns(prevtemp6, df = 2)2 -0.051644   0.022670  -2.278 0.023129 *  
ns(day2temp, df = 2)1  -0.051299   0.015409  -3.329 0.000933 ***
ns(day2temp, df = 2)2  -0.029402   0.009181  -3.202 0.001446 ** 
ns(avetemp, 3)1        -0.045531   0.007038  -6.469 2.27e-10 ***
ns(avetemp, 3)2        -0.088303   0.020254  -4.360 1.57e-05 ***
ns(avetemp, 3)3        -0.071700   0.013000  -5.515 5.49e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0311 on 520 degrees of freedom
Multiple R-squared:  0.9146,    Adjusted R-squared:  0.9095 
F-statistic: 179.6 on 31 and 520 DF,  p-value: < 2.2e-16
```

6.1.10 Theodore ZSS HH Model

6.1.10.1 Theodore summer HH model summary (Example: 16:30 PM model)

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.64152 -0.04723 -0.00197  0.05007  0.25140

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.124068   0.040127  -3.092 0.002042 **
dayMon                  0.023557   0.009047   2.604 0.009350 **
daySat                  0.074561   0.009004   8.281 3.73e-16 ***
daySun                  0.120203   0.009088  13.226  < 2e-16 ***
dayThu                 -0.001786   0.009019  -0.198 0.843092
dayTue                  0.005414   0.009009   0.601 0.548047
dayWed                  0.001795   0.009005   0.199 0.842054
holidayDay before       0.021226   0.019689   1.078 0.281249
holidayHoliday          0.005248   0.017980   0.292 0.770415
holidayNormal           0.015313   0.015088   1.015 0.310375
ns(timeofyear, 9)1      0.010623   0.018460   0.575 0.565127
ns(timeofyear, 9)2      0.039756   0.022926   1.734 0.083197 .
ns(timeofyear, 9)3      0.033159   0.022319   1.486 0.137652
ns(timeofyear, 9)4     -0.005264   0.022310  -0.236 0.813504
ns(timeofyear, 9)5     -0.023864   0.021924  -1.088 0.276635
ns(timeofyear, 9)6     -0.029045   0.022613  -1.284 0.199264
ns(timeofyear, 9)7      0.012536   0.017701   0.708 0.478954
ns(timeofyear, 9)8     -0.031729   0.036318  -0.874 0.382512
ns(timeofyear, 9)9     -0.048986   0.016605  -2.950 0.003248 **
ns(temp, df = 2)1      -0.321187   0.111623  -2.877 0.004092 **
ns(temp, df = 2)2      -0.004017   0.079311  -0.051 0.959611
ns(prevtemp1, df = 2)1  0.328678   0.167494   1.962 0.049991 *
ns(prevtemp1, df = 2)2  0.399583   0.103290   3.869 0.000116 ***
ns(prevtemp2, df = 2)1  0.203829   0.143795   1.417 0.156638
ns(prevtemp2, df = 2)2  0.264092   0.081797   3.229 0.001283 **
ns(prevtemp4, df = 2)1  0.228388   0.096158   2.375 0.017723 *
ns(prevtemp4, df = 2)2  0.232467   0.069964   3.323 0.000923 ***
ns(prevtemp6, df = 2)1  0.228740   0.080594   2.838 0.004626 **
ns(prevtemp6, df = 2)2  0.125936   0.063480   1.984 0.047535 *
ns(day1temp, df = 2)1  -0.002243   0.042583  -0.053 0.958011
ns(day1temp, df = 2)2  -0.026750   0.037324  -0.717 0.473727
ns(day5temp, df = 2)1   0.054808   0.028401   1.930 0.053910 .
ns(day5temp, df = 2)2   0.005978   0.017175   0.348 0.727860
ns(day6temp, df = 2)1  -0.027234   0.028320  -0.962 0.336442
ns(day6temp, df = 2)2  -0.036645   0.017049  -2.149 0.031830 *
ns(lastmin, 3)1         0.094340   0.022523   4.189 3.05e-05 ***
ns(lastmin, 3)2         0.242099   0.069876   3.465 0.000553 ***
```

```
ns(lastmin, 3)3         0.109338   0.038276   2.857 0.004368 **
ns(lastmax, 3)1         0.043066   0.026565   1.621 0.105289
ns(lastmax, 3)2        -0.189549   0.067698  -2.800 0.005207 **
ns(lastmax, 3)3        -0.187561   0.051168  -3.666 0.000259 ***
ns(avetemp, 3)1         0.091498   0.039404   2.322 0.020424 *
ns(avetemp, 3)2        -0.066549   0.100389  -0.663 0.507537
ns(avetemp, 3)3         0.134316   0.062638   2.144 0.032239 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.07818 on 1036 degrees of freedom
Multiple R-squared:  0.9049,    Adjusted R-squared:  0.9009
F-statistic: 229.1 on 43 and 1036 DF,  p-value: < 2.2e-16
```

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

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.48206 -0.02217 -0.00117  0.02297  0.10926

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.568451   0.026475  21.471  < 2e-16 ***
dayMon                  0.104651   0.004546  23.019  < 2e-16 ***
daySat                  0.061890   0.004459  13.878  < 2e-16 ***
daySun                  0.138267   0.004543  30.437  < 2e-16 ***
dayThu                  0.058459   0.004444  13.155  < 2e-16 ***
dayTue                  0.084010   0.004531  18.539  < 2e-16 ***
dayWed                  0.074418   0.004443  16.750  < 2e-16 ***
holidayDay before      -0.119844   0.015379  -7.792 1.46e-14 ***
holidayHoliday          0.040051   0.015418   2.598 0.009506 **
holidayNormal          -0.017586   0.010075  -1.745 0.081180 .
ns(timeofyear, 9)1      0.025466   0.009107   2.796 0.005255 **
ns(timeofyear, 9)2      0.031413   0.011563   2.717 0.006695 **
ns(timeofyear, 9)3     -0.030569   0.010407  -2.937 0.003375 **
ns(timeofyear, 9)4      0.012383   0.010906   1.135 0.256447
ns(timeofyear, 9)5     -0.012591   0.010478  -1.202 0.229744
ns(timeofyear, 9)6     -0.050796   0.010589  -4.797 1.82e-06 ***
ns(timeofyear, 9)7     -0.075799   0.008743  -8.670  < 2e-16 ***
ns(timeofyear, 9)8     -0.130229   0.018034  -7.221 9.33e-13 ***
ns(timeofyear, 9)9     -0.132903   0.008543 -15.558  < 2e-16 ***
ns(temp, df = 2)1       0.029912   0.063587   0.470 0.638146
ns(temp, df = 2)2       0.201169   0.046510   4.325 1.66e-05 ***
ns(prevtemp1, df = 2)1 -0.006918   0.076993  -0.090 0.928422
```

```
ns(prevtemp1, df = 2)2 -0.238249   0.058145   -4.097 4.47e-05 ***
ns(prevtemp4, df = 2)1 -0.355167   0.055804   -6.365 2.82e-10 ***
ns(prevtemp4, df = 2)2 -0.190044   0.043579   -4.361 1.41e-05 ***
ns(prevtemp6, df = 2)1 -0.167044   0.062087   -2.690 0.007237 **
ns(prevtemp6, df = 2)2 -0.179838   0.046726   -3.849 0.000125 ***
ns(day1temp, df = 2)1  -0.005972   0.022883   -0.261 0.794144
ns(day1temp, df = 2)2   0.015875   0.017350    0.915 0.360373
ns(day2temp, df = 2)1  -0.043726   0.018943   -2.308 0.021158 *
ns(day2temp, df = 2)2  -0.029978   0.012641   -2.371 0.017880 *
ns(lastmin, 3)1         0.012344   0.014454    0.854 0.393258
ns(lastmin, 3)2        -0.032615   0.035719   -0.913 0.361380
ns(lastmin, 3)3         0.034819   0.020255    1.719 0.085877 .
ns(lastmax, 3)1         0.017552   0.021401    0.820 0.412295
ns(lastmax, 3)2        -0.007933   0.058869   -0.135 0.892824
ns(lastmax, 3)3         0.005097   0.042156    0.121 0.903776
ns(avetemp, 3)1        -0.087666   0.019873   -4.411 1.12e-05 ***
ns(avetemp, 3)2        -0.131075   0.050497   -2.596 0.009559 **
ns(avetemp, 3)3        -0.144401   0.028988   -4.981 7.27e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0408 on 1156 degrees of freedom
Multiple R-squared:  0.8807,    Adjusted R-squared:  0.8766
F-statistic: 218.7 on 39 and 1156 DF,  p-value: < 2.2e-16
```

6.1.11 Wanniassa ZSS HH Model

6.1.11.1 Wanniassa summer HH model summary (Example: 16:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.297573 -0.035615  0.001081  0.035054  0.165752

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -0.071266   0.027181   -2.622 0.008872 **
dayMon                  0.016403   0.006199    2.646 0.008265 **
daySat                 -0.112203   0.006166  -18.198  < 2e-16 ***
daySun                 -0.137928   0.006226  -22.153  < 2e-16 ***
dayThu                  0.013810   0.006177    2.236 0.025568 *
dayTue                  0.014400   0.006171    2.334 0.019800 *
dayWed                  0.010662   0.006168    1.729 0.084190 .
holidayDay before       0.008887   0.013488    0.659 0.510130
holidayHoliday         -0.136342   0.012301  -11.084  < 2e-16 ***
```

```
holidayNormal            0.024597   0.010328   2.381 0.017423 *  
ns(timeofyear, 9)1       0.049022   0.012611   3.887 0.000108 ***
ns(timeofyear, 9)2       0.071571   0.015686   4.563 5.65e-06 ***
ns(timeofyear, 9)3       0.087956   0.015245   5.769 1.05e-08 ***
ns(timeofyear, 9)4       0.059961   0.015285   3.923 9.33e-05 ***
ns(timeofyear, 9)5       0.064275   0.015021   4.279 2.05e-05 ***
ns(timeofyear, 9)6       0.057118   0.015489   3.688 0.000238 ***
ns(timeofyear, 9)7       0.043934   0.012128   3.622 0.000306 ***
ns(timeofyear, 9)8       0.003874   0.024869   0.156 0.876251    
ns(timeofyear, 9)9      -0.112718   0.011374  -9.910  < 2e-16 ***
ns(temp, df = 2)1       -0.036124   0.076403  -0.473 0.636451    
ns(temp, df = 2)2       -0.030322   0.054324  -0.558 0.576844    
ns(prevtemp1, df = 2)1  0.219381   0.114664   1.913 0.055992 .  
ns(prevtemp1, df = 2)2  0.378371   0.070732   5.349 1.09e-07 ***
ns(prevtemp2, df = 2)1  0.106849   0.098503   1.085 0.278293    
ns(prevtemp2, df = 2)2  0.131016   0.055994   2.340 0.019480 *  
ns(prevtemp4, df = 2)1  0.180109   0.065821   2.736 0.006318 ** 
ns(prevtemp4, df = 2)2  0.164960   0.047903   3.444 0.000597 ***
ns(prevtemp6, df = 2)1  0.167661   0.055156   3.040 0.002427 ** 
ns(prevtemp6, df = 2)2  0.074106   0.043468   1.705 0.088520 .  
ns(day1temp, df = 2)1   0.019117   0.029147   0.656 0.512042    
ns(day1temp, df = 2)2   0.011476   0.025570   0.449 0.653680    
ns(day5temp, df = 2)1   0.023232   0.017890   1.299 0.194387    
ns(day5temp, df = 2)2  -0.019500   0.009629  -2.025 0.043105 *  
ns(lastmin, 3)1          0.092005   0.015415   5.969 3.28e-09 ***
ns(lastmin, 3)2          0.196876   0.047795   4.119 4.11e-05 ***
ns(lastmin, 3)3          0.073097   0.026186   2.791 0.005343 ** 
ns(lastmax, 3)1         -0.008862   0.018201  -0.487 0.626448    
ns(lastmax, 3)2         -0.103339   0.046368  -2.229 0.026048 *  
ns(lastmax, 3)3         -0.119482   0.035053  -3.409 0.000678 ***
ns(avetemp, 3)1          0.049128   0.026993   1.820 0.069044 .  
ns(avetemp, 3)2         -0.125224   0.068792  -1.820 0.068998 .  
ns(avetemp, 3)3          0.095965   0.042917   2.236 0.025558 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05357 on 1038 degrees of freedom
Multiple R-squared:  0.9242,    Adjusted R-squared:  0.9212 
F-statistic: 308.5 on 41 and 1038 DF,  p-value: < 2.2e-16
```

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

```
Residuals:
      Min        1Q    Median        3Q       Max 
```

```
-0.186628 -0.018825 -0.000029  0.017870  0.084316

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)    
(Intercept)             5.342e-01  1.920e-02  27.821  < 2e-16 ***
dayMon                  5.006e-02  3.316e-03  15.098  < 2e-16 ***
daySat                 -3.035e-02  3.261e-03  -9.307  < 2e-16 ***
daySun                 -7.958e-05  3.319e-03  -0.024 0.980876    
dayThu                  3.329e-02  3.255e-03  10.228  < 2e-16 ***
dayTue                  4.465e-02  3.312e-03  13.481  < 2e-16 ***
dayWed                  3.994e-02  3.245e-03  12.309  < 2e-16 ***
holidayDay before      -9.707e-02  1.122e-02  -8.655  < 2e-16 ***
holidayHoliday         -3.764e-02  1.123e-02  -3.350 0.000835 ***
holidayNormal          -2.139e-02  7.278e-03  -2.938 0.003370 ** 
ns(timeofyear, 9)1      2.293e-02  6.654e-03   3.446 0.000592 ***
ns(timeofyear, 9)2      3.673e-02  8.482e-03   4.331 1.62e-05 ***
ns(timeofyear, 9)3     -3.231e-02  7.628e-03  -4.236 2.48e-05 ***
ns(timeofyear, 9)4      2.511e-02  7.978e-03   3.147 0.001695 ** 
ns(timeofyear, 9)5      2.048e-03  7.691e-03   0.266 0.790011    
ns(timeofyear, 9)6     -3.007e-02  7.741e-03  -3.884 0.000109 ***
ns(timeofyear, 9)7     -5.608e-02  6.412e-03  -8.746  < 2e-16 ***
ns(timeofyear, 9)8     -9.429e-02  1.318e-02  -7.153 1.58e-12 ***
ns(timeofyear, 9)9     -1.060e-01  6.190e-03 -17.127  < 2e-16 ***
ns(temp, df = 2)1       5.308e-02  4.083e-02   1.300 0.193873    
ns(temp, df = 2)2       5.099e-02  3.546e-02   1.438 0.150714    
ns(prevtemp1, df = 2)1 -8.629e-02  5.539e-02  -1.558 0.119593    
ns(prevtemp1, df = 2)2 -5.952e-02  4.654e-02  -1.279 0.201172    
ns(prevtemp3, df = 2)1 -1.645e-01  3.921e-02  -4.195 2.96e-05 ***
ns(prevtemp3, df = 2)2 -1.750e-01  3.106e-02  -5.634 2.25e-08 ***
ns(prevtemp6, df = 2)1 -2.439e-01  3.978e-02  -6.130 1.23e-09 ***
ns(prevtemp6, df = 2)2 -1.473e-01  3.135e-02  -4.698 2.97e-06 ***
ns(day1temp, df = 2)1  -2.309e-02  1.386e-02  -1.665 0.096133 .  
ns(day1temp, df = 2)2   1.466e-02  1.302e-02   1.126 0.260473    
ns(day2temp, df = 2)1  -4.011e-02  1.134e-02  -3.538 0.000421 ***
ns(day2temp, df = 2)2  -1.663e-02  9.472e-03  -1.756 0.079449 .  
ns(lastmin, 3)1         6.165e-03  1.056e-02   0.584 0.559438    
ns(lastmin, 3)2        -1.249e-02  2.630e-02  -0.475 0.634920    
ns(lastmin, 3)3         4.786e-02  1.472e-02   3.252 0.001182 ** 
ns(lastmax, 3)1         2.656e-02  1.562e-02   1.700 0.089402 .  
ns(lastmax, 3)2         1.431e-02  4.337e-02   0.330 0.741479    
ns(lastmax, 3)3         6.617e-03  3.166e-02   0.209 0.834476    
ns(avetemp, 3)1        -7.189e-02  1.308e-02  -5.495 4.90e-08 ***
ns(avetemp, 3)2        -1.466e-01  3.164e-02  -4.633 4.06e-06 ***
ns(avetemp, 3)3        -1.720e-01  2.030e-02  -8.473  < 2e-16 ***
```

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

Residual standard error: 0.02867 on 1064 degrees of freedom
Multiple R-squared:  0.9125,    Adjusted R-squared:  0.9093
F-statistic: 284.4 on 39 and 1064 DF,  p-value: < 2.2e-16
```

6.1.12 Woden ZSS HH Model

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

```
Residuals:
     Min       1Q   Median       3Q      Max 
-0.35164 -0.03460  0.00202  0.03759  0.22922 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)            -0.109435   0.047854  -2.287 0.022404 *  
dayMon                  0.018526   0.006698   2.766 0.005776 ** 
daySat                 -0.196077   0.006637 -29.542  < 2e-16 ***
daySun                 -0.223268   0.006707 -33.291  < 2e-16 ***
dayThu                  0.017766   0.006655   2.670 0.007713 ** 
dayTue                  0.021418   0.006673   3.210 0.001369 ** 
dayWed                  0.019926   0.006663   2.990 0.002851 ** 
holidayDay before       0.022632   0.014560   1.554 0.120382    
holidayHoliday         -0.143303   0.013257 -10.810  < 2e-16 ***
holidayNormal           0.041370   0.011198   3.695 0.000232 ***
ns(timeofyear, 9)1      0.087460   0.013605   6.429 1.96e-10 ***
ns(timeofyear, 9)2      0.099151   0.016932   5.856 6.36e-09 ***
ns(timeofyear, 9)3      0.113372   0.016308   6.952 6.37e-12 ***
ns(timeofyear, 9)4      0.090531   0.016453   5.502 4.72e-08 ***
ns(timeofyear, 9)5      0.082196   0.016180   5.080 4.47e-07 ***
ns(timeofyear, 9)6      0.079176   0.016653   4.754 2.27e-06 ***
ns(timeofyear, 9)7      0.058210   0.012992   4.481 8.27e-06 ***
ns(timeofyear, 9)8      0.032534   0.026729   1.217 0.223805    
ns(timeofyear, 9)9     -0.150182   0.012200 -12.310  < 2e-16 ***
ns(prevtemp1, df = 2)1  0.440651   0.093327   4.722 2.66e-06 ***
ns(prevtemp1, df = 2)2  0.400286   0.061057   6.556 8.70e-11 ***
ns(prevtemp2, df = 2)1 -0.099566   0.131387  -0.758 0.448738    
ns(prevtemp2, df = 2)2 -0.007584   0.072635  -0.104 0.916863    
ns(prevtemp4, df = 2)1  0.139469   0.093214   1.496 0.134899    
ns(prevtemp4, df = 2)2  0.154637   0.060698   2.548 0.010989 *  
ns(prevtemp6, df = 2)1  0.118049   0.068321   1.728 0.084309 .  
ns(prevtemp6, df = 2)2 -0.024493   0.053682  -0.456 0.648297    
```

```
ns(day1temp, df = 2)1   0.030719   0.028553   1.076 0.282240
ns(day1temp, df = 2)2  -0.014542   0.018293  -0.795 0.426833
ns(day5temp, df = 2)1   0.027098   0.019573   1.384 0.166520
ns(day5temp, df = 2)2  -0.020241   0.009828  -2.059 0.039697 *
ns(prevdtemp1, 3)1      0.013424   0.015807   0.849 0.395922
ns(prevdtemp1, 3)2      0.086313   0.059368   1.454 0.146282
ns(prevdtemp1, 3)3      0.126857   0.037157   3.414 0.000665 ***
ns(day6dtemp, 3)1       0.010383   0.014701   0.706 0.480185
ns(day6dtemp, 3)2      -0.010083   0.053565  -0.188 0.850733
ns(day6dtemp, 3)3      -0.012354   0.032707  -0.378 0.705718
ns(lastmin, 3)1         0.113582   0.017455   6.507 1.19e-10 ***
ns(lastmin, 3)2         0.235186   0.052369   4.491 7.88e-06 ***
ns(lastmin, 3)3         0.082139   0.034724   2.365 0.018190 *
ns(avetemp, 3)1         0.005807   0.029007   0.200 0.841356
ns(avetemp, 3)2        -0.225243   0.069151  -3.257 0.001161 **
ns(avetemp, 3)3         0.040420   0.046523   0.869 0.385142
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05773 on 1037 degrees of freedom
Multiple R-squared:  0.9133,    Adjusted R-squared:  0.9098
F-statistic: 260.2 on 42 and 1037 DF,  p-value: < 2.2e-16
```

6.1.12.2 Woden winter HH model summary (Example: 18:30 PM model)

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.104386 -0.017611 -0.001663  0.016762  0.150344

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.4391490  0.0279210  15.728  < 2e-16 ***
dayMon                  0.0418142  0.0039120  10.689  < 2e-16 ***
daySat                 -0.0786464  0.0038144 -20.618  < 2e-16 ***
daySun                 -0.0614510  0.0039311 -15.632  < 2e-16 ***
dayThu                  0.0249993  0.0038042   6.571 9.08e-11 ***
dayTue                  0.0358513  0.0038413   9.333  < 2e-16 ***
dayWed                  0.0326020  0.0038187   8.537  < 2e-16 ***
holidayDay before      -0.0881205  0.0128971  -6.833 1.67e-11 ***
holidayHoliday         -0.0680222  0.0128896  -5.277 1.70e-07 ***
holidayNormal          -0.0305655  0.0080146  -3.814 0.000148 ***
ns(timeofyear, 9)1      0.0221450  0.0078466   2.822 0.004890 **
ns(timeofyear, 9)2      0.0262191  0.0100251   2.615 0.009085 **
ns(timeofyear, 9)3     -0.0207193  0.0091291  -2.270 0.023503 *
```

```
ns(timeofyear, 9)4       0.0158450  0.0093240   1.699 0.089646 .
ns(timeofyear, 9)5       0.0129017  0.0089842   1.436 0.151388
ns(timeofyear, 9)6      -0.0305183  0.0090531  -3.371 0.000786 ***
ns(timeofyear, 9)7      -0.0195170  0.0075862  -2.573 0.010274 *
ns(timeofyear, 9)8      -0.0842680  0.0152572  -5.523 4.53e-08 ***
ns(timeofyear, 9)9      -0.0873173  0.0071146 -12.273  < 2e-16 ***
ns(temp, df = 2)1       -0.0364014  0.0448531  -0.812 0.417285
ns(temp, df = 2)2        0.0222587  0.0317829   0.700 0.483926
ns(dtemp, 3)1           -0.0078299  0.0067539  -1.159 0.246682
ns(dtemp, 3)2           -0.0364202  0.0250814  -1.452 0.146879
ns(dtemp, 3)3           -0.0327090  0.0171141  -1.911 0.056339 .
ns(prevtemp1, df = 2)1   0.0117749  0.0548866   0.215 0.830188
ns(prevtemp1, df = 2)2  -0.0616564  0.0387721  -1.590 0.112188
ns(prevtemp4, df = 2)1  -0.1730070  0.0439808  -3.934 9.11e-05 ***
ns(prevtemp4, df = 2)2  -0.1146695  0.0322989  -3.550 0.000408 ***
ns(prevtemp6, df = 2)1  -0.1079367  0.0420078  -2.569 0.010370 *
ns(prevtemp6, df = 2)2  -0.0938478  0.0401184  -2.339 0.019572 *
ns(day6temp, df = 2)1    0.0163351  0.0128917   1.267 0.205494
ns(day6temp, df = 2)2    0.0143336  0.0073061   1.962 0.050131 .
ns(prevdtemp6, 3)1      -0.0028890  0.0108540  -0.266 0.790183
ns(prevdtemp6, 3)2       0.0137569  0.0431269   0.319 0.749822
ns(prevdtemp6, 3)3      -0.0004322  0.0144277  -0.030 0.976111
ns(lastmin, 3)1          0.0049197  0.0118561   0.415 0.678293
ns(lastmin, 3)2          0.0019035  0.0303120   0.063 0.949943
ns(lastmin, 3)3          0.0571924  0.0188772   3.030 0.002528 **
ns(lastmax, 3)1         -0.0001794  0.0140232  -0.013 0.989794
ns(lastmax, 3)2         -0.0100274  0.0363377  -0.276 0.782659
ns(lastmax, 3)3          0.0390574  0.0315893   1.236 0.216675
ns(avetemp, 3)1         -0.0667526  0.0136025  -4.907 1.12e-06 ***
ns(avetemp, 3)2         -0.1492681  0.0334295  -4.465 9.18e-06 ***
ns(avetemp, 3)3         -0.1584816  0.0237341  -6.677 4.61e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02887 on 784 degrees of freedom
Multiple R-squared:  0.8938,    Adjusted R-squared:  0.888
F-statistic: 153.4 on 43 and 784 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 Other Important Information

6.3.1 Distribution Loss Factors

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

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

And the Evoenergy 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

6.3.2 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.

6.3.2.1 Summer Diversity Factor per Zone Substation

Zone	2016	2017	2018
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%

6.3.2.2 Winter Diversity Factor per Zone Substation

Zone	2016	2017	Average
Belconnen	100%	100%	99%
City East	98%	96%	100%
Civic	85%	94%	97%
East Lake	55%	55%	80%
Fyshwick	63%	53%	80%
Gilmore	92%	95%	92%
Gold Creek	97%	99%	86%
Latham	92%	100%	90%
Telopea Park	93%	93%	97%
Theodore	98%	87%	78%
Wanniassa	100%	100%	97%
Woden	98%	100%	100%

6.5 Reference

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