



Demand Forecasting Update and Support

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Appendix A. Description of Steps Taken to Select Final Model

Executive Summary

ActewAGL Distribution (AAD) engaged Jacobs to assist with the development of the demand forecast for the ActewAGL distribution network. Jacobs provided assistance to AAD in two phases. The first phase included a detailed review of AAD's existing demand forecasting methodology and draft results, providing recommendations for improvement. The second phase comprised support and collaboration between AAD and Jacobs to implement the recommendations put forward.

We have summarised the recommendations in Table 1 below, indicating what actions have been taken to address and/or implement the recommendations in AAD's demand forecasting approach, methodology and report. Nearly all the recommendations put forward have been implemented by AAD.

The most important recommendations were related to the improving the forecasting methodology by including approaches to address structural changes in the demand. Jacobs assisted in redeveloping the solar PV modelling approach and provided data and suggested methods to incorporate other structural developments like increasing energy efficiency, retail price developments and electric vehicle penetration. Jacobs also assisted with improving AAD's in-house approach for demand forecasting, mostly in redeveloping the average demand models at the zone substation level.

Furthermore, Jacobs reviewed the draft versions of AAD's demand forecasting report, focussing on improving the structure, overall methodology, explanations and justifications of the final demand forecasts, as well as the reconciliation of the system level (top-down) and zone substation level (bottom-up) demand projections.

The final demand forecasting report produced by AAD has in Jacobs' opinion vastly improved from both a structural perspective as well as from an explanatory view as compared to AAD's initial draft. The methodology and approach currently used by AAD is now in line with industry's best practise, and (where possible) reflects the important structural developments in demand observed in the Australian electricity market.

AAD's revised demand forecasting report, when read in conjunction with Jacobs' Demand Forecasting Update Report, provides a solid justification for the projected demand in the FY2019-2024 regulatory period.

Glossary

AAD = ActewAGL Distribution

ACT = Australian Capital Territory

addUL = Average Daily Underlying Demand

AEMO = Australian Energy Market Operator

AER = Australian Energy Regulator

AIC = Akaike Information Criterion

AR = Auto Regression

ARIMA = Auto Regression Integrated Moving Average (model)

ARMA = Auto Regression Moving Average (model)

AUD = Australian Dollar

AVGBC = Average Back-Cast Model

bbl = Barrels

CER = Clean Energy Regulator

CDD = Cooling Degree Days

DLF = Distribution Loss Factor

DNSP = Distribution Network Service Provider

DSO = Distribution System Operator

DUoS = Distribution Use of System (Charges)

EEIS = Energy Efficiency Improvement Scheme

EITE = Emissions Intensive Trade Exposed

ESS = Energy Savings Scheme

EV = Electric Vehicle

GJ = Gigajoule

HDD = Heating Degree Days

HV = High Voltage

LGC = Large-scale Generation Certificates

LRET = Large-scale Renewable Energy Target

LV = Low Voltage

MEFM = Monash Electricity Forecasting Model

NEFR = National Electricity Forecasting Report

NEM = National Electricity Market

MA = Moving Average

MVAR = Mega Volt Ampere Reactive

MWh = Megawatt Hour

NSW = New South Wales

PVBC = Photovoltaic Back-Cast Model

RET = Renewable Energy Target

RPP = Renewable Power Percentage

SCADA = Supervisory Control and Data Acquisition

SFD = State Final Demand

SME = Small- and Medium-size Enterprises

SRES = Small-scale Renewable Energy Target

STP = Small-scale Technology Percentage

TUoS = Transmission Use of System (Charges)

TWh = Terawatt Hour

UL = Underlying Demand (gross demand = metered demand + solar PV generation)

USD = United States Dollar

VARH = Volt Ampere Reactive Hours

WH = Watt Hour

ZSS = Zone Substation

Important note about your report

The sole purpose of this report is to provide advice to ActewAGL that will improve existing approaches for demand forecasting. During the preparation of this report Jacobs has relied upon information provided by ActewAGL, as well as information in the public domain. In the event that ActewAGL changes its approach independently from this review, or otherwise materially changes its operations in response to changes in market operation or from introduction of new technologies, some elements of the report may require re-evaluation. Jacobs does not provide any warranty (expressed or implied) to the data, observations and findings in this report to the extent permitted by law. The report must be read in full with no excerpts to be taken as representative of the findings. This report has been prepared exclusively for ActewAGL and no liability is accepted for any use or reliance on the report by third parties.

1. Introduction

ActewAGL is preparing its regulatory proposal to the AER for the 2019 to 2024 regulatory period. This requires development of models for projecting peak demand, energy throughput and customer numbers. These projections are vital inputs to ActewAGL's capital development plans especially for augmentation expenditure projects and programs.

The development and penetration of disruptive technologies (e.g. distributed on-site generation, storage) as well as energy efficient appliances have altered the historic effect of socio-economic factors and weather patterns on demand, which makes it challenging to predict the future demand.

In addition, the policy and regulatory focus has shifted from a traditional electricity network service provider model to a 'distribution system operator' (DSO) model where the distributor is encouraged - e.g. through redevelopment of the Demand Management Information System - and challenged to explicitly take into account the impact of disruptive technologies and usage of non-network investments. This means an increasing focus on operating the distribution network more efficiently, and a better understanding of what is happening in the network, especially behind the meter.

Jacobs has been commissioned by ActewAGL Distribution (ActewAGL) to assist with development of the demand and energy throughput forecasts for its distribution network.

This report covers the following activities:

- i. Documenting the impact of technology change such as:
 - a. Sourcing of data to estimate the impact of energy efficiency
 - b. Sourcing of data to estimate the impact of electric vehicles
 - c. Development of data to account for the impact of solar photovoltaic technology (solar PV) and batteries
- ii. Development of retail price projections for use in econometric modelling

Jacobs has assisted in improving ActewAGL's in-house approach for demand forecasting, mostly in redeveloping the average demand models at the zone substation level. Details are provided in this report.

Finally, Jacobs has developed volume projections for ActewAGL and provided a description of the assumptions and methodology underlying those projections, as well as a review of the results with a description of how the key drivers have impacted on that forecast in a separate report.

2. Critique, Recommendations and Actions

2.1 Recommendations and Actions Taken

This section includes a summary of the critique and associated recommendations that Jacobs included in the report for phase one of the project. The table below provides information on how the identified issues were addressed in the revised forecast and associated documentation.

Table 1: Main Recommendations and Actions

No.	Description of critique/recommendation	Addressed as
1a	<p>Invest in forecasting</p> <p>Management need to understand the forecast and be comfortable with the modelled outputs. This will mean that greater effort will be needed in explaining the processes, input variables and how and why the model makes sense in a dynamic and evolving energy market. This could be achieved through a template documentation process, and increased communication and education of stakeholders.</p>	<p>Regular meetings between the ActewAGL forecaster, Jacobs and management have been held to discuss the progress and outcomes of the work on the forecasts. This helped to build confidence with Jacobs and internal stakeholders and consequently the development process became more transparent. The report template has been updated with the help of Jacobs to provide better explanations of the forecasting steps and the different modelling approaches.</p>
2a	<p>Incorporate structural change other than PV</p> <p>Changes in the underlying structure of demand from uptake of electric vehicles, energy efficient appliances and batteries should be incorporated into the forecast. If information is not readily available, AEMO data could be used.</p>	<p>Jacobs provided historical data and projections on EV, energy efficiency and batteries based on published AEMO reports. The modifications were:</p> <p>The energy efficiency data was used to develop the seasonal average Zone Substation (ZSS) demand forecast (ref section 5)</p> <p>Electric vehicles and battery uptake were treated as post modelling adjustments in the final demand model (ref ActewAGL demand forecasting report)</p>
2b	<p>Directly integrate structural change due to solar PV in the projections</p> <p>We recommend upgrading this approach, at least at the system level, as the impact of PV capacity on peak demand will be time-dependant. Specifically, we recommend using historic PV capacity figures to 'back out' the impact of PV on the historic load and perform model fitting on this 'underlying' demand.</p>	<p>The modelling of the solar PV impact on the demand forecast has been completely reworked with the help of Jacobs. The new solar PV integration method has been detailed in section 3.3 of this report.</p>
3	<p>Improve model parsimony</p> <p>The annual model series could be based on all seasons of historic data rather than just summer and winter. Importantly, the average demand is measured only once per season, which means in the model fitting there are only 11 data points to fit to each of the summer and winter models. Basing the annual model on an all seasons approach may simplify analysis and presentation (i.e. get one good model rather than two), and incorporates more data points for model fitting which will improve parsimony and be more effective. Such a model could incorporate seasonal dummy variables or similar to adjust for wide seasonal variation.</p>	<p>Model parsimony has been improved by using all seasons and integrating these in one average demand model at the system level as well as the zone substation level.</p> <p>The newly developed models are now based on more than 40 data points and are tested thoroughly by using two econometric estimation tools: R and Eviews. Jacobs has assisted ActewAGL to develop the models at the ZSS level. The method for modelling average demand at the ZSS level can be found in section 5 of this report.</p>
5a	<p>Daylight saving</p> <p>Check if daylight saving has been handled properly in the ZSS time-series.</p>	<p>The handling of daylight saving has been assessed and corrected by the ActewAGL forecaster.</p>

<p>5b</p>	<p>Solar profile</p> <p>The initial solar PV generation profile is based on generation data from the Royalla solar farm. Rooftop PV impact on demand may be materially different than a profile based on metered data from the Royalla utility scale installation (loss factors, optimal orientation, inverter size relative to panels etc.). We suggest extending this data set to include other sites.</p>	<p>Since net metering data for other small scale embedded solar sites is limited, Jacobs has developed a solar PV profile based on locational characteristics of Royalla, but adjusted to private rooftop installation characteristics based on a large database of solar PV generation from the NSW network. The details on the adjustment process are included in section 3.3.</p>
<p>5c</p>	<p>Retail price projections</p> <p>Update the retail price projections. We understand that the current forecast is indexed with AEMO 2015/16 projections and ActewAGL is planning to update the forecast upon release of AEMO's 2017/18 projections. Assistance was required to convert the NSW projections to ACT specific ones using the ACT distribution tariffs (Jacobs' authored the relevant report as published by AEMO).</p>	<p>Jacobs provided these projections for three different scenarios:</p> <ul style="list-style-type: none"> • Neutral Economic Growth • Weak Economic Growth • Strong Economic Growth <p>The above scenarios and the retail price projections methodology are described in detail in section 4.</p>
<p>6a</p>	<p>Document data preparation</p> <p>Document approach to cleaning zone substation data, including the nature and reason for any outliers removed.</p>	<p>Jacobs has supported this process by providing resources to assist ActewAGL's forecaster during the data preparation and with the development of the final forecasting report. Jacobs believes that some of the data preparation has been documented, but is offering ongoing support to improve this process.</p>
<p>6b</p>	<p>Document models and assumptions</p> <p>Jacobs has recommended that ActewAGL puts more effort in documenting the different forecasting models, approaches and method used as well as noting all the assumptions made. The latter should include a description of the development process of the demand forecasts.</p>	<p>Jacobs supported ActewAGL in providing this documentation. This report will be an important input for ActewAGL to their description of the process, assumptions and recommendations. The remaining sections in this report will detail how some of the major inputs to the base MEFM model were derived and what assumptions were taken.</p>
<p>7a</p>	<p>Improve ex-ante and ex-post assessment</p> <p>We recommend that the ex-ante and ex-post assessments be undertaken, and that these be undertaken in greater detail and under greater oversight. We suggest:</p> <p>Review of forecasts of each independent variable is needed. For example, did retail prices jump when a fall was expected? Did this have the effect on the forecast that one would expect (e.g. fall in demand rather than a rise)? If not, what other input variables might explain the deviation of actuals to forecast? If no input variables reasonably explain the deviations, is there another variable that should be included?</p> <p>It is generally best practice to have forecasts reviewed by someone who did not do the work.</p> <p>At the system level weather corrected peak back cast would demonstrate whether there is any evidence of a long term change in peak demand, which could support any arguments made about structural changes to the load profile.</p>	<p>Jacobs developed average demand models for each zone substation and at the system level. These models and corresponding demand forecasts are evaluated in detail in section 5.3. The independent variables used in each forecast have been reviewed and their effect assessed against expectations.</p> <p>Jacobs included a forecast evaluation section (5.4) to this report, discussing the developed average demand models' Theil Inequality Coefficient and Theil U2 Coefficient that demonstrate the performance of the developed forecasting models.</p> <p>Additionally, ActewAGL included forecast evaluation by means of ex-ante and ex-post assessments of the system forecast for both summer and winter peak demand.</p>

2.2 AER Critique on Demand Forecasts of Victorian DNSPs

On 25 September 2015 Darryl Biggar released a report on the assessment of the Victorian DNSP's demand forecasting methodol, he had performed for the AER as part of the evaluation of the regulatory submissions of the Victorian distribution businesses.

Darryl Biggar's summary of critique is around the concern that network businesses are using drivers in their models that do not capture a range of effects including long-term trends and more recent developments in the industry. In particular, he was not confident that the models used had fully captured:

1. Energy efficiency trends (both increasing efficiency of houses and appliances);
2. The rapid growth in solar PV;
3. Slowing of the rate of growth in penetration of air-conditioners;
4. The impact of changing tariff structures, like demand based tariffs;
5. Growth of battery storage; and
6. Structural changes in the economy;

The enhancements and changes of ActewAGL's forecasting methodology has addressed points 1, 2 and 5 extensively (also discussed in Table 1).

The slowing rate of growth in the penetration of air-conditioners (3) is well captured in the improved average demand models that mostly lack the inclusion of any positive trends due to re-specification, therefore showing limited growth. However, as ACT has a dominant winter peak there is the expectation that part of this slowing rate of air-conditioner penetration is partially negated by increased fuel shifting from gas heating to cheaper (and more efficient) electric heating with heat pumps (reverse cycle air-conditioners).

ActewAGL is 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.

Other structural factors to consider in the ACT are the relatively low penetration of batteries, solar PV penetration remains steady around 10% of residential customers, and house sizes are decreasing with the rising development of apartment buildings.

Finally, structural changes in the economy are less of a concern for the ACT as compared with Victoria, because ACT's economy is significantly less industrialised than the Victorian economy.

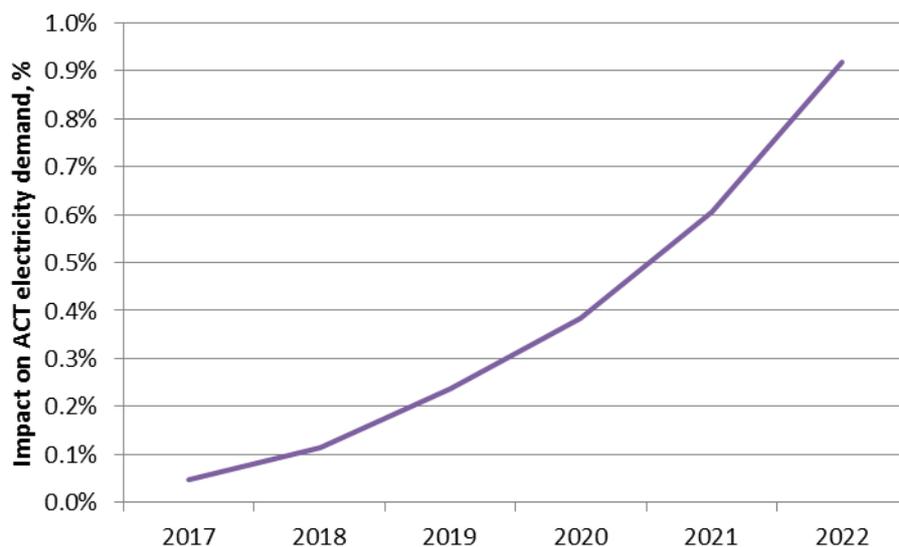
3. Structural Change

3.1 Electric Vehicles

Electric vehicles include small scale vehicles used for residential or business purposes. The light rail network under construction in Canberra, as well as the upgrade to electric buses in the public transport system, which together will increase demand by around 9MW in 2019 growing to 15MW by 2022, are treated as block loads in the forecasting process.

Electric vehicles as defined above are not present in great numbers in the ACT, and are anticipated to have a marginal impact on demand in the future. AEMO projections of electric vehicle impacts have been used, and it is anticipated that these vehicles will impact operational demand by less than 0.6% in 2024, the end of the regulatory period under consideration. The post modelling adjustment assumptions are displayed in Figure 1.

Figure 1: Post Modelling Impact on ACT Electricity Consumption – Electric Vehicles



Source: AEMO NEFR 2017

3.2 Energy Efficiency

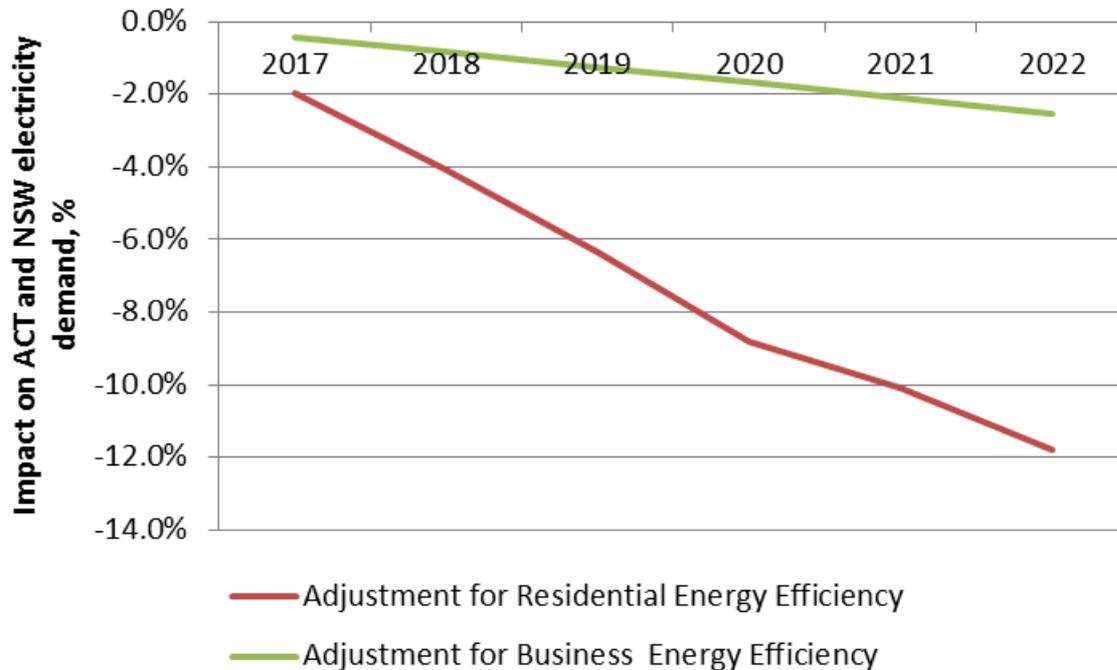
Energy efficiency has made a significant impact on energy consumption in recent years, and is expected to have a continuing and ongoing impact.

Unfortunately, the impact of energy efficiency has been difficult to measure, and there are limited studies available that adequately describe its impact, particularly over different time periods.

AEMO has commissioned work to estimate the impact of energy efficiency, and reported results cover the whole of NSW and the ACT in combination, which may not be as granular as required for ActewAGL. NSW has implemented some energy efficiency programs such as the Energy Savings Scheme (ESS), while the ACT has implemented the Energy Efficiency Improvement Scheme (EEIS). While these two schemes may have had differing impacts, their presence at least provides some surety that both regions have made an effort to further improve the way energy is used, and therefore it may be reasonable to apply the estimates for both areas to the ACT alone. The alternative would be to exclude any estimate of energy efficiency, potentially resulting in biased regression coefficients in the forecasting models, a result that may be less desirable than not considering energy efficiency in the modelling.

The estimates extracted from AEMO are based on energy efficiency as a proportion of underlying demand (i.e. metered demand including on-site generation). The results are displayed in Figure 2 in the form of post modelling adjustments.

Figure 2: Post Modelling Impact on ACT Electricity Consumption – Energy Efficiency



Source: AEMO NEFR 2017

3.3 Solar PV

One of the key recommendations from Jacobs' previous paper is to integrate solar PV and batteries into the MEFM forecasting approach used by ActewAGL. The MEFM approach provides for two layers of modelling to inform demand projections:

- Econometric modelling to inform the impact of variables such as retail price and income variables on average demand
- Time series modelling of the ratio of actual to average demand to determine the hour of day demand impacts

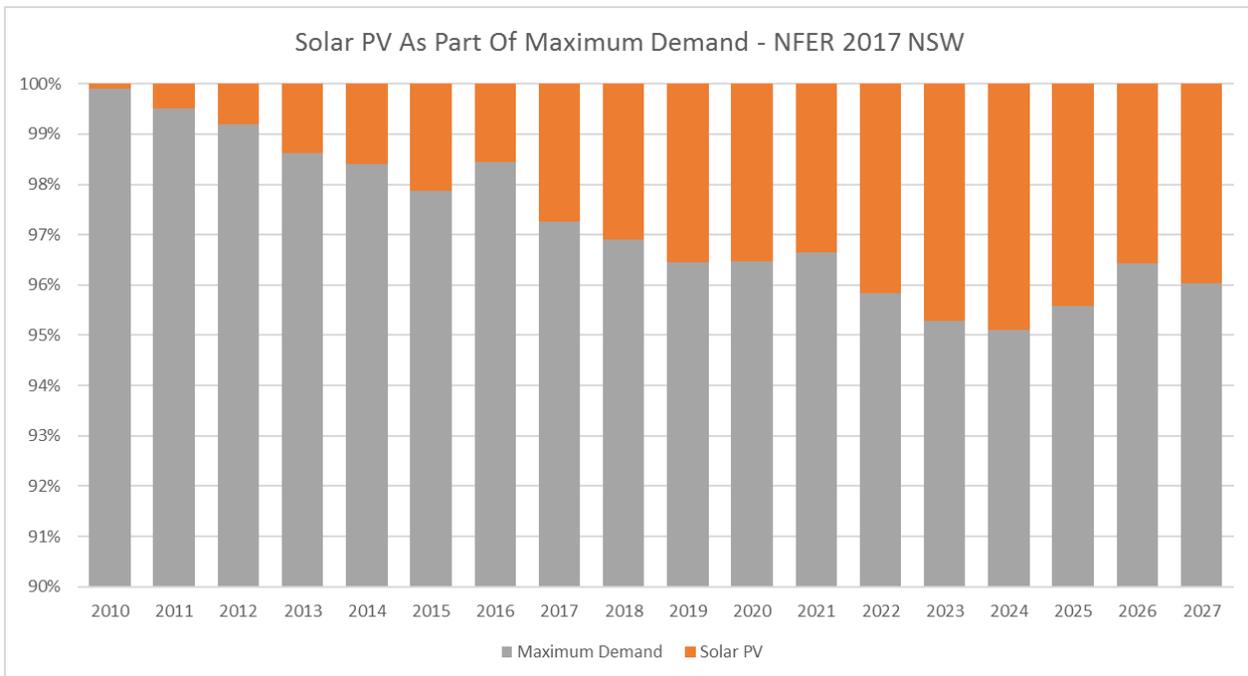
Adequately understanding the PV load and its impact on average demand and demand profiles is an essential part of a distribution utility's forecasting toolkit.

3.3.1 Long Term Projections of PV Uptake

Jacobs' has assumed the same long term projections of PV uptake as stated in the AEMO 2017 NEFR. This uptake is plotted below and illustrated as the share of the maximum demand in NSW (including ACT). The share is expected to reach approximately 4-5% of total underlying¹ maximum demand in the next decade.

¹ Underlying maximum demand is equivalent to maximum demand with PV added back, reflecting what consumers use before distributed generation offsets it.

Figure 3: NEFR 2017 Solar PV Part of Maximum Demand (Summer Historic and Neutral 50 PoE Projections)



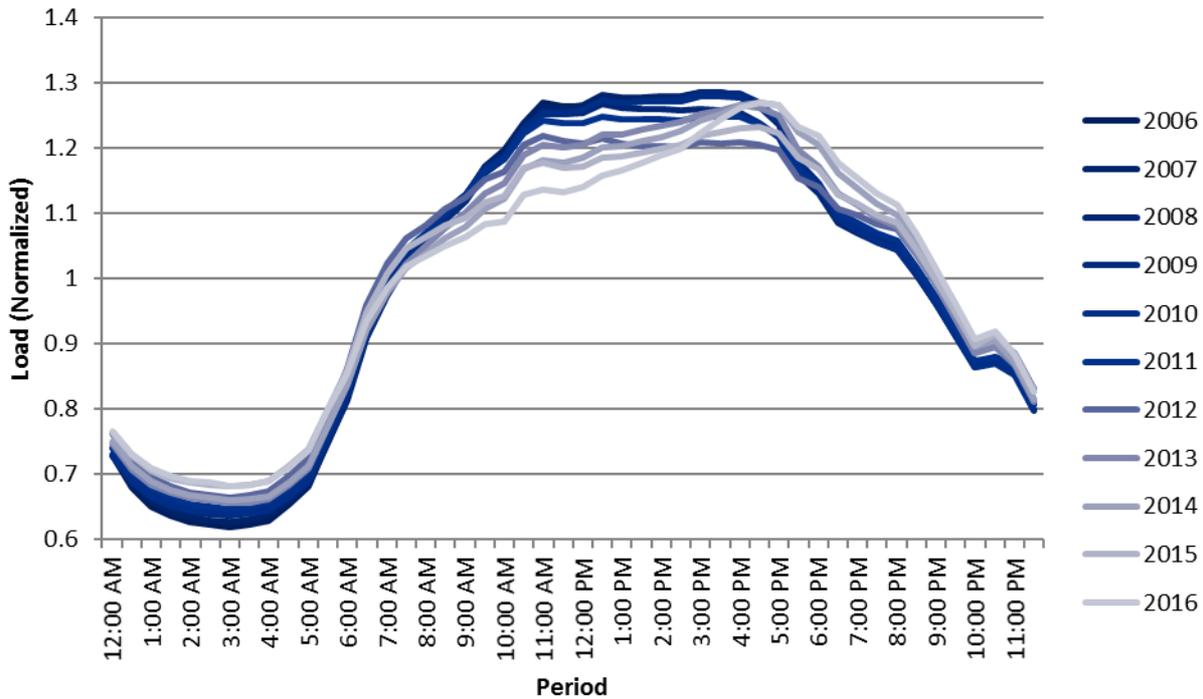
3.3.2 How PV Impacts Electricity Demand

The uptake of small scale photovoltaic systems over the past decade has had a material impact on the load characteristics of the ACT electrical system. Distributed solar systems have had the impact of reducing demand for centralised generation from the middle of the day to later in the day, effectively shifting the daily peak even in summer from around 4pm to around 7pm after the sun has gone down.

Accounting for the rise in residential PV systems is becoming increasingly important for accurate demand forecasting. However, we are not typically able to directly measure how much load is being met 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. The impact of PV generation can 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.

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.

Figure 4: Normalized Observed Demand, 2006-2016



Over time, the average demand observed by the network during daylight hours has declined, and has gone up in other hours of the day. 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.

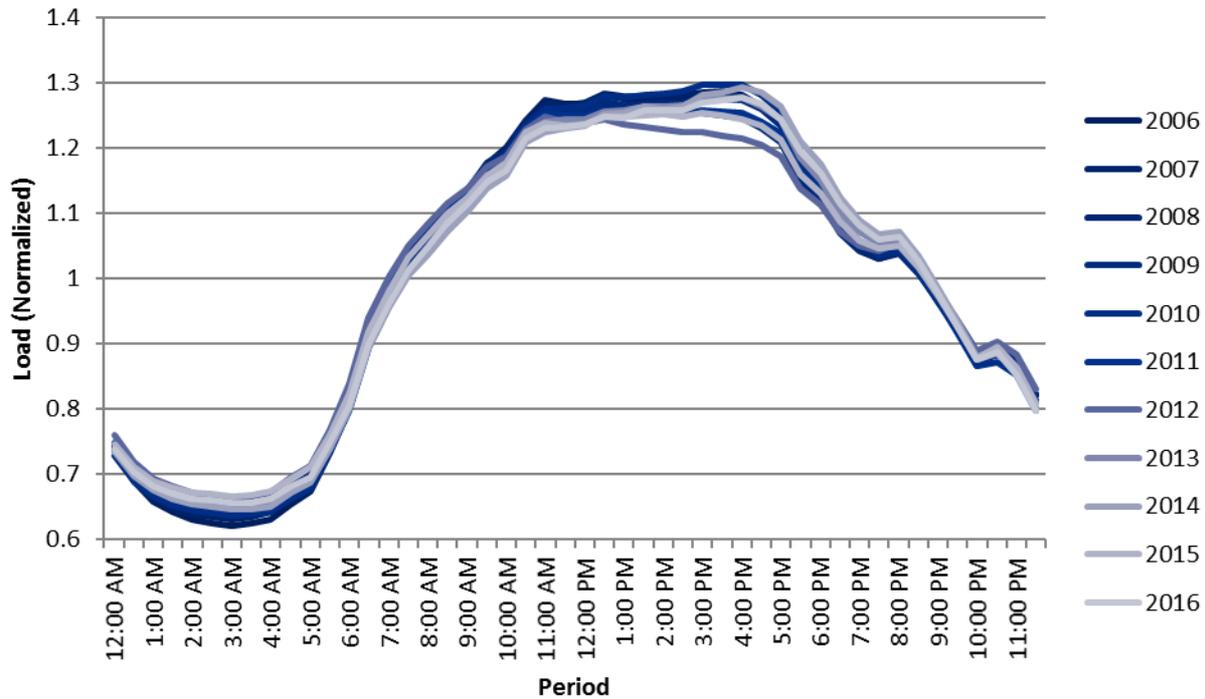
The MEFM approach blends a long-term model that captures growth in overall demand over years with a short-term model that predicts how temperature and other short term phenomena affect the half-hourly load shape. The MEFM approach assumes that the normalized demand profile used does not change in any structural manner over time.

However, the PV effect challenges this assumption. PV generation has both a long term component (in 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.

We can do so by adding the residential solar production to the historically observed demand profile, and model the 'underlying' demand for energy by consumers rather than the demand observed by the network. The load shape characteristics of underlying demand are more stable over time, and therefore are more suitable for use with the forecasting method.

Figure 5 shows the normalized demand profile of underlying demand, with the contribution by small-scale PV added. It is likely that some energy efficiency has reduced demand between 6am and 1pm, whereas demand is higher in the overnight and afternoon hours.

Figure 5: Normalized Underlying Demand, 2006-2016



The following sections outline 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 ActewAGL forecasting methodology.

The process has three stages:

- 1) Develop Model of Historic Solar against weather;
- 2) Back-cast Historic Small-Scale Solar production;
- 3) Integrate the Solar PV model into demand forecasting.

These stages are described in the following sections.

3.3.3 Step 1: Develop Model of Historic Solar Against Weather

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

- Typically, information on gross output of PV systems is not shared with DNSPs, and happens 'behind the meter'.
- There is considerable variation in the operating parameters of small-scale systems, with differing panel efficiencies, inverter ratios, orientations and shading characteristics.
- There is some uncertainty in estimating the installed capacity. The CER collects information on PV system capacity at a postcode level in order to manage certificate schemes, which is expected to capture the vast majority of installed systems, but does not give any information on when or whether systems are removed, or how large the panel sizes are in relation to inverter sizes. DNSPs collect information on PV systems as part of connection agreements, but system sizes may be entered inconsistently, and this information is difficult to verify for accuracy.
- 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 overcast conditions.

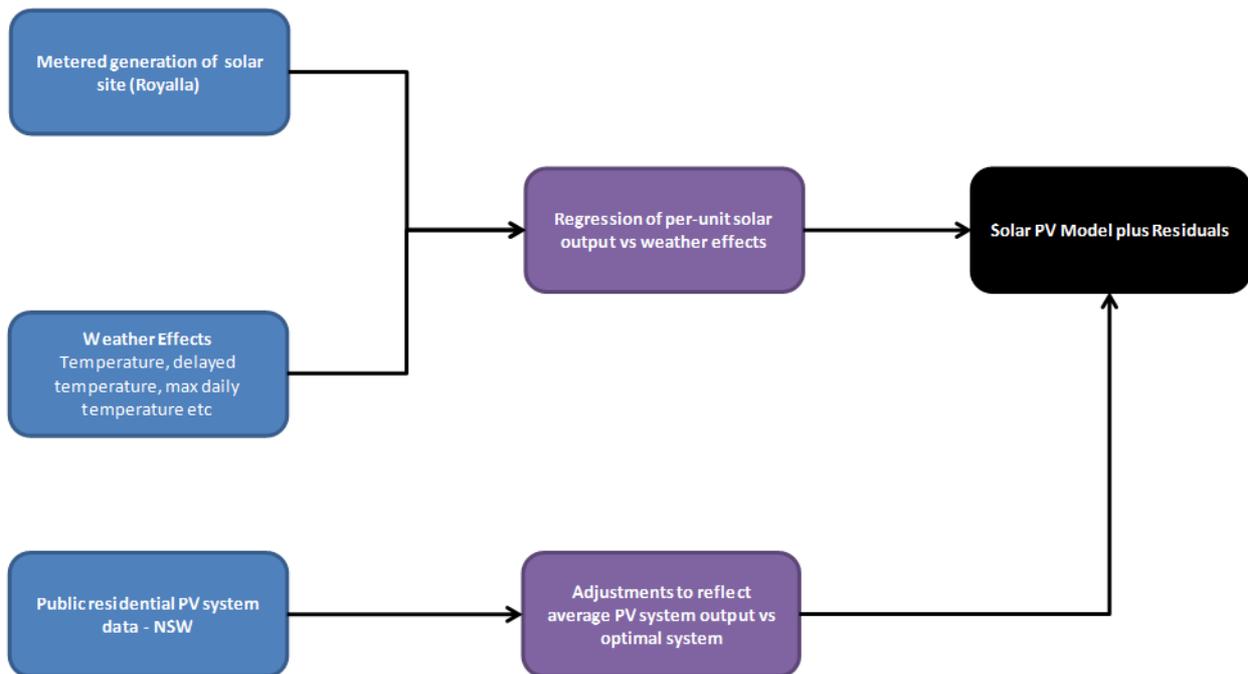
- There is significant uncertainty as to how the behaviour of groups of PV systems spread over a large geographic area compares with single systems. During days of consistent cloud cover the majority of all systems in the ACT may experience reduced production, while intermittent cloud cover may affect 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 estimate PV system output as a function of weather, as this allows us to produce estimates of PV output in our forecasting simulations. We have developed this model in two stages:

- Using metered output from the Royalla Solar Farm to develop a statistical model of Royalla's output as a function of weather
- Using publically released residential PV system data from a NSW distributor to estimate how average residential systems perform compared with optimally sited and located systems like Royalla.

This approach is illustrated in Figure 6 . The modelling approach was implemented using the 'R' statistical programming language in order to better integrate with ActewAGL's existing approach, with the code provided to ActewAGL in the form of R function blocks and sample control code.

Figure 6: Illustration of Solar Model Development



*Delayed temperature refers to the effect of temperatures earlier in the day i.e. heat build-up effects.

We have used Royalla to develop the solar model because this is a site for which there is interval metered data 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 ActewAGL has several series of gross metered residential 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.

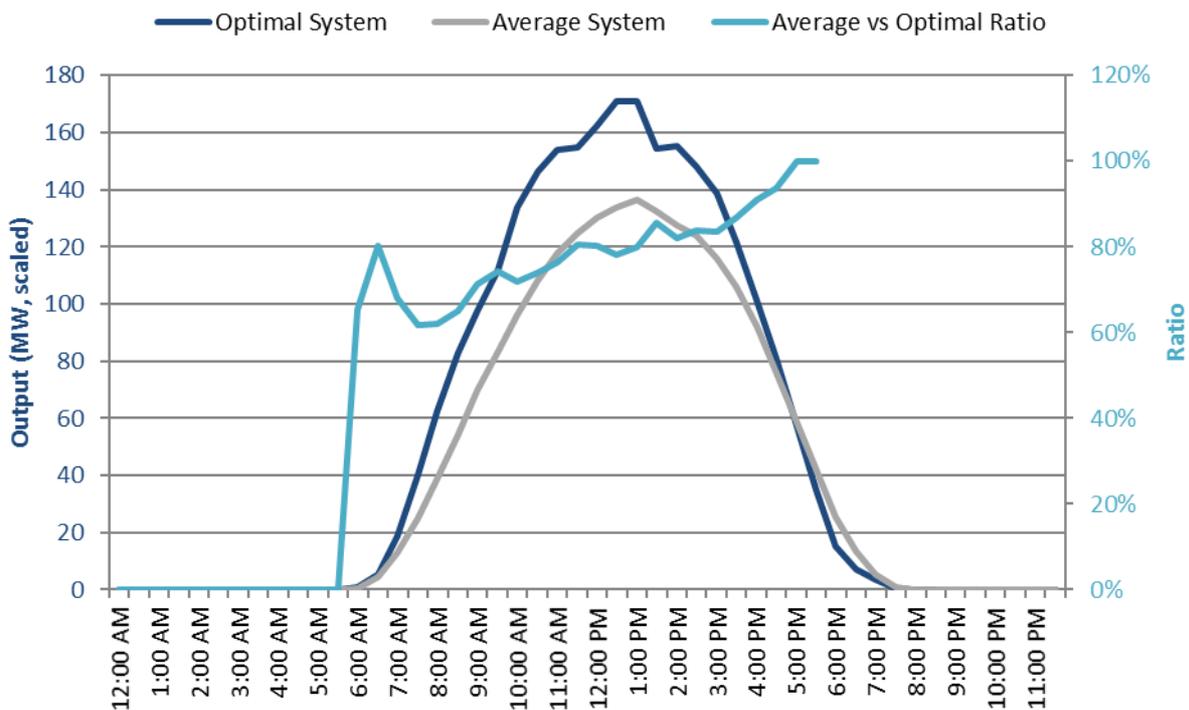
The weather model is developed using a similar statistical model to the half-hourly demand. We model solar output as a non-linear function of temperature, as well as derived temperature variables such as temperature from several periods ago, maximum and minimum temperatures from the previous day, and average temperature from the past week. We create separate statistical models for each half hour period of the day, and

for each season in the year. Residuals of this model are preserved in the model development, as we resample these when forecasting solar output to reflect the statistical prediction power of the weather model.

As the scope of this work was to develop a methodology to integrate with ActewAGL’s forecasting approach we have not performed an exhaustive test of all model variables to determine the best formula for the solar model. We anticipate that ActewAGL will test to select the optimal solar model using the same criteria as in the demand forecasting – an AIC² test on model performance at minimising the mean-square-error of the daytime model performance.

Once we have developed the weather model based on Royalla’s output, we make two adjustments to reflect residential system characteristics. We first 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 have derived these ratios by examining a dataset of the output of 300 residential NSW PV systems. These output profiles represent a range of system configurations – we compare the mean output by hour of all systems in this dataset with the output of the best systems in the data set – which we assume to be equivalent to the Royalla system on a per MW basis in their performance. Figure 7 illustrates the ratios calculated in this way.

Figure 7: Average to Optimal System Performance, January



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 apply these ratios to the forecast output of the solar model, which is based on an optimally orientated system.

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

² The AIC test is a statistical approach for model selection using 'Akaike's Information Criterion'. Thee approach has been formulated to maximise the information provided by a model structure with penalties for overfitting that may reduce model parsimony.

P_i^* = smoothed production in period i

P_i = model output production in period i

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 NSW 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.

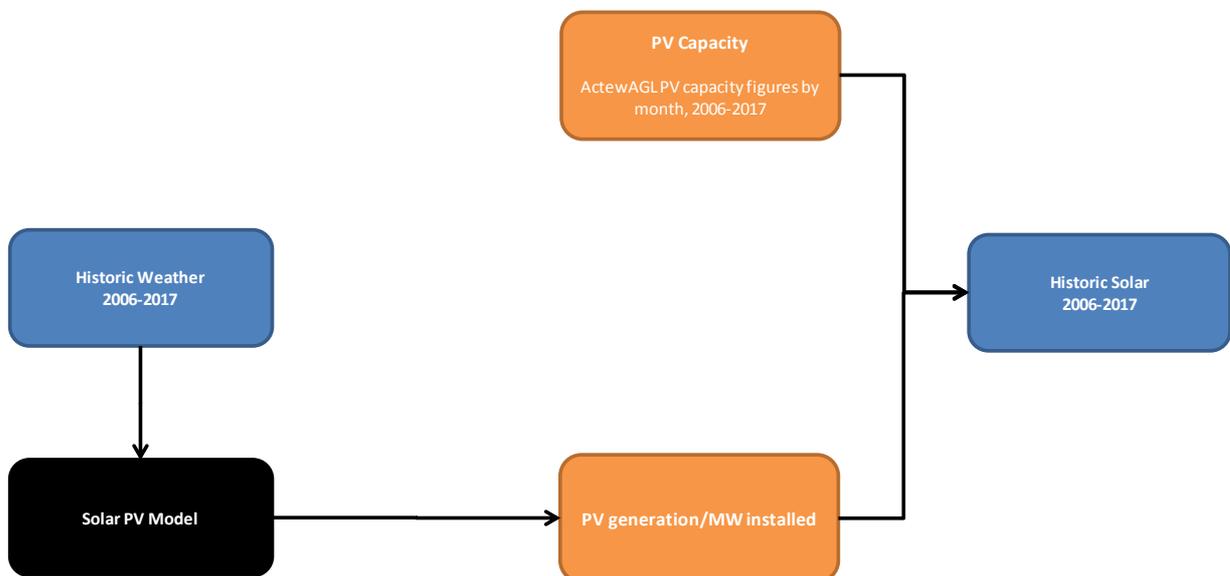
The result of this process is a statistical model that predicts the output of small-scale PV systems on a half-hourly basis as a function of weather and temperature variables (which are used as a proxy for solar exposure). The model produces results on a per-MW basis, which lets us adjust the results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

3.3.4 Step 2: Back-cast Historic Small-Scale Solar Production

The second step is to produce a half-hourly estimate of small-scale production, so that we can 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 8. Solar back-casts as well as the 'R' code to produce the back-casts were provided to ActewAGL in the form of 'R' scripts to produce the forecast on a per-MW basis, and a spreadsheet model to adjust for historic installed PV capacity.

Figure 8: Illustration of Solar Back-cast Process



ActewAGL provided historic PV installed capacity by month, which was used to develop the back-cast. PV uptake only becomes significant after 2012, as before this point 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 to benchmark the model. We would typically use a process of adding 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. 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 give us confidence that the model is calibrated

adequately. Figure 2 (in Introduction section) demonstrates that our model adjustment is sufficient to explain the changing profile of observed demand.

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 then used as the basis of the demand forecasting model used by ActewAGL.

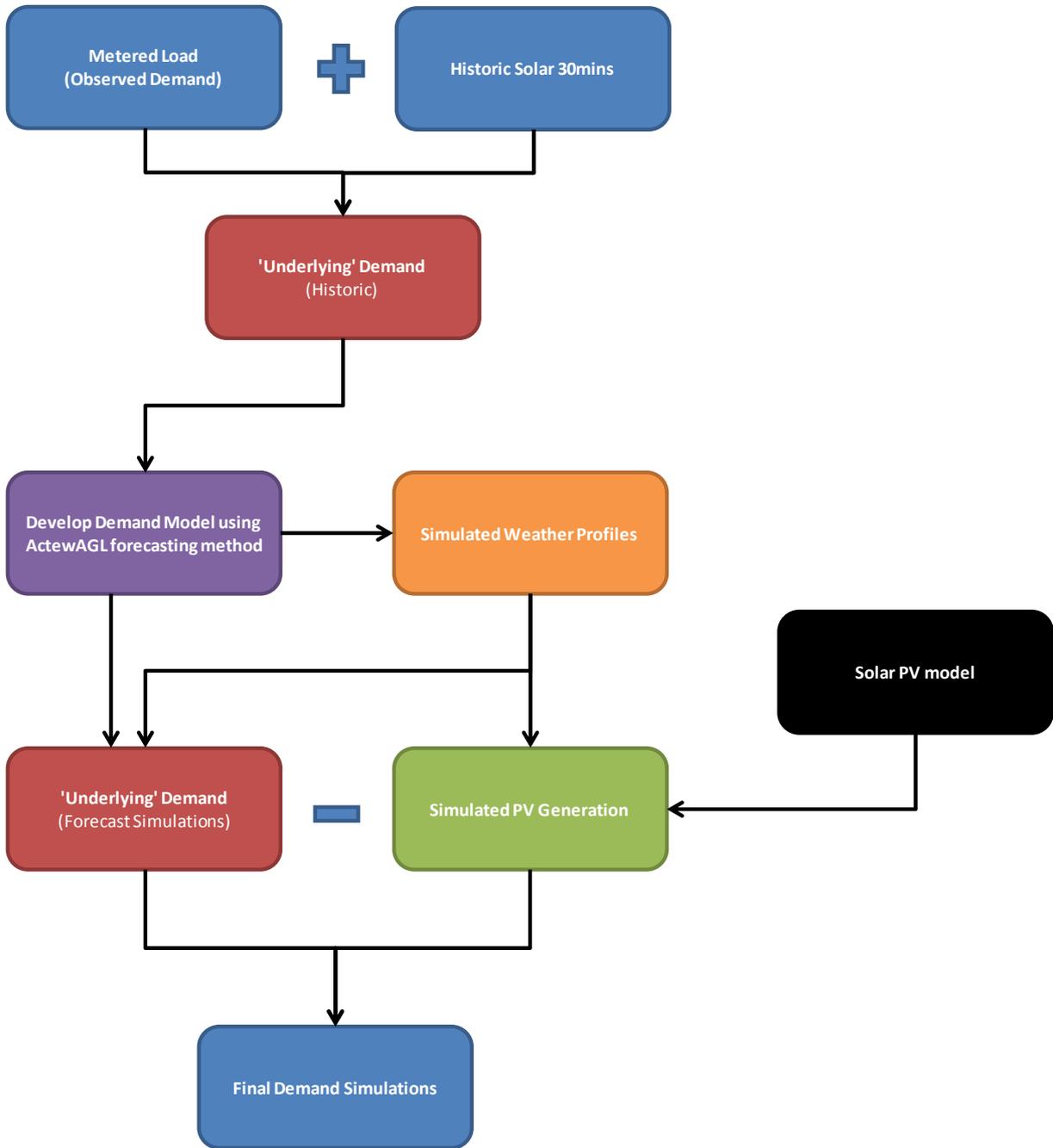
3.3.5 Step 3: Integrate The Solar PV Model Into Demand Forecasting

The final step in the PV modelling process is to integrate the PV forecasts into the demand forecasting process. As ActewAGL is developing its forecasts on the basis of underlying demand, we need to subtract our forecast of solar PV from these results in order to accurately forecast the actual demand observed 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 involved 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.

This process is illustrated visually in Figure 9. We provided 'R' code and function blocks to ActewAGL designed to integrate with the R code used in the businesses demand forecasting process and produce solar PV forecasts consistent with the temperature simulations used.

Figure 9: Illustration of Solar PV Integration Into Demand Forecasting



The integration proceeds as follows:

- 1) We add the solar PV back-cast to the historic trace of observed system demand to produce the 'underlying' demand trace.
- 2) The underlying demand trace is used within ActewAGL's existing forecasting methodology to create a demand model using the MEFM.
- 3) When ActewAGL produces demand forecasts based on n 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.
- 5) These observed demand simulations are used as the basis of the reported demand forecasts.

3.3.6 Limitations and Discussion

The lack of available, reliable metered data for residential PV systems means that there is no way to completely validate the models of residential PV generation. We also make several assumptions in our PV models, such as how the average ACT system performs compared with optimal systems, and how well these system outputs can be predicted by weather.

Additionally, we note that the reduction in observed demand (by the DNSP) will not be equivalent to the sum of the generation of residential PV systems. Depending on the location of the embedded system in the network, and whether that system is exporting to the grid or not, the change in observed demand may be lesser or greater than the generation of the system once network losses are accounted for.

Nevertheless, we consider that this approach is valid for the purposes of demand forecasting, for the following reasons.

- Despite the difficulty in measuring actual PV generation, the model results predict and explain the change in the load shape during daylight hours, which is predominantly attributed to PV production (see Figure 5). This gives us confidence that the model is producing credible results.
- Peak demand in the ACT occurs in the evening, when solar generation is falling or minimal. Errors in single-period forecasts of PV production are therefore unlikely to have a material impact on demand forecasts.
- Even though demand forecasts are likely to be immaterially impacted by PV, PV will have a significant impact on average demand and average load shape. The approach suggested enables the effects of PV production on average demand and average load shape to be accounted for appropriately for use in longer term forecasts.
- Much of the impact of errors introduced by the PV model assumptions are accounted for directly in the statistical forecasting approach, which embeds the model's ability to predict actual outcomes in the confidence range of the forecast.
- The impact of PV on system load profiles is material enough that an imperfect representation is better than the 'do nothing approach' which would lead to more significant errors including introducing biased estimates of regression coefficients in the econometric models.

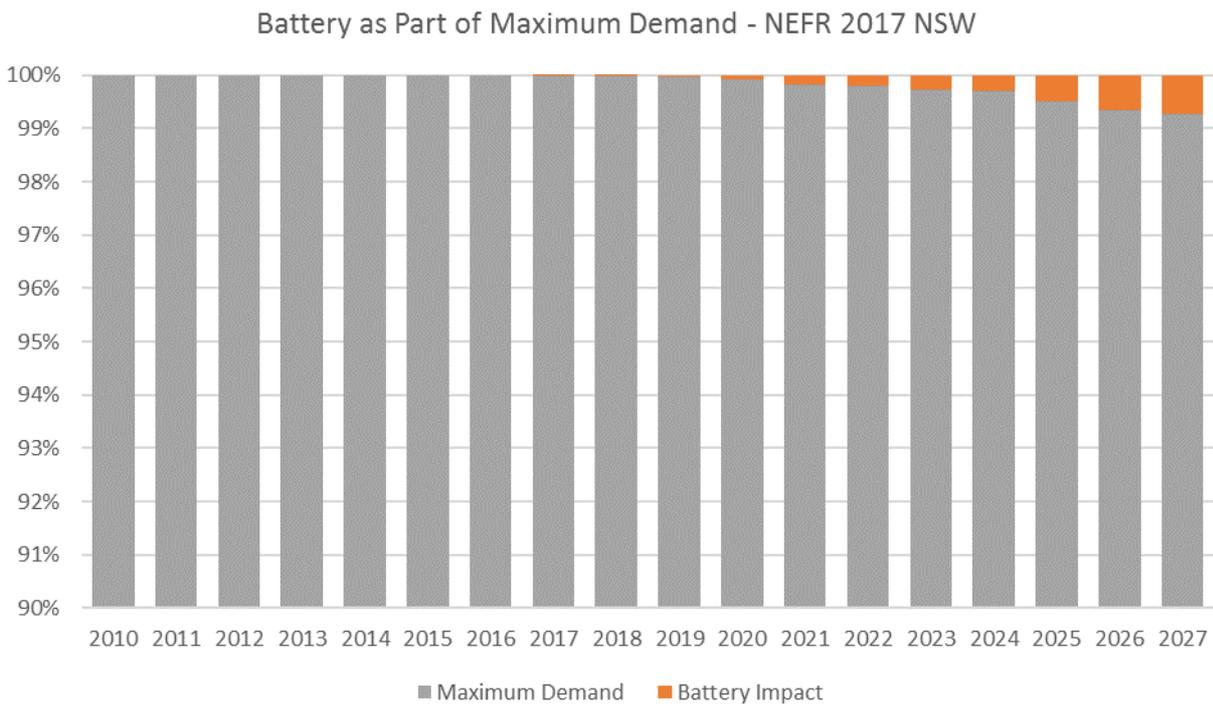
All forecasting models contain some level of simplification, assumptions and error, and we consider that the PV forecasting approach we have used captures the significant impacts of small scale PV on the system load profile without compromising the accuracy or confidence range of the demand forecasts.

3.4 Batteries

3.4.1 Long Term Projections of Battery System Uptake

Jacobs' has assumed the same long term projections of battery system uptake as stated in the AEMO 2017 NEFR. As per Figure 10 it can be observed that the projected impact of batteries on the maximum demand by 2027 is low with a reduction of less than 1% of the total peak demand in summer.

Figure 10: Battery as Part of the Maximum Demand (Summer Historic and Neutral 50 PoE Projections)



4. Retail Price Projections

4.1 Overview

In June 2017, Jacobs prepared retail electricity price forecasts under three market scenarios for the Australian Energy Market Operator (AEMO). The NSW projections used for that work were adapted to use ACT network tariffs rather than NSW network tariffs for the preparation of this work.

The three scenarios that were provided to AEMO under the “Neutral”, “Strong” and “Weak” scenarios were based on a bottom up approach including all known retailer costs such as wholesale market costs, network tariffs, costs of environmental schemes, market administration costs and retailer margins and costs. The key differences between the retail price series under each scenario are the wholesale market scenario conditions that underlie them.

The wholesale market scenarios reflect what AEMO consider to be the most likely future development paths of the market and reflect economic conditions, including consideration of factors such as population growth, the state of the economy and consumer confidence. The neutral scenario reflects a neutral economy with medium population growth and average consumer confidence. Likewise, the strong scenario reflects a strong economy with high population growth and strong consumer confidence and the weak scenario a weak economy with low population growth and weak consumer confidence. The key assumptions underlying the wholesale market work are provided in Table 2 below:

Table 2: Key Scenario Assumptions

	Neutral	Weak	Strong
Demand	2016 NEFR ³ neutral economic growth scenario	2016 NEFR weak economic growth scenarios	2016 NEFR strong economic growth scenarios
Carbon policy	COP21 emissions target, with emission reduction trend extended beyond 2030		
LRET target	33TWh by 2020		
Exchange rate	1 AUD = 0.75 USD	1 AUD = 0.65 USD	1 AUD = 0.95 USD
Oil price	\$USD 60/bbl	\$USD 30/bbl	\$USD 90/bbl
Gas price	Neutral gas price scenario; any gas violating total NEM gas constraint priced at \$20/GJ ⁴	Weak gas price scenario; any gas violating total NEM gas constraint after 2030 priced at \$20/GJ	Strong gas price scenario; any gas violating total NEM gas constraint priced at \$20/GJ
Climate policy up to 2030	Assume 28% reduction in NEM emissions relative to 2005 levels		

Source: AEMO

³ The March 2017 update of the 2016 NEFR was used

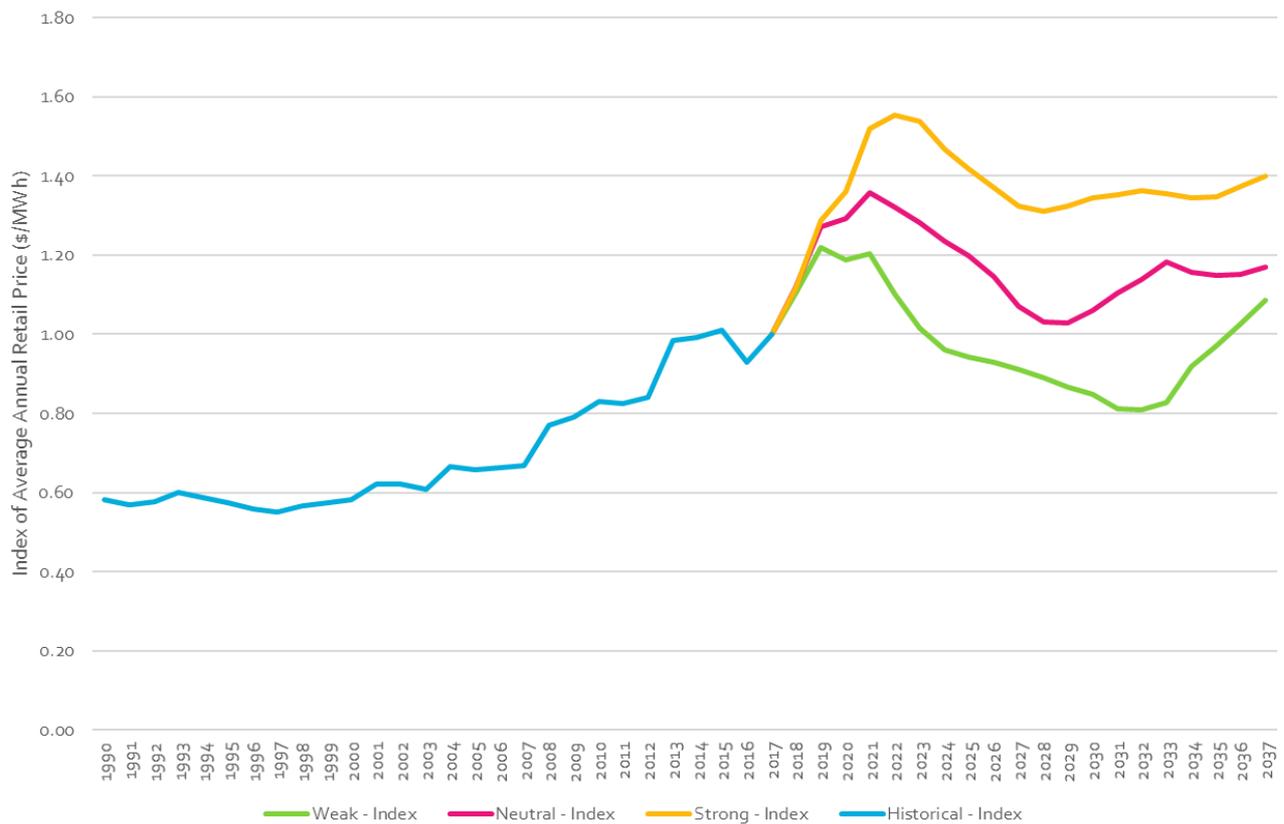
⁴ AEMO provided a total gas constraint for the NEM from 2017 until 2030, which varied by year. Any gas usage beyond this constraint was priced at \$20/GJ.

4.2 Residential Retail Price History Compared with Forecasts

Figure 11 shows historical and forecast residential retail prices for the ACT under the neutral scenario. Historical trends are based on ABS data, while forecast trends are based on the building block approach described above. The chart shown is indexed because AEMO have published the indexed rather than the full retail price information. The key features of the graph, specifically referencing the neutral scenario, are as follows:

- Residential retail prices exhibited relatively little movement in real terms from 1983 until 2003.
- Prices increased from 2003 until the present, and this increase was mostly driven by rising network charges. A price bump is evident in 2013 and 2014 with the introduction and subsequent repeal of the carbon price.
- Retail prices increased in January 2017 following the announced retirement of Hazelwood power station in November 2016 in addition to tightening gas supply available for power generation. This occurred despite Hazelwood retiring in March rather than January as a result of increases to forward contract prices.
- Retail price forecasts exhibit three distinct behaviours across all markets and scenarios: (i) increasing trend between 2017 and 2020; (ii) declining trend between 2020 and 2030; and (iii) levelling out from 2030.

Figure 11: Residential Retail Price Indices – Historical and Forecast Trends by Scenario



Source: Jacobs' analysis

From 2017 to 2022, residential retail prices are expected to grow by 5.7% per annum on average, and this is largely driven by increasing wholesale prices. From 2022 to 2025, a reduction of 3.2% per annum is expected, and over that whole period prices increase by 2.3% per annum on average.

Over the longer term change is driven by the wholesale market and this is based on longer term expectations of decline in demand. From 2030 plant retirements cause some rebounding of price.

4.3 Methodology and Retail Price Components

The methodology applied is equivalent to that summarised in AEMO's retail price projections underlying the NEFR, and is based on a bottom up calculation looking at wholesale market costs, network charges, environmental scheme charges, market operator charges and retailer charges. For convenience each of these elements is summarised in the following sub sections.

4.3.1 Wholesale Market Costs

The wholesale market costs faced by retailers include:

- Spot energy cost as paid to AEMO adjusted by the applicable transmission and distribution loss factors
- Hedging costs around the spot energy price consisting of swaps, caps and floor contracts

Spot energy costs are the only source of price variation across the three scenarios. Spot energy exposure is minimised by retailers but cannot be completely avoided due to the variability of the retail load supplied. Retailers must formulate a contracting strategy that enables them to manage trading risk according to their own risk profile. Generally, contracts are available at a premium to spot market prices, and this represents the cost of managing trading or price risk. Retailers may arrange for a long term hedging contract to manage the price risk, and perhaps a shorter term contract closer to the time the load is to eventuate as the retailer better understands how much load may be required. Uncertainty around future loads can lead to purchases of portions of load that have no corresponding revenue associated with them, and these purchases of peaky load can often be at prices significantly above contract (e.g. peak pricing in high demand conditions). To complicate matters further, demand and spot prices are generally correlated, so large portions of uncovered load will normally lead to large amounts of price related risk associated with very high spot prices in high demand periods. This means that there may exist uncovered load where wholesale market costs exceed expected contract costs.

An allowance of 30% was added to wholesale market costs to account for both price risk and forecasting risk for smaller customer markets (i.e. residential and small to medium business (SME) markets). This was based on prior work undertaken by Jacobs for the Essential Services Commission⁵. For larger customers, Jacobs considered that the ability to forecast loads and the presence of temperature sensitivity in the loads may be lesser, and reduced the risk premium to 25% for large commercial customers and to 20% for industrial customers.

Because retailers are also likely to hedge prices for some portion of their load well before the load eventuates, Jacobs applied a smoothing profile to the risk adjusted spot prices to mimic the time lag associated with hedging wholesale purchase contracts. The weighting rates assumed were 15% of the spot price 2 years prior, 60% of the spot price 1 year prior and 25% of the spot price in the current year.

In the short term wholesale prices generally increase due to a combination of rising gas prices and the rapid retirement of the Hazelwood power station in Victoria. In the medium term the consistent downward trend in wholesale prices is driven by declining demand. This is partially due to assumed closure of energy intensive industry.

Prices rebound after 2030 due to the anticipated closure of a number of large coal-fired power stations across the NEM. By the end of the forecast period wholesale prices are at new-entry price levels because of the retirement of coal-fired power stations and the expectation that wind and solar will set new entry price levels. Renewable generation costs slightly more under the Weak scenario relative to the Neutral scenario because of the exchange rate (1AUD = 0.65 USD for Weak, whereas 1AUD = 0.75 USD for Neutral).

4.4 Network Prices

Network tariffs consist of two components: Distribution Use of System (DUoS) and Transmission Use of System Charges (TUoS), which represent the costs of distribution and transmission businesses respectively. Network tariffs are published by the Australian Energy Regulator (AER) and the distribution network service providers.

⁵ See "Analysis of electricity retail prices and retail margins", May 2013, SKM-MMA (note this is a previous trading name of Jacobs), available at <http://www.esc.vic.gov.au/getattachment/94b535ef-70d3-4434-a98a-fa03da202a51/SKM-MMA-Retail-Margin-for-Residential-Supply-Report.pdf>

The distribution networks consist of different levels of voltage supply serving different end users (e.g. Residential, Commercial and Industrial). Given that costs allocated to customers are based on connection to, and use of, the transmission system at different voltage levels, the charges to different groups will vary depending on the number of voltage levels accessed. That is, different charging rates will be applied to different user groups in a broadly cost-reflective manner.

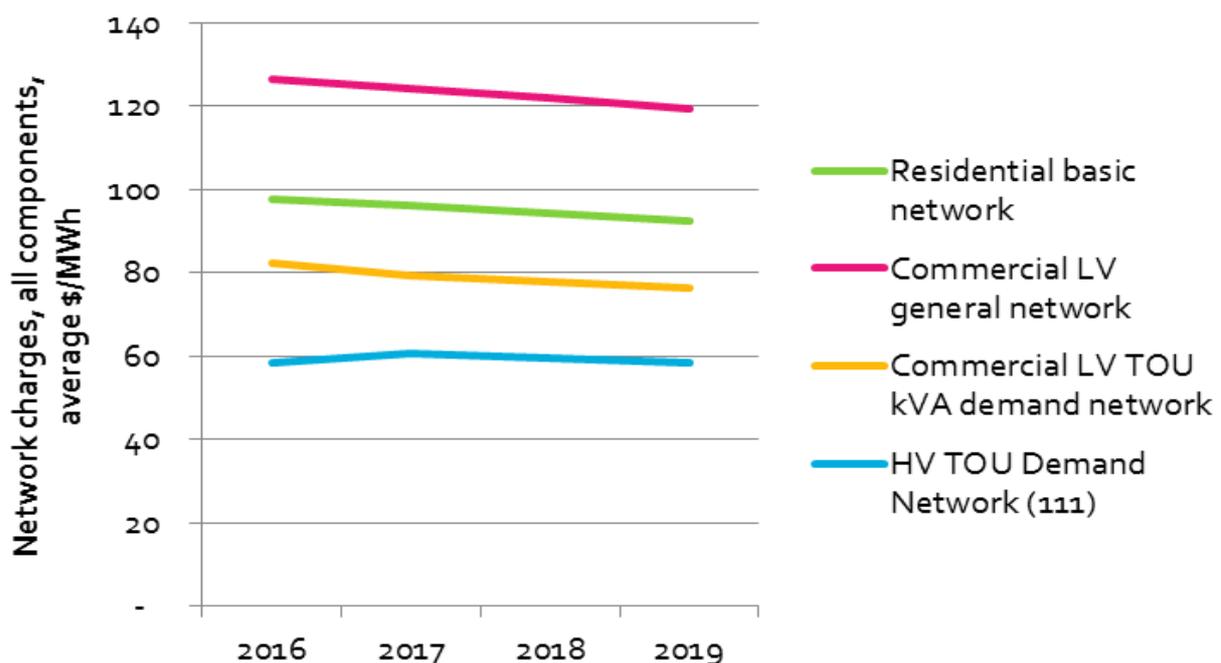
The individual network tariff is made up of different cost components. Fixed charges such as standing charges and prescribed metering service charges are the charges applying to all the connected retailers in the distribution zone irrespective of their network usage. There are also variable charge components in the network tariff in which the charges are differentiated by usage. In the tariff, the usage is categorised by block definitions with different charging rates applying to different blocks of usage.

Estimates of network costs include GST but do not require application of loss factors as network charges are applied at the customer connection point. Representative⁶ network charges were converted to average cost rates assuming the average usage levels shown in Table 3. Jacobs has assumed a load factor of 0.8 for industrial (large business) and 0.7 for commercial (medium business) categories to estimate maximum capacity and determine the impact of capacity charges for medium and large business customers. Most charges for residential and small business do not include a demand component, but where one is required a load factor of 0.5 is assumed. Where business tariffs consisted of a triple rate time of use charge, Jacobs has assumed that 42% of load is consumed in peak hours, 27% in shoulder hours and 31% in off-peak hours.

In many states volume based charges have trended downwards while fixed and demand charges have trended upwards, so apparent declines in average tariffs may occur for average consumption, while at the same time increasing average costs for smaller consumers and reducing average costs for larger consumers. For demand forecasting, it is possible that the change in tariff structure could result in lower price sensitivity than has been evident in the past.

Published indicative tariffs have been used where available to determine tariff impacts between now and 2020. For ActewAGL, tariff structure statements only provide indicative tariffs to the end of 2018. In 2019 the published X-factor of 2% was used to adjust tariffs and in 2020 an X-factor of 2% was assumed. Beyond 2020, we assume zero growth. The resulting average tariffs are shown in Figure 12.

Figure 12: Indicative Network Tariff Movement Assumptions



⁶ A representative tariff is a generalised tariff published by a given network. Some customers in the given customer class may be on alternative tariff arrangements. The representative tariff is intended to be indicative of likely network charges applying to the given customer class.

Source: Jacobs' analysis

4.5 Cost of Environmental Schemes

4.5.1 Carbon Schemes

In the modelling it was assumed that Government's commitment to a 28% reduction on carbon emissions by 2030 relative to 2005 levels was met. The electricity sector was assumed to observe its pro-rata share of the national carbon emission reduction target. This was implemented as a global constraint on emissions from 2020 to 2030 in the modelling, following a linearly declining trajectory. In the modelling this produced an implied carbon price in the years where the global carbon constraint was binding. For the Neutral scenario the constraint was binding from 2025 until 2032, and the implied carbon price peaked in 2029 when it was on average \$45.4/t CO_{2e}.

Table 3: Average Usage Assumptions by Distributor and Customer Class

Region	Provider	Residential	Small Business	Medium Business	Large Business
<i>Annual usage, kWh/customer/year</i>					
ACT	ActewAGL	6,811	32,257	480,319	13,474,139
<i>Representative tariff</i>					
ACT	ActewAGL	Residential basic network	General network	Low voltage TOU demand	High voltage TOU demand

Source: Average usage derived from Jacobs' analysis of latest AER Economic Benchmarking RINs, 3.4.1.4 & 3.4.2.1.

4.5.2 Renewable Energy Schemes

The Renewable Energy Target (RET) is a legislated requirement on electricity retailers to source a given proportion of specified electricity sales from renewable generation sources, ultimately creating material change in the Australian technology mix towards lower carbon alternatives.

Since January 2011 the RET scheme has operated in two parts—the Small-scale Renewable Energy Scheme (SRES) and the Large-scale Renewable Energy Target (LRET). The target mandates that 33 TWh of generation must be derived from renewable sources by 2020, maintaining this level to 2030. Emissions Intensive Trade Exposed (EITE) industry are exempt from the RET.

Large-scale renewable energy target

The LRET provides a financial incentive to establish or expand renewable energy power stations by legislating demand for large-scale generation certificates (LGCs), where one LGC is equivalent to one MWh of eligible renewable electricity produced by an accredited power station. LGCs are sold to liable entities who must surrender them annually to the Clean Energy Regulator (CER). Revenue earned by renewable power stations is supplementary to revenue received for generated power. The number of LGCs to be surrendered to the CER will ramp up to a final target of 33 TWh in 2020.

Small-scale renewable energy scheme

The SRES provides a financial incentive for households, small businesses and community groups to install eligible small-scale renewable energy systems. Systems include solar water heaters, heat pumps, solar photovoltaic (PV) systems, or small-scale hydro systems. The SRES facilitates demand for Small Scale Technology Certificates (STCs), which are created at the time of system installation based on the expected future production of electricity.

Retailer costs

The SRES and LRET impose obligations on retailers. In order to meet the obligations under these schemes, retailers must acquire and surrender renewable energy certificates (LGCs/STCs) each year. The average cost of these retailer obligations can be determined by calculating the following:

$$\text{Average cost of SRES and LRET} = (\text{RPP} * \text{LGC} + \text{STP} * \text{STC}) * \text{DLF}$$

where

RPP = Renewable Power Percentage, a mandated value which reflects the proportion of energy sales which must be met by renewable generation under the schemes. Historical RPP values can be obtained from the Clean Energy Regulator website⁷, but these are not available for future years. Instead Jacobs has estimated the RPP using current AEMO projections and assuming a straight line target until 2020.

STP = Small scale technology percentage,

LGC = Large-scale generation certificate price

STC = Small-scale technology certificate price

DLF = Distribution loss factor

For this study, we approximate the value of LGCs using Jacobs' REMMA model which models the economic uptake of large scale technology. Note that the STP is non-binding, and is based on modelling undertaken each year estimating likely uptake of small scale technology. If the target is not met the shortfall can be met in the following year, and the RPP would be adjusted accordingly so that overall a 33 TWh target is applicable by 2020.

Small scale generation certificate (STC) prices under the SRET are expected to range between \$39.80 and \$40/certificate in nominal terms. Allocation of certificates to the market is based on history, adjusted downward by STC reductions in deeming periods so that the current rate of 10% is expected to fall gradually to 1% by 2030.

Charges for LGCs are based on volume at the transmission bulk supply point, so DLFs are applied to define the LGC share required.

Table 4: Components of Renewable Energy Costs That Must Be Recovered by Retailers

Financial year ending June	RPP	LGC (\$/certificate)
2017	14.22%	89.16
2018	16.23%	86.99
2019	17.72%	61.40
2020	19.34%	35.82
2021	19.79%	10.23
2022	19.61%	5.12
2023	19.63%	2.56
2024	19.67%	1.28
2025	19.76%	0
2026	19.70%	0
2027	19.64%	0
2028	19.64%	0
2029	19.64%	0
2030	19.64%	0

Source: Jacobs' analysis.

⁷ <http://ret.cleanenergyregulator.gov.au/For-Industry/Liable-Entities/Renewable-Power-Percentage/rpp> provides the renewable power percentage.

4.5.3 State and Territory Policies

4.5.3.1 Feed-in Tariffs

Feed-in tariffs are equivalent to payments for exported electricity. Feed-in tariff schemes have been scaled back in most jurisdictions so that the value of exported energy does not provide a significant incentive to increase uptake of solar PV systems.

Between 2008 and 2012, state governments in most states mandated feed-in tariff payments to be made by distributors to owners of generation systems (usually solar PV). A list of such schemes is provided in Table 5. Following a commitment by the Council of Australian Governments in 2012 to phase out feed-in tariffs that are in excess of the fair and reasonable value of exported electricity, most of these schemes are now discontinued and have been replaced with feed-in tariff schemes with much lower rates.

However, the costs of paying for legacy feed-in tariff schemes from those schemes to customers must still be recouped as eligible systems continue to receive payments over a period that could be as long as twenty years. Network service providers provide credits to customers who are eligible to receive feed-in payments, and recover the cost through a jurisdictional scheme component of network tariffs. Networks are able to estimate the required payments each year and include these amounts in their tariff determinations adjusting estimated future tariffs for over and under payments annually as needed. Where this has occurred, it would be reasonable to assume that cost recovery components are included in the distribution tariffs under 'jurisdictional' charges, so no additional amounts are included in the Jacobs' estimates of retail price. In all cases where distributors are responsible for providing feed-in tariff payments, the distributors would have been aware of the feed-in tariffs prior to the latest tariff determination, so it is reasonably safe to assume inclusion.

Retailers may also offer market feed-in tariffs, and the amount is set and paid by retailers. Where such an amount has been mandated, the value has been set to represent the benefit the retailer receives from avoided wholesale costs including losses, so theoretically no subsidy is required from government or other electricity customers. In a voluntary feed-in tariff situation, no subsidy should be required from government or other electricity customers. Nevertheless, Jacobs' wholesale price projections are based on a post-scheme generation profile which incorporates new solar PV, and therefore may understate the cost compared with what may have been the case had the schemes not been implemented. Therefore, we suggest that retailer feed-in tariffs be added to wholesale prices by adding the following quantity to the wholesale price:

$$\text{Retailer feed-in tariff} \times \% \text{ share of solar PV generation}$$

Table 5: Summary of Mandated Feed-in Tariff Arrangements in the ACT Since 2008

Feed-in tariff	Cost recovery
<p><u>ACT feed-in tariff (large scale)</u></p> <p>ACT feed-in tariff (large scale) supports the development of up to 210 MW of large-scale renewable energy generation capacity for the ACT. This scheme has been declared to be a jurisdictional scheme under the National Electricity Rules, and is therefore recovered in network charges.</p> <p><u>ACT feed-in tariff (small scale, legacy)</u></p> <p>ACT feed-in tariff (small scale), is already declared to be a jurisdictional scheme under the National Electricity Rules, and is therefore recovered in network charges. In July 2008 the feed-in tariff was 50.05 c/kWh for systems up to 10 kW in capacity for 20 years, and 45.7 c/kWh for systems up to 30 kW in capacity for 20 years. The feed-in tariff scheme closed on 13 July 2011.</p>	<p>Network tariffs include provision for feed-in tariffs.</p> <p>Assume 5.5 c/kWh over projection period to cover retailer benefit (based on NSW estimates)</p>

4.5.3.2 Renewable Energy Policies

ACT renewable target

In April 2016, the ACT Government announced that it would extend its existing renewable energy target from 90% to 100%. The target is achieved through large scale solar and wind auctions which enable the territory to economically undertake power purchase contracts with renewable energy generators in the ACT and other

states to produce an equivalent amount of power to what is used within the ACT. This is modelled by Jacobs as a small increase to the RET and no additional charges are applied to ACT customers.

4.5.3.3 Energy Efficiency Policies

Some states and territories in Australia have implemented energy efficiency policies. Schemes that require retailers to surrender certificates to meet a given energy efficiency target are referred to in this document as white certificates. Energy efficiency scheme impacts require adjustment for the distribution loss factor.

The ACT Energy Efficiency Improvement Scheme (EEIS) commenced in 2013 and was due to finish in 2015. However, in 2014 the ACT Government announced that the EEIS will be extended to 2020. Based on the regulatory impact statement⁸ for the extension, the estimated retail price impact was estimated to be \$3.80/MWh.

4.5.4 Market Fees

Market fees are regulated to recover the costs of operating the wholesale market, the allocation of customer meters to retailers, and settlement of black energy purchases. These fees, charged by the Australian Energy Market Operator (AEMO) to retailers, are applicable to wholesale black energy purchases and are budgeted at \$0.39/MWh in 2017 according to the AEMO 2016 budget⁹. In addition to these fees, AEMO also recovers the costs for Full Retail Contestability (\$0.061/MWh), National Transmission Planning (\$0.016/MWh) and Energy Consumers Australia, a body which promotes the long term interests of energy consumers (\$0.01/MWh). The assessed market fees are shown in Table 6. Conversions from nominal to real values are undertaken assuming an inflation rate of 2.5%.

Table 6: AEMO Projected Fees for the NEM (indicative), \$/MWh

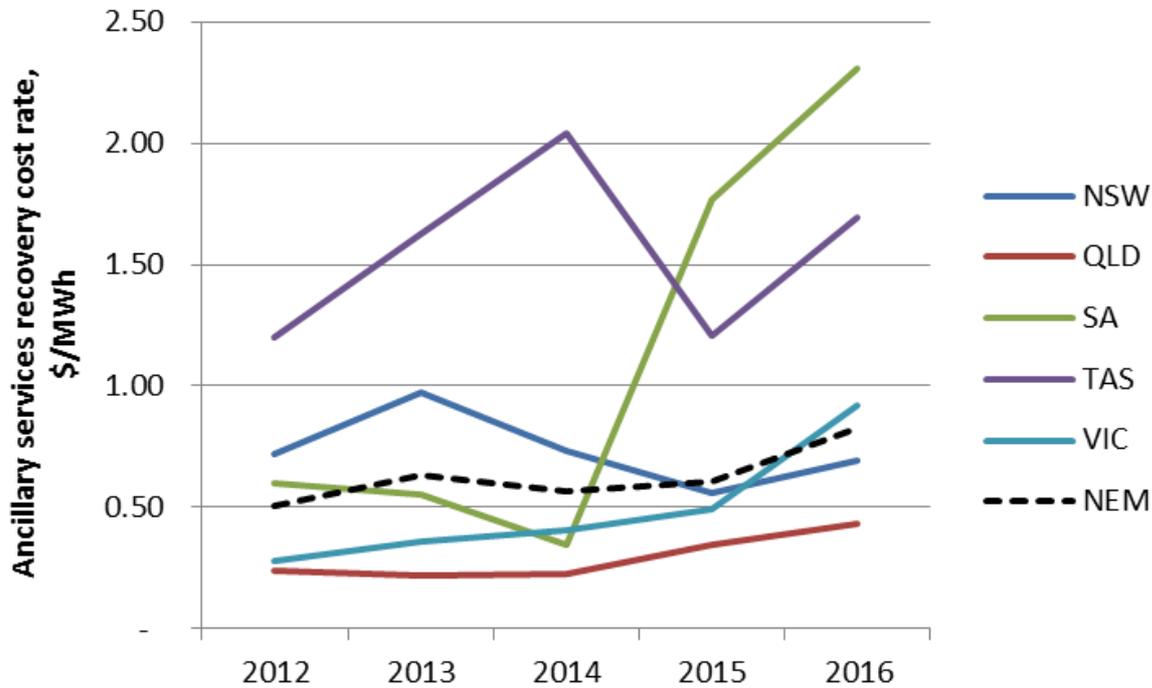
Year ending June	NEM Fees, Nominal	NEM Fees, Real	Full Retail Contestability	National Transmission Planner	Energy Consumers Australia	Total
2017	0.39	0.39	0.06	0.02	0.01	0.48
2018	0.40	0.39	0.06	0.02	0.01	0.49
2019	0.41	0.39	0.06	0.02	0.01	0.48
2020	0.42	0.39	0.06	0.02	0.01	0.49
Post 2020 assumption		0.39	0.06	0.02	0.01	0.49

Ancillary service charges are also passed through by AEMO to retailers. Retailers are charged ancillary service costs according to load variability. Over the last few years the charges have varied over time and by region, as demonstrated in Figure 13. Due to the volatility of these values, retailers are not able to foresee variations in these costs. and therefore the average values have been applied over the study period as indicative. As shown in Table 7.

⁸ http://www.environment.act.gov.au/_data/assets/pdf_file/0006/735990/Attachment-C-Regulatory-Impact-Statement-EEIS-Parameters-to-2020-FINAL.pdf

⁹ "Electricity final budget and fees: 2016-17", AEMO, May 2016

Figure 13: Ancillary Services Recovery Cost Rate, \$/MWh



These market and ancillary service charges are adjusted by DLFs as the charges are related to the wholesale metered quantity purchased by retailers.

Table 7: Ancillary Services Cost Assumption, \$/MWh

State/ Territory	Ancillary services cost
NSW / ACT	0.74
QLD	0.29
SA	1.11
TAS	1.55
VIC	0.49
NEM	0.63

Source: Jacobs' analysis using AEMO published Ancillary services payments data from 2012 to 2016 and published native energy statistics, accessed 23 March 2017

4.5.5 Retailer Charges

The Jacobs report to AEMO identified that there has thus far been no conclusive evidence of changing trends in retailer costs, net or gross retail margins over time or across states and territories. A fairly wide range of gross margins is probable, and that these could be influenced by the level of competition in markets as well as the size of the cost base that these gross margins will be applied to. Jacobs therefore believes that a safer option will be to use a net retail margin estimate and an estimate of retail cost, which itself will remain largely fixed over time in real terms. The net retail margin (expected to be 5-10% in most cases) and retail costs (\$118 per customer) as discussed are appropriate for smaller markets such as the residential and small business markets.

As a check that the derived retail prices are consistent with available market estimates, a calibration process was undertaken for the residential markets, where some estimates of current values are available. The estimated average retail prices were derived from published AER estimates of average standing and market offer prices in the 2015 AER State of the market report, which estimated that the average residential price was \$228/MWh for a 6.5 MWh/year customer. The derived retail margins (net) was estimated to be 9.3%.

5. Zone Substation Average Demand Forecasts

5.1 Introduction

Jacobs assisted ActewAGL in the development of the average demand forecast for each of their 12 zone substations. In particular, we assisted with the following tasks:

- Verification of historical demand data from the ActewAGL SCADA system for each of the twelve zone substations;
- Development of econometric seasonal (quarterly) average demand models and forecasts for each of the zone substations, using an econometric time-series modelling tool (EViews); and
- Integration of the average demand forecasts into the MEFM demand forecasting model.

5.2 Approach

5.2.1 Tools

The average demand forecasting models were developed using EViews. EViews is a Windows based statistical package used mainly for time-series analysis. EViews can handle almost all interval time-series data, panel (dated, cross-section) and unstructured data. One of the reasons we chose EViews was because it has a forecasting tool that automatically reports useful forecast evaluation metrics.

5.2.2 Objective

The objective for the zone substation average demand forecasts is to create a 10-year average demand forecasts to support the development of the MEFM maximum demand forecasts by zone substation in the ActewAGL distribution network. The forecast changes in the average demand will form an important input to the maximum demand projections, that are used to justify the capex proposals for the FY2019-2024 regulatory period.

Table 8 includes all twelve ZSS in the ActewAGL distribution area. The zone substations of Belconnen and Latham are situated in the ACT north-west, while City East, Civic and Gold Creek are in north Canberra. Zone substations in south and south-east Canberra (below the Molonglo River/ Lake Burley Griffin) are East Lake, Telopea and Fyshwick. Furthermore, in the ACT south-west we can find Woden and in the ACT South (around Lake Tuggeranong) the ZSS of Theodore, Wanniasa and Gilmore.

Table 8: Zone Substations in the ActewAGL Distribution Network

ActewAGL Zone Substations			
Zone Substation	Area	Zone Substation	Area
Belconnen	ACT North-west	Gold Creek	ACT North
City East	North Canberra	Latham	ACT North-west
Civic	North Canberra	Telopea	South Canberra
East Lake	South-east Canberra	Theodore	ACT South
Fyshwick	South-east Canberra	Wanniasa	ACT South
Gilmore	ACT South	Woden	ACT South-west

From initial analysis of the areas surrounding the different zone substations, we can observe the following:

- The population in the area surrounding Lake Tuggeranong including zone substations Theodore, Wanniasa. Gilmore and Woden is showing a significant historical and projected decline. Therefore, we expect this will have an impact on the average demand for these zone substations.
- The zone substation of Fyshwick is in a predominantly commercial/ industrial area and therefore we expect that the average demand forecasting model will be significantly different than the models for the other zone substations.
- Gold Creek zone substation is in a residential development area showing significant projected growth in population, Jacobs is expecting this growth to positively impact the average demand forecast of Gold Creek ZSS.
- Other zone substations in Canberra will contain a mix of commercial and residential activities and mostly stable population projections, development of average demand may not be straightforward (e.g. increase or decrease).

The above observations are used to validate some of the forecasting outcomes.

5.2.3 Verification and Cleaning of Historic Demand Data

Jacobs assisted with the verification and transformation cleaning of historic demand data for each of the ActewAGL zone substations. The main tasks performed included:

- Compiling data into a usable form as required for analysis in Eviews
- Adjustments in response to unexpected 'glitches' in the data, or time-periods in the data set showing zero demand.
- Improving data quality assurance by devising a transparent file structure applicable across all ZSS locations allowing for better document version control. This was essential because naming files identically, without any specific identifiers to the station or season would increase the risk that the wrong input files would be run in the prepared models, resulting in errors or misspecification of demand projections.
- Updating the R-code (for assessment in R) so that it would work with the current (adjusted) modelling structure¹⁰, and automation of some manual processes. These changes also allowed us to run the model from top to bottom, rather than in stages, increasing the overall efficiency.

The transformed and verified historic average demand time-series were then used by Jacobs to develop average demand models for each zone substation. The method is discussed in the following sections of this report.

5.2.4 Development of ZSS Average Demand Forecasting Models

The zone substation average demand forecasts were developed using Eviews econometric time-series software following a multi-step approach summarised as follows:

1. Visual inspection of data for each ZSS to check for potential anomalies, breakpoints and outliers
2. Development of potential models to be tested for each zone substation
3. Running of identified models with Eviews time-series software

¹⁰ Partially the result of Jacobs modelling the average demand forecasts by ZSS with Eviews.

4. Residual analysis of the most promising models
5. Manual and automatic time series modelling using a statistical approach based on Box-Jenkins 'Auto Regressive Moving Average' (ARMA), including residual analysis to verify model adequacy
6. Test for Multicollinearity
7. Selection of the best model based on:
 - a. Model evaluation criteria (e.g. AIC);
 - b. Forecast evaluation criteria (e.g. Theil Inequality Coefficient); and
 - c. Visual inspection against historic data and development expectations at the different ZSS.
8. Reporting of forecasting model (coefficients) and forecasting data (forecast and model standard error) to ActewAGL

The above steps will be briefly discussed in the following subsections

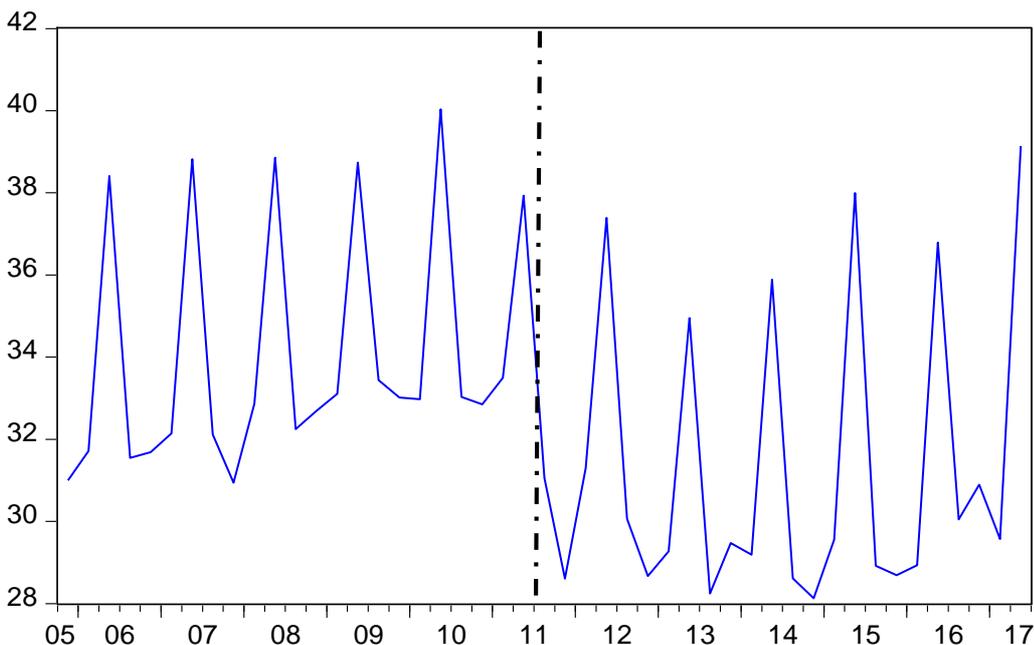
5.2.4.1 Visual Inspection of Historic Data

A visual analysis of the historic data on the average demand is a way of identifying any issues or structural changes in time-series data. For each of the 12 zone substations in ActewAGL's network area we have plotted the data and analysed the output.

In several cases we identified irregularities in the historical data and discussed the observations with ActewAGL. In some cases, this has led to the correction of erroneous data.

In other cases, the analysis resulted in inclusion of dummy variables to control for outliers and/or structural changes in the historical data. An example of this is included in Figure 14.

Figure 14: Belconnen visual representation of the historic average demand in MVA.



The above graph shows a clear structural change of the level of average demand in Belconnen from 2011 Q3 onwards (dotted black line). To test this visual hypothesis, we ran a Chow Breakpoint Test on 2011 Q2 which

confirmed our hypothesis by rejecting the Null Hypothesis that there are no breaks at the specified breakpoint (prob. 0.000). The output of the Chow Breakpoint Test is included below in Table 9.

Further investigation into this particular structural change did not provide any clear answer. ActewAGL noted that this could have been the result of several smaller load transfers to other substation.

Table 9: Chow Breakpoint Test for Belconnen

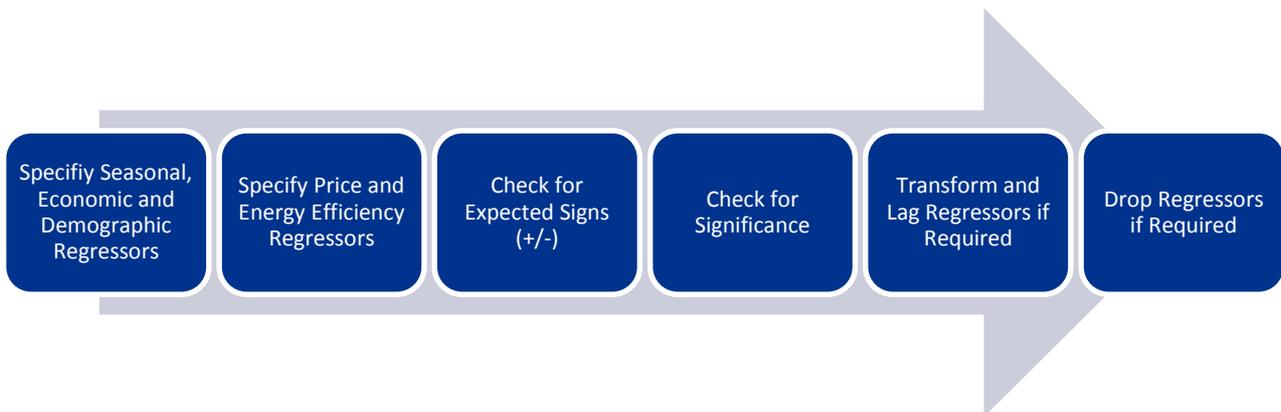
Chow Breakpoint Test: 6/01/2011
 Null Hypothesis: No breaks at specified breakpoints
 Varying regressors: All equation variables
 Equation Sample: 12/01/2005 6/01/2017

F-statistic	45.35581	Prob. F(3,41)	0.0000
Log likelihood ratio	68.75905	Prob. Chi-Square(3)	0.0000
Wald Statistic	136.0674	Prob. Chi-Square(3)	0.0000

On other occasions we have included single dummy variables for certain outliers in the data, improving the models significantly.

5.2.4.2 Specification of Models

The following process-chart provides a high-level summary of the steps we have followed to specify the average demand models for each zone substation. The steps are discussed in more detail in the remainder of this section.



Jacobs specified quarterly models of average demand by zone substation, therefore for each of the models we included seasonal independent variables (regressors). The most important seasonal variables are the Heating Degree Days (HDD) and Cooling Degree Days (CDD). These variables include the daily number of degrees the average minimum and maximum temperature is above or below a certain threshold (>18°C for CDD and <19°C for HDD). Thus the variable measures the number of degree days heating or cooling load significantly impacts the average demand. These variables essentially ‘weather correct’ the time-series as they will pick up a significant part of the seasonal variety in average demand.

Specification of the models was also determined on general regressors for average demand as well as geographic, demographic and other variables. We initially specified a model that contained at least one independent variable that served as a proxy for the impact of the economy on average demand. For this we had a number of variables available representing country wide and state level economic development over time. These variables are Australian Real GDP¹¹, State Final Demand (SFD) and the Unemployment Rate (as per Table 10 below). For each model we tested the inclusion of the two local economic variables and if they did not

¹¹ We note that the local economic structure in the ACT is very different from the Australian economic structure as a whole, and we therefore prefer to include the local economic regressors, only when we did not find any significant relationship we used Australian Real GDP.

provide the expected impact, we substituted with the country wide GDP regressor. However, sometimes none of these economic variables had any significant impact and that demographic factors are more relevant.

Table 10: Independent Variables Used in Average Demand Modelling

Class	Independent Variable	Series	Source – Year Published
Seasonal	Heating Degree Days – historic and simulations	2006Q1- 2027Q2	ActewAGL/ BOM (2017)
Seasonal	Cooling Degree Days – historic and simulations	2006Q1- 2027Q2	ActewAGL/ BOM (2017)
Economic	Australian Real GDP – historic and projections	2006Q1- 2027Q2	ABS/ Jacobs (2016)
Economic	ACT State Final Demand – historic and projections	2006Q1- 2027Q2	ABS/ Jacobs (2016)
Economic	ACT Unemployment Rate – historic and projections	2006Q1- 2027Q2	ACT Gov./ Jacobs (2016)
Demographic	ACT Population – historic and projections	2006Q1- 2027Q2	ACT Treasury (2017)
Demographic	ACT Spatial Population – historic and projections	2006Q1- 2027Q2	ACT Treasury (2017)
Price	Residential Retail Prices – historic and projections	2006Q1- 2027Q2	ABS/ AEMO/ Jacobs (2016)
Price	Commercial Retail Prices – historic and projections	2006Q1- 2027Q2	ABS/ AEMO/ Jacobs (2016)
Price	Industrial Retail Prices – historic and projections	2006Q1- 2027Q2	ABS/ AEMO/ Jacobs (2016)
Efficiency	Total Energy Efficiency – historic and projections	2006Q1- 2027Q2	AEMO/ Jacobs (2017)
Efficiency	Total Energy Efficiency – historic and projections	2006Q1- 2027Q2	AEMO/ Jacobs (2017)

To capture the demographic impact on the average demand we used a geographic approach by utilising the spatial historic and projected population time-series, developed by the ACT Treasury (2017). We applied the most relevant spatial population time-series to the different zone substations. This provided more accurate models as spatial population levels and growth may differ from the overall population projections in the ACT (e.g. while overall population in ACT is projected to grow, we observed a decrease in the projections in the Tuggeranong area).

Table 11: Zone Substations and Corresponding Population Time-series

Zone Substation	Spatial/ Regional Population Time-series
Belconnen, Latham	Belconnen
City East, Civic	North Canberra
East Lake	Fyshwick
Fyshwick	None, as mostly industrial/ commercial
Gilmore	None, exception - no significant impact
Gold Creek	Gungahlin
Telopea	South Canberra
Theodore, Wanniasa	Tuggeranong
Woden	Cotter

Finally, we included other independent variables that could estimate the potential impact of price levels and energy efficiency. Both variables are applied on the basis of geographic and demographic specifications of the zone substation we modelled. For example, in areas with significant commercial activity we initially tested a model using the energy efficiency times-series for business and the commercial price time-series. Alternatively, in residential dominated areas we specified the model based on residential time-series.

When we specified the models in the time-series forecasting tool, one initial step was to assess whether the coefficients had the proper sign (e.g. population is expected to be positively correlated with average demand) and/or were significant regressors (by means of analysing the t-Statistic). Where the coefficients of the specified independent variables did not show the appropriate sign, we transformed, used differences or lagged the independent variables to see if there was any improvement.

However, the above steps were only taken if it made sense to do so. For example, the retail price of electricity may have a lagged impact of several periods as most customers do not receive (near) real-time invoices and therefore the demand adjustment can very well take effect a few periods later.

Finally, if no improvements could be made to the variable and the goodness of fit of the complete model did not improve (by means of assessing the R^2 and AIC, discussed in detail below), the independent variable was dropped from the model specification.

5.2.4.3 Residual Analysis and ARMA

After running the specified models, Jacobs performed a residual analysis for each model to determine the existence of any autocorrelation within the residuals. The EViews software package includes several tools to perform a residual analysis. The most important tools are discussed in this section.

The first step we performed in the residual analysis was a visual check for serial correlation in the residuals, after the model was specified and ran in EViews. Serial correlation can be observed in typical auto regression patterns (AR: future values of the dependent variable are (partially) based on past values) or moving average patterns (MA: future values of the dependent variable are (partially) based on past errors). In addition, the EViews standard model output also reports the Durbin-Watson Statistics showing the existence of potential serial correlation. However, this particular output does not indicate the type of serial correlation. To determine the type of serial correlation we used visual and numerical representations of the residuals and correlograms or ACF and PACF plots.

The above information was then used to determine a solution (e.g. including AR and/or MA regressors) that satisfies the removal of autocorrelation from the residuals and other statistical requirements and provided an optimal level of fit for the specified model.

In some cases, we used the automatic ARMA modelling function available in EViews to verify if we had chosen a reasonable model. The automatic ARMA function selects the best model by trialling a predetermined set of ARMA order terms and lagged terms and chooses the best model (e.g. based on the Akaike info criterion, discussed in next section).¹²

5.2.4.4 Tests for Multicollinearity

Jacobs also tested for potential multicollinearity and associated impact on the developed models.¹³ EViews has a number of tests available to check for the existence and the impact of collinearity. We have used the Variance Inflation Factors (VIF) and Coefficient Variance Decomposition tests to address potential multicollinearity issues, and determined that across a number of specified models multicollinearity is present, but that the measured effects are low and thus the risk of model over-specification is relatively limited.

5.2.4.5 Selection of Best Performing Model

After specification of complete models including potential ARMA terms, we were left with several slightly different models we could select (e.g. dropping or including specific independent variables). For the selection of the best (final) model we had several tools available.

¹² In many cases the model selected by the automatic ARMA function includes multiple (insignificant) ARMA terms reducing the model's explanatory value and usefulness for the purpose of demand forecasting (i.e. too many ARMA terms erode the explanatory value of the independent regressors in the specified model). The best way of selecting a model is still a manual process taking into account different selection criteria.

¹³ Multicollinearity is a phenomenon in which one independent variable in a multiple regression model can be linearly predicted from the other independent variables with a substantial degree of accuracy. This may result in over-specification of models if the latter phenomenon is present and the measured impact is high.

First of all, there are a number of model selection criteria were reported in the standard output of the Eviews modelling tool, these included:

- R-squared
- Adjusted R-squared
- Akaike info criterion
- Schwarz criterion
- Hannan-Quinn criterion

Of the above list the R-squared and the Akaike Info Criterion (AIC) are the most commonly used for the selection of the 'best performing' model. In short the R^2 (or adjusted R^2) is a very useful tool to determine the model's fit, where an R^2 of 1 would constitute as a perfect fit and an R^2 of 0 as the opposite. The R^2 statistic does not adequately penalise over-fitted models however, and is therefore not the most practical option for model selection.

A general description of the steps taken to select the final model is included in Appendix A.

5.2.4.6 Reporting to ActewAGL

After choosing the most suitable models, we provided the forecasting output directly to ActewAGL for integration in their MEFM forecasting model.

The following outputs were reported to ActewAGL for each of the twelve zone substations:

- The model output report (e.g. coefficients, evaluation criteria, R^2)
- The forecasting model data output, including the back-cast proportion that is available¹⁵;
- The standard error (SE) of the forecast output, this SE generally increases further into the future;
- The residual graph (refer to section 5.2.4.3);
- The forecast evaluation and graph (refer to section 5.2.4.3);
- The original (historic) dependent series; and
- A graph, comparing the original series with the forecast.

The reported results were also discussed with ActewAGL's forecaster.

5.3 Modelling and Forecast Results

5.3.1 Introduction

In this section all developed models and corresponding forecasts will be discussed in detail.

Each of the developed average demand model uses a log-transformed dependent variable. The dependent variables are the average demand at a specific zone substation or at the system level. Variables for population, and state final demand (SFD) included in the models were also log-transformed to generate 'normally distributed' variables, improving model results and reducing potential serial correlation.

5.3.2 Summary of Results

The system wide forecasting results for annual average demand are included in Figure 15. The stacked bar chart shows the total average demand (historic and projected) up to quarter 2 year 2027. The black line represents the results of the system level forecast. The results of the system level average yearly demand forecast are tracking closely to the sum of the average yearly demand of the individual substations.

¹⁵ This may differ per model as lagged variables may be used in several models.

The figure shows a slight reduction of the average demand for the next 10-year period, with a small increase observable in 2027. However, this yearly average demand does not include any post-modelling corrections as a result of block-loads or developments of large scale infrastructure projects. Post modelling adjustments will be included during the maximum demand modelling executed by ActewAGL.

Figure 16 represents the winter average demand (June – July – August), slightly more volatile year-to-year, but again somewhat decreasing over time. Also our system model projections are again tracking the aggregated forecasts by zone substation very closely. The latter provides us with additional confidence over the chosen models for the individual zone substations.

Moreover, we have found similar results for the summer (December – January – February) average model and forecasts. ActewAGL will be using the summer average demand model and the winter average demand model as the basis for the development of the peak demand models for each of the zone substations.

Figure 15: System Total Yearly Average Demand by ZSS

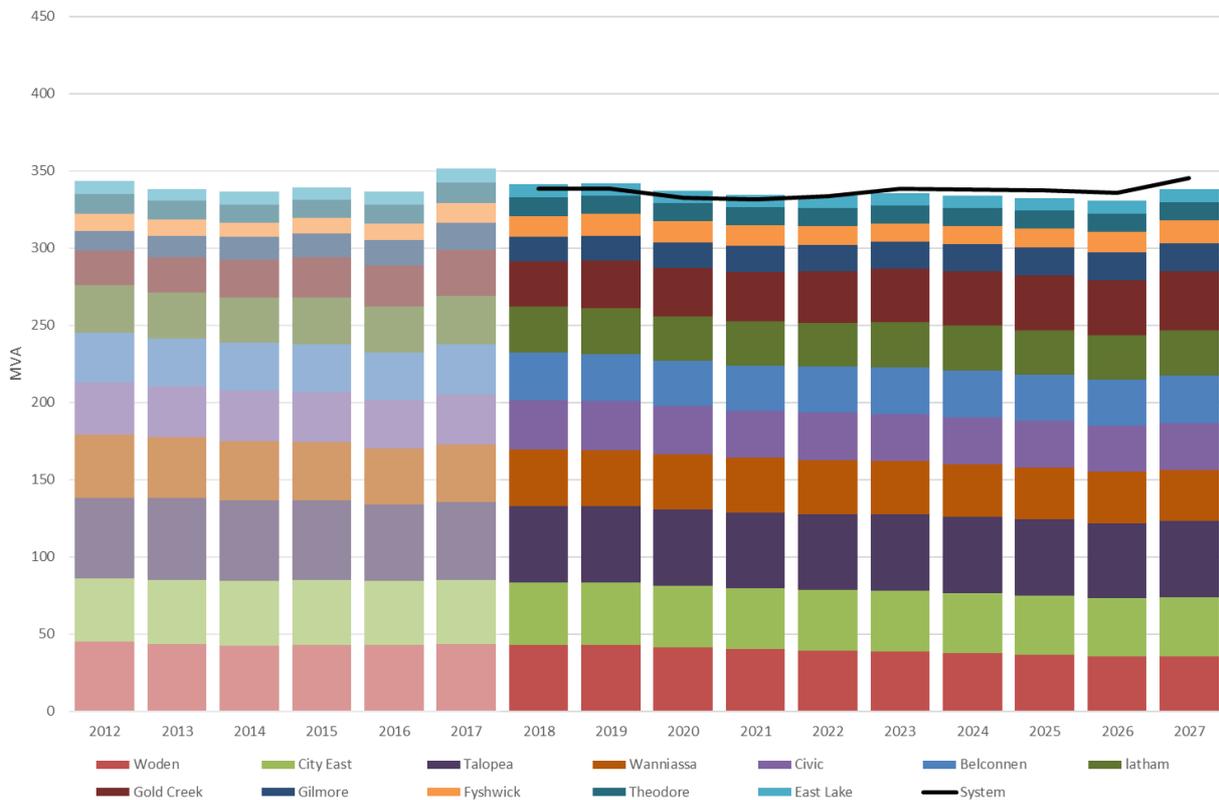
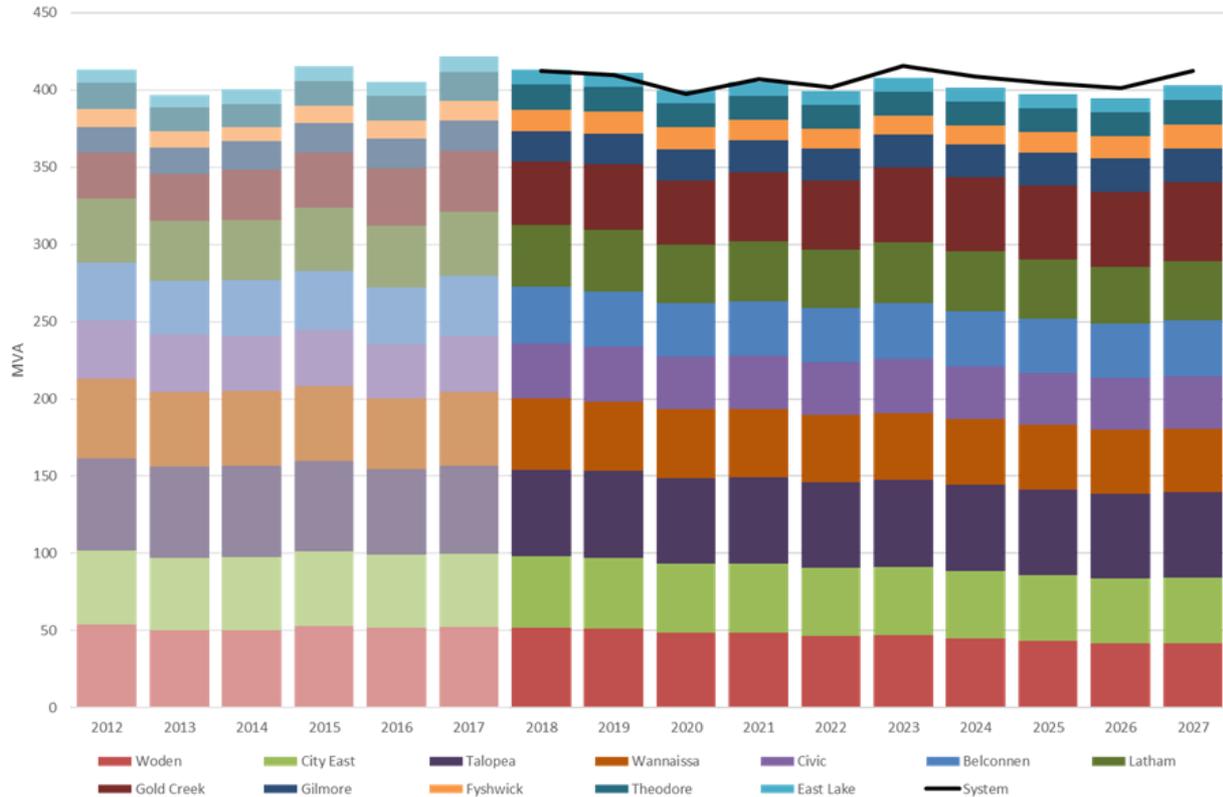


Figure 16: System Winter (June-July-August) Average Demand by ZSS



5.3.3 System Level Forecast

The system level forecast has been developed including as many independent variables possible, as we have included in the individual zone substation quarterly average demand models.

We have included the following variables:

- Heating Degree Days;
- Cooling Degree Days;
- ACT Population;
- Residential Price;
- Commercial Price;
- Energy Efficiency for Businesses; and
- Energy Efficiency for Residential Customers;

We constructed a single variable for price and a single variable for energy efficiency by simply adding them up, thus avoiding collinearity issues. Including both variables separately may have biased the model or generated insignificant coefficients or coefficients with improper signs due to interaction effects.

Including the population variable and the one of the economic variables did not lead to robust modelling results due to interdependencies, and therefore we dropped the inclusion of an economic variable in the model. However, it is likely that the ACT population incorporates the effects of economic development and can therefore serve as a proxy for both impact of population size and economic development on the average system demand.

Table 12 shows the model output for the system average demand. It shows significant correlations of CDD, HDD and energy efficiency regressors with system demand, and the expected signs, and although strictly not significant; the price also has the expected negative correlation with average demand. This variable was not dropped because it played a crucial role in some of the model for individual zone substations, and its inclusion still significantly improved the AIC and adjusted R² as compared to the model without this variable.

Table 12: Model Output for System Average Demand

Dependent Variable: LOG(SYSTEM)

Method: Least Squares

Date: 10/19/17 Time: 18:18

Sample (adjusted): 6/01/2006 6/01/2017

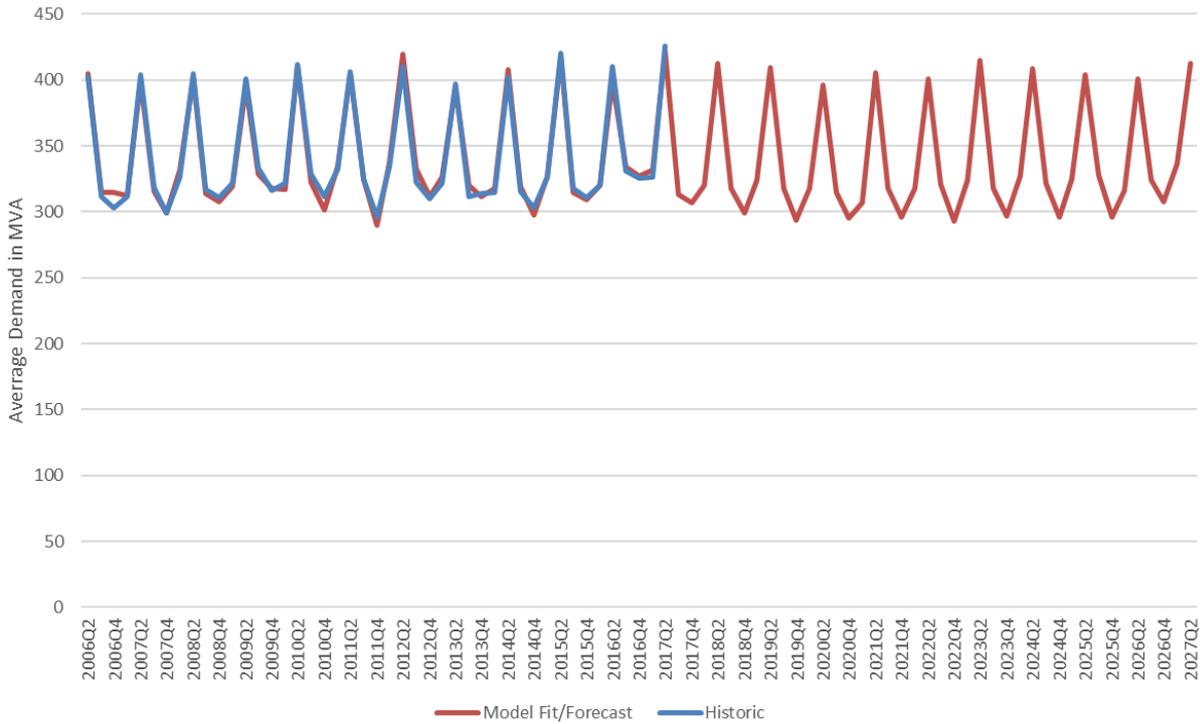
Included observations: 45 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CDD	0.000539	3.24E-05	16.64335	0.0000
HDD	0.000416	1.02E-05	40.63487	0.0000
LOG(POPULATION)	0.441020	0.002946	149.6990	0.0000
RESIDENTIAL_PRICE_N+COMMERCIAL_LV_PRICE_N(-2)	-0.000210	0.000141	-1.487996	0.1446
EE_RESIDENTIAL_N+EE_BUSINESS_N	-0.000109	5.60E-05	-1.953096	0.0578
R-squared	0.983818	Mean dependent var	5.827979	
Adjusted R-squared	0.982200	S.D. dependent var	0.115141	
S.E. of regression	0.015362	Akaike info criterion	-5.409416	
Sum squared resid	0.009439	Schwarz criterion	-5.208675	
Log likelihood	126.7119	Hannan-Quinn criter.	-5.334582	
Durbin-Watson stat	1.678511			

Furthermore, upon analysis of the residuals we found that these were most likely normally distributed, and therefore the model required no inclusion of any ARMA terms.

The high model fit is observable in the below figure where we have plotted the model fit against the actual historical data (blue line). The model shows a very good fit with the historical data. Moreover, the forecast shows a slight decrease in average system demand, starting this summer, mainly as a result of expected increasing electricity prices (residential and commercial) as well as continuing energy efficiency, offsetting the effects of the moderate population growth in the ACT.

Figure 17: ActewAGL System Average Demand - Model Fit and Forecast



5.3.4 Belconnen Zone Substation

The model output for Belconnen Zone Substation average demand is presented in Table 13. The Belconnen average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days;
- Commercial Price (with a 3 period lag);
- Population in Belconnen; and
- Unemployment.

All variables show the right signs and most variables show large t-Statistics, indicating significant correlation to Belconnen average demand. Although unemployment does not show significant correlation to the dependent variable in this model, we have decided not to drop this regressor as the AIC significantly improved compared to the model without unemployment as a regressor. In addition, the Belconnen area has a strong commercial, primarily services related, profile and therefore as good practice an economic variable should be retained if it improves the model significantly. Therefore, as ‘unemployment’ provided the most increase in model fit and lowest AIC, we decided to retain it.

Table 13: Model Output for Belconnen Zone Substation Average Demand

Dependent Variable: LOG(BELCONNEN)
 Method: ARMA Maximum Likelihood (OPG - BHHH)
 Date: 09/15/17 Time: 17:52
 Sample: 9/01/2006 6/01/2017
 Included observations: 44
 Convergence achieved after 19 iterations
 Coefficient covariance computed using outer product of gradients

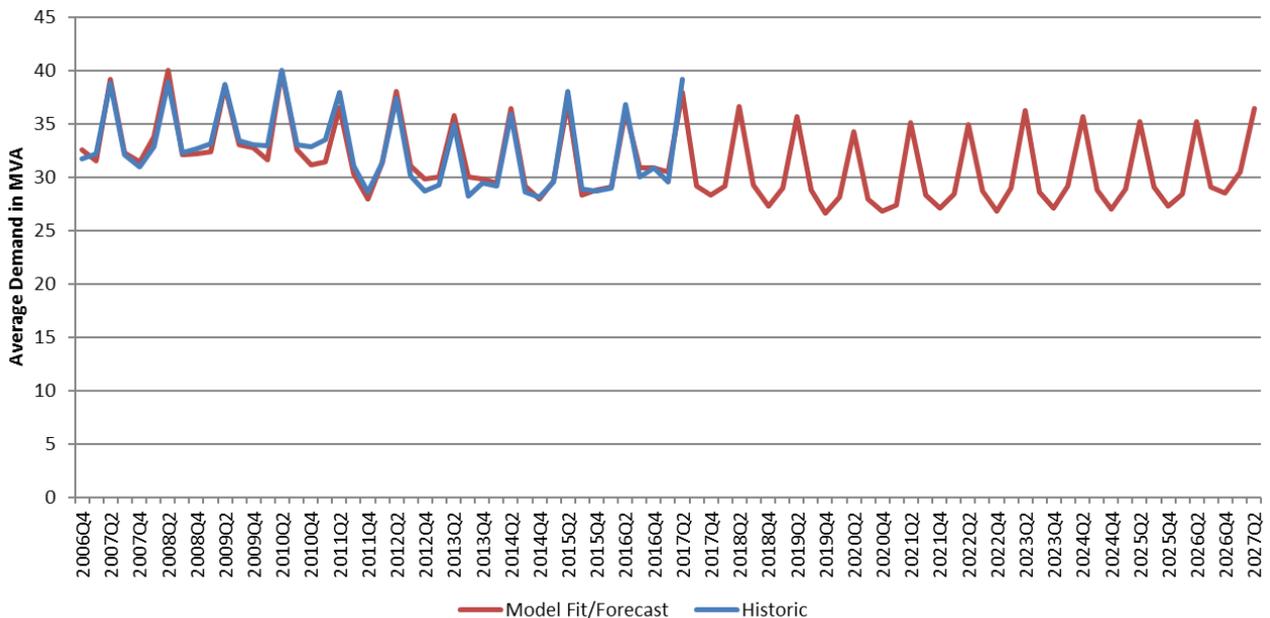
Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000375	1.66E-05	22.61915	0.0000
CDD	0.000545	4.17E-05	13.06995	0.0000
COMMERCIAL_PRICE_N(-3)	-0.000797	0.000410	-1.942794	0.0599
LOG(BELCONNEN_POP)	0.295318	0.007227	40.86062	0.0000
D_BELCONNEN	0.057892	0.014969	3.867368	0.0004
UNEMPLOYMENT	-0.015444	0.013009	-1.187214	0.2429
AR(1)	0.540656	0.131162	4.122051	0.0002
SIGMASQ	0.000469	0.000159	2.945113	0.0056

R-squared	0.956806	Mean dependent var	3.478465
Adjusted R-squared	0.948407	S.D. dependent var	0.105370
S.E. of regression	0.023934	Akaike info criterion	-4.456215
Sum squared resid	0.020622	Schwarz criterion	-4.131817
Log likelihood	106.0367	Hannan-Quinn criter.	-4.335913
Durbin-Watson stat	2.085772		

Presented in Figure 18 below is the model fit and forecast for the Belconnen Zone Substation average demand. The model fit (red line) tracks well with the historical data (blue line).

For the forecast a slight reduction of the average demand from winter 2018 until winter 2020 is expected, after which the average demand seems to be slowly recovering to 2017 levels. The main reason for reduction is the expected impact of rising commercial prices for electricity in the next few years in combination with a relatively stable population in the Belconnen area and a steady unemployment rate in the ACT.

Figure 18: Belconnen Zone Substation Average Demand – Model Fit and Forecast



5.3.5 City East Zone Substation

The model output for City East Zone Substation average demand is presented in Table 14. The City East average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days;
- Population in North Canberra; and
- Energy Efficiency for Businesses.

The Included independent variables all have the proper signs. HDD, CDD and population are as expected positively correlated to with the average demand in City East and energy efficiency is as expected negatively correlated. We dropped independent variables for economic development and price as they did not improve the model through the AIC and R^2 and showed insignificant coefficients (t-Statistics).

The serial correlation in this model has been addressed by adding a first order autoregression term (AR[1]) and a seasonal autoregression (AR[4]) term.

Table 14: Model Output for City East Zone Substation Average Demand

Dependent Variable: LOG(CITY_EAST)

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 09/15/17 Time: 16:49

Sample: 12/01/2005 6/01/2017

Included observations: 47

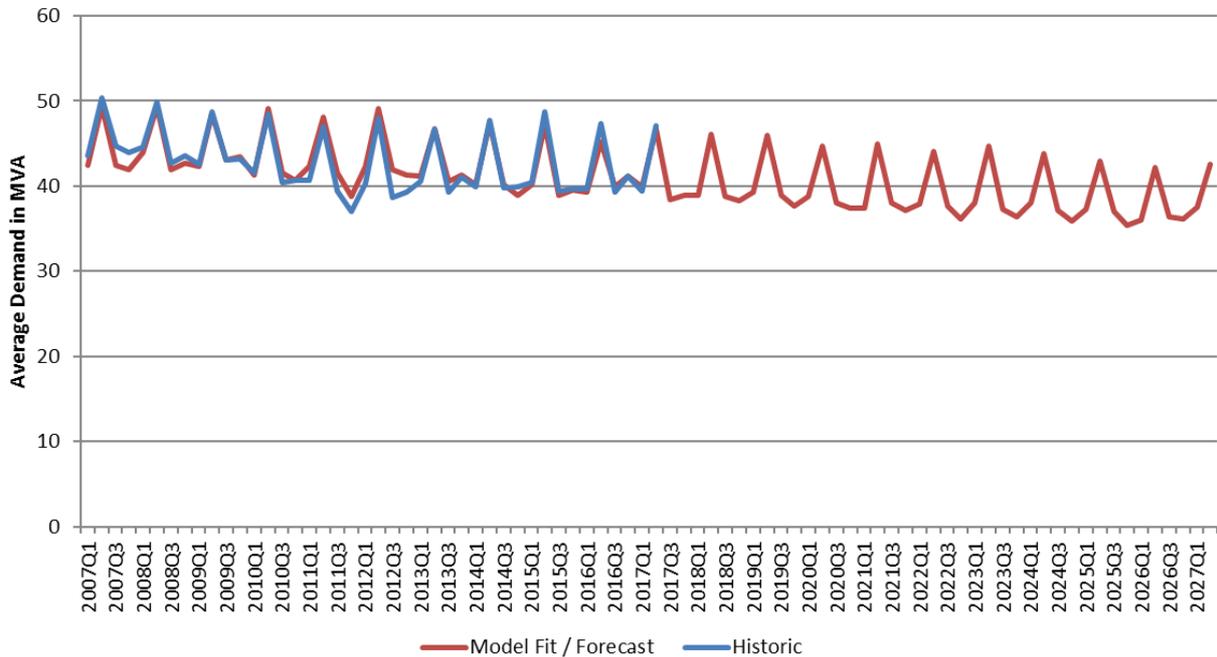
Convergence achieved after 15 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CDD	0.000496	4.62E-05	10.73956	0.0000
HDD	0.000286	1.98E-05	14.44220	0.0000
LOG(NORTH_CANBERRA_POP)	0.336386	0.003175	105.9514	0.0000
EE_BUSINESS_N	-0.000982	0.000316	-3.109635	0.0034
AR(1)	0.658492	0.128314	5.131858	0.0000
SAR(4)	0.480475	0.198240	2.423706	0.0200
SIGMASQ	0.000378	0.000104	3.626386	0.0008
R-squared	0.942149	Mean dependent var		3.758065
Adjusted R-squared	0.933471	S.D. dependent var		0.081707
S.E. of regression	0.021075	Akaike info criterion		-4.706397
Sum squared resid	0.017766	Schwarz criterion		-4.430843
Log likelihood	117.6003	Hannan-Quinn criter.		-4.602704
Durbin-Watson stat	2.277300			

Figure 19 illustrates the model fit and forecast for City East zone substation. The graph shows a strong fit in particular for the period from 2013 onwards. A decline in average demand is observable in the City East area. The area has a mixture of commercial-retail connections and suburban areas, including suburbs like Reid and Campbell, which have an history of relatively stable populations. Thus even though there is an overall moderate growth in the population of North Canberra, the effect on the average demand in City East is limited. On the other hand, increasing energy efficiency for businesses have impacted the average demand over the last decade or so and are expecting to continue until 2027 as shown in the figure below.

Figure 19: City East Zone Substation Average Demand – Model Fit and Forecast



5.3.6 Civic Zone Substation

The model output for Civic Zone Substation average demand is presented in Table 15. The Civic average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days;
- Population in North Canberra;
- State Final Demand;
- Energy Efficiency for Businesses; and
- Commercial Price.

The included independent variables all have the proper signs. HDD, CDD, SFD and population are as expected positively correlated to with the average demand in Civic and energy efficiency and commercial price are as expected negatively correlated. Although the commercial price regressor and the state final demand did not show a significant effect, the decision was taken not to drop these as they improved the model through the AIC and R2. Moreover, because of the presence of high commercial activity in this zone substation it would be prudent to add an economic regressor in the model.

The serial correlation in this model has been addressed by adding a moving average (MA[1]) to the model.

The model fit and forecast for Civic are included in Figure 20 below. The model shows a good fit with the historic data. The forecast shows a relatively flat development up to 2020 with a slight drop of the average demand after this date.

The area connected to Civic zone substation is dominated by retail-commercial activity with some residential areas, therefore a relatively stable forecast, with some reduction as a result of increasing business related energy efficiency seems very reasonable. Correspondingly, even though the average load for Civic zone substation is a bit lower than City East (around 35 MVA versus 40 MVA) the coefficient of the business energy efficiency variable has a similar (slightly higher) value as the coefficient in the City East model. The latter is in line with expectations, as the Civic zone substation covers more commercial areas than the City East zone

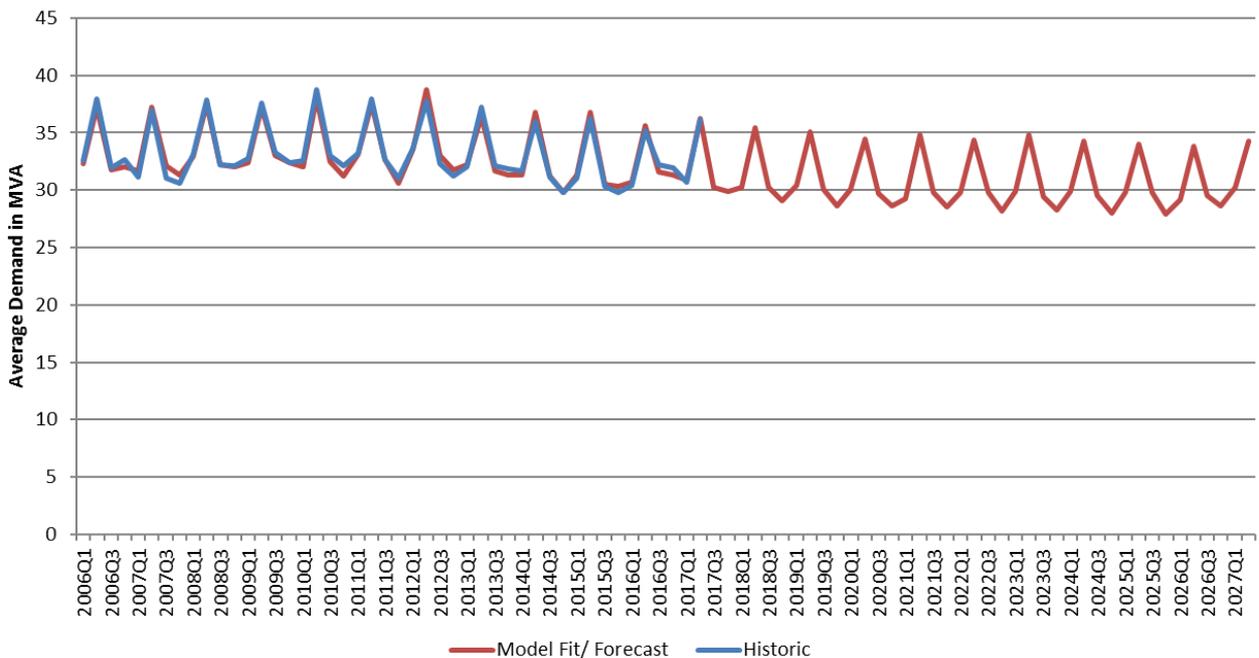
substation, therefore energy efficiency for businesses is expected to have the higher impact on the average demand in Civic zone substation.

Table 15: Model Output for Civic Zone Substation Average Demand

Dependent Variable: LOG(CIVIC)
 Method: ARMA Maximum Likelihood (OPG - BHHH)
 Date: 11/24/17 Time: 12:25
 Sample: 12/01/2005 6/01/2017
 Included observations: 47
 Convergence achieved after 10 iterations
 Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000261	8.67E-06	30.14693	0.0000
CDD	0.000345	2.10E-05	16.47011	0.0000
COMMERCIAL_LV_PRICE_N	-0.000391	0.000317	-1.231397	0.2255
EE_BUSINESS	-0.000996	0.000172	-5.798825	0.0000
LOG(NORTH_CANBERRA_POP)	0.215097	0.032624	6.593184	0.0000
LOG(SFD)	0.120993	0.039885	3.033551	0.0043
MA(1)	0.426448	0.163444	2.609139	0.0128
SIGMASQ	0.000203	6.04E-05	3.361167	0.0017
R-squared	0.962672	Mean dependent var		3.499503
Adjusted R-squared	0.955973	S.D. dependent var		0.074572
S.E. of regression	0.015647	Akaike info criterion		-5.318936
Sum squared resid	0.009549	Schwarz criterion		-5.004017
Log likelihood	132.9950	Hannan-Quinn criter.		-5.200429
Durbin-Watson stat	1.891630			

Figure 20: Civic Zone Substation Average Demand – Model Fit and Forecast



5.3.7 East Lake Zone Substation

The East Lake Zone Substation covers a large rural area east of Canberra with commercial and limited (widely spread) population activities. This zone substation was the most difficult to forecast on the basis of historical data.

Table 16 includes the model estimation output for East Lake Zone Substation. The East Lake average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days;
- Population in Fyshwick; and
- Commercial (HV/Industrial) Price.

All regressors have the expected signs and are all significant. The R^2 of this model is not as high as the other average demand models we have developed, however with a model fit of around 0.8 this model can still provide a reasonable forecast.

Two dummy variables have been included in this model as well. The dummy “D_EASTLAKE” is included to account for an outlier value for summer 2012 (potentially due to the hot and dry summer).

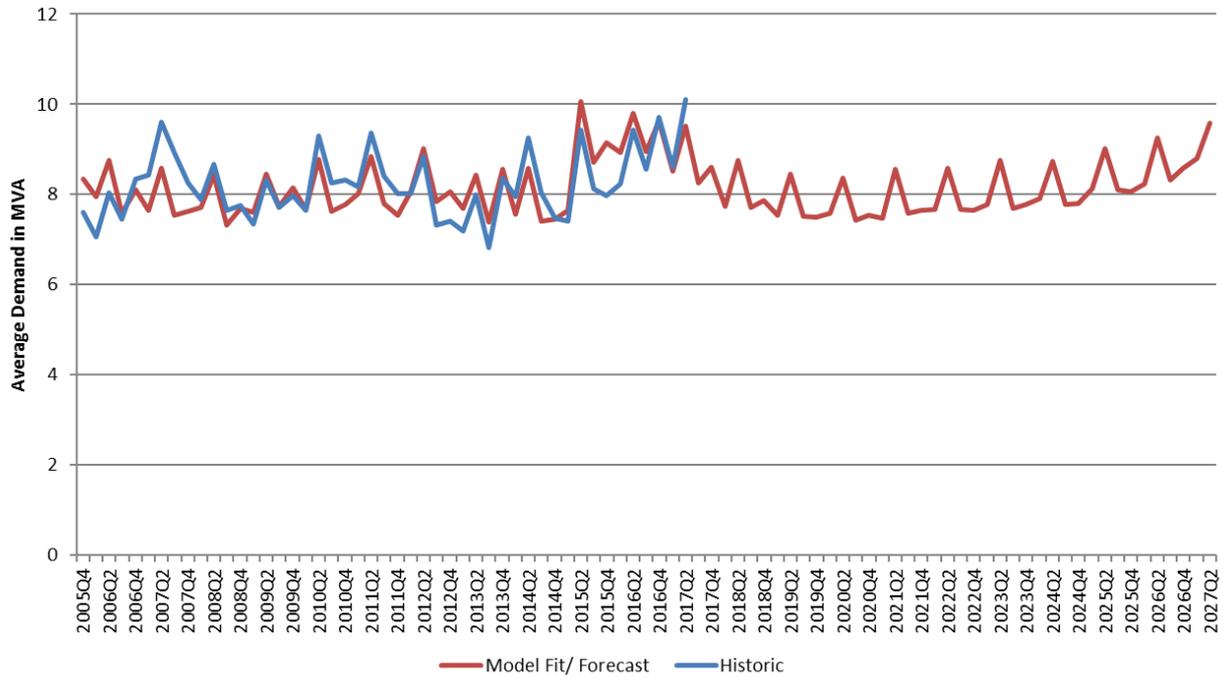
Table 16: Model Output for East Lake Zone Substation Average Demand

Dependent Variable: LOG(EAST_LAKE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/20/17 Time: 12:36
Sample: 12/01/2005 6/01/2017
Included observations: 47
Convergence achieved after 41 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000224	2.00E-05	11.20395	0.0000
CDD	0.000516	3.86E-05	13.34549	0.0000
LOG(FYSHWICK_POP)	0.294118	0.013959	21.07021	0.0000
D_EASTLAKE	0.091519	0.026859	3.407451	0.0016
D_EASTLAKE2	0.154968	0.054708	2.832656	0.0074
COMMERCIAL_HV_PRICE_N	-0.001687	0.000775	-2.176979	0.0359
MA(1)	1.038597	0.169839	6.115171	0.0000
MA(2)	0.750371	0.185507	4.044964	0.0003
SMA(3)	0.512815	0.172583	2.971411	0.0052
SIGMASQ	0.001292	0.000412	3.132658	0.0034
R-squared	0.837409	Mean dependent var		2.103895
Adjusted R-squared	0.797860	S.D. dependent var		0.090095
S.E. of regression	0.040507	Akaike info criterion		-3.347905
Sum squared resid	0.060710	Schwarz criterion		-2.954257
Log likelihood	88.67578	Hannan-Quinn criter.		-3.199773
Durbin-Watson stat	1.865141			

The dummy variable “D_EASTLAKE2” was included to account for the clear step-up in the average demand, which is visible in Figure 21 below starting winter (Q2) 2015. Moreover, the historical data lacks a clear seasonal pattern, observable in the historical data of many other zone substations. The forecast shows first a bit of decline, resulting from moving average processes and the impact of increasing commercial prices, but is expected to recover by the end of the forecasting period to levels of 2015-2017.

Figure 21: East lake Zone Substation Average Demand – Model Fit and Forecast



5.3.8 Fyshwick Zone Substation

Fyshwick, is an area with predominantly commercial and (light) industrial activities, and therefore has a very different seasonal average demand profile compared to the other zone substations.

Table 17 includes the model estimation output for East Lake Zone Substation. The East Lake average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days; and
- State Final Demand;

All regressors have the expected signs and are all significant. Adding variables for commercial price and energy efficiency did not improve the AIC and where not significant and therefore these were dropped.

A dummy variable was included to account for a negative spike in the summer of 2013/2014, improving the model significantly.

In the Fyshwick average demand model, the main driving factor is the ACT State Final Demand, representing economic development in the ACT. This matches with expectations as most customers in this area are commercial. Furthermore, automatic ARMA modelling was used to estimate the ARMA structure for the average demand.

Several auto-regression, seasonal auto-regression, moving average and seasonal moving average terms were included in the model to address the significant serial correlation issues.

As shown below in Figure 22 the forecasting model (and historical data) shows a cyclical time-series of average demand, with an increasing mean. In this case automatic ARMA modelling was helpful in determining this dynamic non-linear long-term pattern. Also observable is the less pronounced (though still significant) seasonal pattern compared to zone substations covering large residential areas.

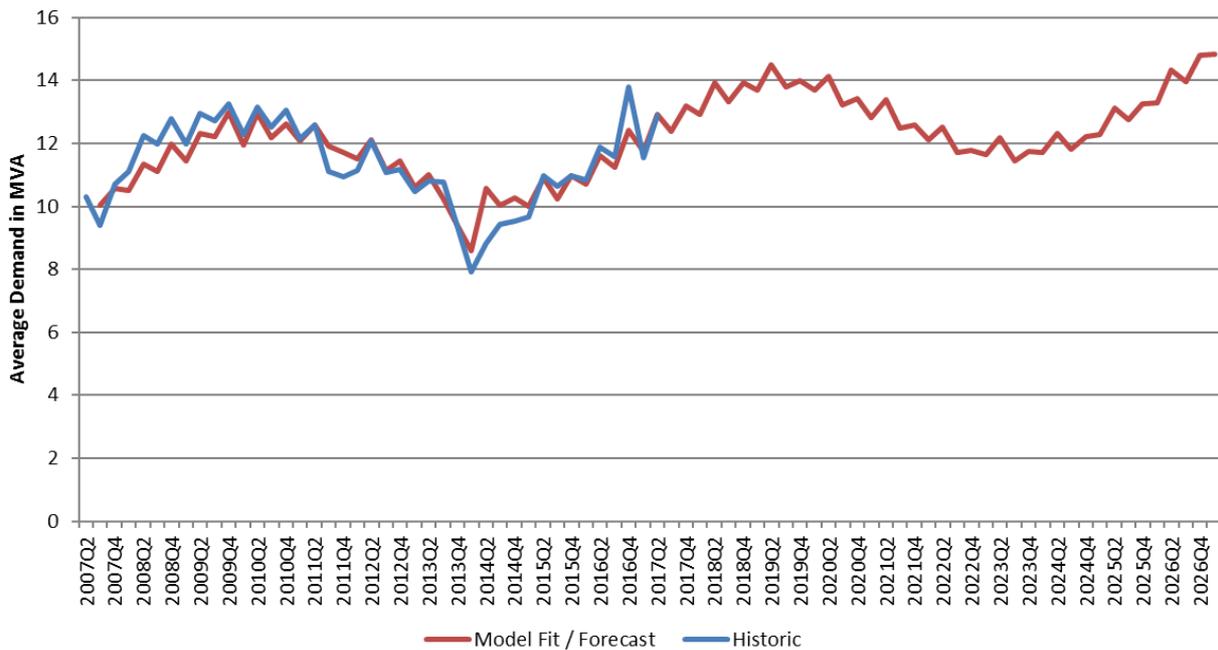
Table 17: Model Output for Fyshwick Zone Substation Average Demand

Dependent Variable: LOG(FYSHWICK)
 Method: ARMA Maximum Likelihood (OPG - BHHH)
 Date: 09/15/17 Time: 16:29
 Sample: 12/01/2005 6/01/2017
 Included observations: 47
 Convergence not achieved after 500 iterations
 Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CDD	0.000339	7.70E-05	4.396830	0.0001
HDD	0.000104	2.73E-05	3.804727	0.0005
LOG(SFD)	0.245824	0.002292	107.2426	0.0000
D_FYSHWICK	-0.136978	0.059939	-2.285281	0.0285
AR(1)	1.461691	0.006090	240.0187	0.0000
AR(3)	-0.506455	0.005499	-92.10032	0.0000
SAR(4)	-0.855536	0.767222	-1.115109	0.2724
MA(1)	-1.238979	26.89488	-0.046067	0.9635
MA(2)	-0.500216	6.676312	-0.074924	0.9407
MA(3)	0.752046	20.29585	0.037054	0.9707
SMA(4)	0.999727	155.6245	0.006424	0.9949
SIGMASQ	0.001330	0.194909	0.006825	0.9946

R-squared	0.923181	Mean dependent var	2.395488
Adjusted R-squared	0.899038	S.D. dependent var	0.133012
S.E. of regression	0.042264	Akaike info criterion	-2.977553
Sum squared resid	0.062518	Schwarz criterion	-2.505175
Log likelihood	81.97251	Hannan-Quinn criter.	-2.799794
Durbin-Watson stat	1.701446		

Figure 22: Fyshwick Zone Substation Average Demand – Model Fit and Forecast



5.3.9 Gilmore Zone Substation

Gilmore is situated at the south to north-east of the Wanniasa Hill nature Reserve in the north-eastern Tuggeranong area. The area covers a large suburban area with leisure and commercial activities.

Table 18 includes the model estimation output for Gilmore Zone Substation. The Gilmore average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days; and
- State Final Demand;

All regressors have the expected signs and are all significant.

We estimated models by adding variables for local population, commercial price and energy efficiency, but they did not improve the AIC and where not significant, and were therefore dropped from the equation.

A dummy variable (D_GILMORE2) was included to what looks like a structural change in the average demand from summer 2012. Similarly, we found that the Cooling Degree Days in Tuggeranong regressor only became significant from around summer 2012/13 and only when applied to the summer quarter (quarter 4 for each year). The latter was addressed in the model by interacting the CDD regressor with a dummy variable (CDD_T*D_GILMORE) designed to include CDD_T only in summer.

Furthermore, in the Gilmore ZS average demand model, the main driving factor is the ACT State Final Demand, representing economic development in the ACT. This is according to expectations as a few industrial clients and the Hume commercial zone (postcode 2620) is connected to Gilmore Zone Substation.

A moving average, and two seasonal moving average terms were included in the model to address the serial correlation issues.

Table 18: Model Output for Gilmore Zone Substation Average Demand

Dependent Variable: LOG(GILMORE)

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 09/15/17 Time: 17:18

Sample: 12/01/2005 6/01/2017

Included observations: 47

Convergence achieved after 22 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD_T	0.000450	3.15E-05	14.29038	0.0000
CDD_T*D_GILMORE	0.000791	0.000121	6.557089	0.0000
LOG(SFD)	0.227134	0.004311	52.68225	0.0000
D_GILMORE2	0.237506	0.055910	4.248023	0.0001
MA(1)	0.388383	0.167383	2.320329	0.0256
SMA(2)	0.602243	0.159737	3.770211	0.0005
SMA(4)	0.467204	0.209874	2.226113	0.0319
SIGMASQ	0.003954	0.001030	3.838252	0.0004
R-squared	0.950179	Mean dependent var	2.500313	
Adjusted R-squared	0.941237	S.D. dependent var	0.284749	
S.E. of regression	0.069026	Akaike info criterion	-2.326650	
Sum squared resid	0.185819	Schwarz criterion	-2.011731	
Log likelihood	62.67627	Hannan-Quinn criter.	-2.208144	
Durbin-Watson stat	1.843843			

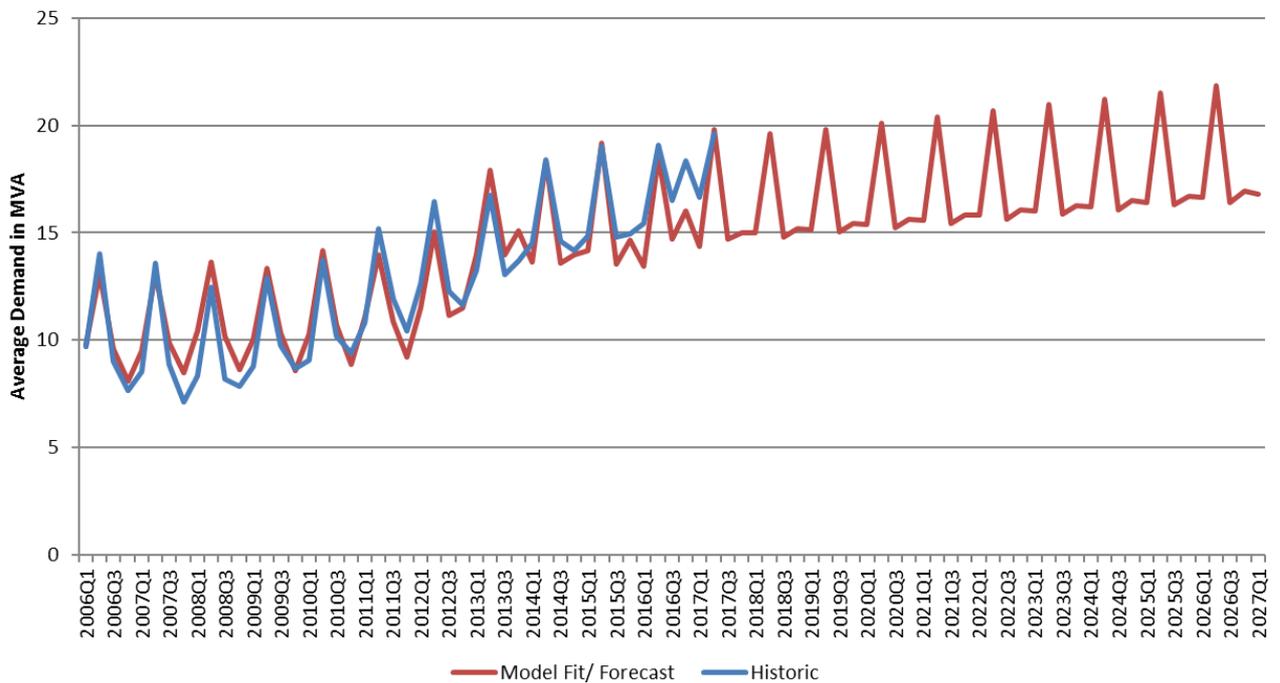
As shown below in Figure 23 the forecasting model (and historical data) depicts a slight increase from approximately 2013 onwards after a short period of very strong growth. This effect is picked up by the model

and a lower growth is projected forward. Also noticeable is the increasing summer load, as before 2013 this was structurally the season with the lowest load and it seems that this is no longer the case. Coincidentally around 2013 the Hume commercial area was in development, which most probably increased the air conditioner load in summer.

Finally, the last year of historical data shows very small differences between the seasonal average loads, potentially related to the relatively mild winter and warm summer of 2016/17.

Overall this model tracks reasonably well to the historical data except for last year’s spring, summer and fall. Therefore, unless the latter is a structural change (unable to determine at this time), the model should provide a reasonable forecast for input to the MEFM model.

Figure 23: Gilmore Zone Substation Average Demand – Model Fit and Forecast



5.3.10 Gold Creek Zone Substation

The model output for Gold Creek Zone Substation average demand is presented in Table 19. The Gold Creek average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days;
- Population in Gungahlin; and
- Residential Price.

The Included independent variables all have the proper signs. HDD, CDD, and population are as expected positively correlated to with the average demand in Civic and the residential price is as expected negatively correlated. Although the residential price did not show a significant effect, the decision was taken not to drop this variable as it improved the model through the AIC and R².

A dummy variable (D_GOLDCREEK) was included to address the effect of an outlier in Q1 of 2007.

The serial correlation in this model has been addressed by adding a moving average (AR[1]) to the model.

Table 19: Model Output for Gold Creek Zone Substation Average Demand

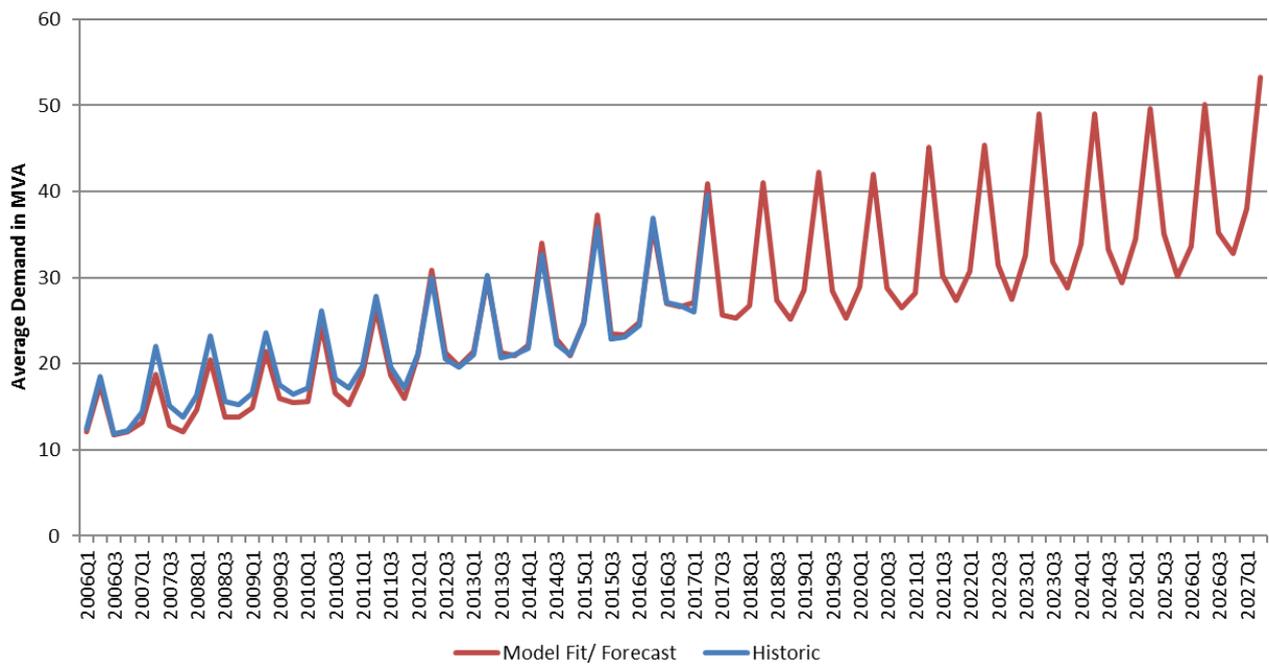
Dependent Variable: LOG(GOLD_CREEK)
 Method: ARMA Maximum Likelihood (OPG - BHHH)
 Date: 10/19/17 Time: 18:00
 Sample: 12/01/2005 6/01/2017
 Included observations: 47
 Convergence achieved after 36 iterations
 Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.579542	1.348902	-5.619047	0.0000
HDD	0.000688	1.89E-05	36.48610	0.0000
CDD	0.000924	5.09E-05	18.14974	0.0000
LOG(GUNGAHLIN_POP)	0.952029	0.131716	7.227920	0.0000
RESIDENTIAL_PRICE_N	-0.000661	0.000427	-1.546592	0.1300
D_GOLDCREEK	0.078250	0.016253	4.814622	0.0000
AR(1)	0.862458	0.102879	8.383208	0.0000
SIGMASQ	0.001095	0.000249	4.393812	0.0001

R-squared	0.987472	Mean dependent var	3.022955
Adjusted R-squared	0.985223	S.D. dependent var	0.298793
S.E. of regression	0.036321	Akaike info criterion	-3.609998
Sum squared resid	0.051451	Schwarz criterion	-3.295079
Log likelihood	92.83495	Hannan-Quinn criter.	-3.491492
F-statistic	439.1352	Durbin-Watson stat	1.967830
Prob(F-statistic)	0.000000		

Figure 24 depicts the average demand in historical and projected MVA for Gold Creek zone substation. Although it looks like the model seems to structurally underestimate the demand before 2012, for the more recent period after this date the model fit is very good.

Figure 24: Gold Creek Zone Substation Average Demand – Forecast and Historic Values



Furthermore, the forecast shows significant increasing average demand up to 2027. This is due to the expected strongly growing population in this area as a result of a significant number of residential developments. In addition, there is a widening gap between seasonal average demand increasing over time, this is partially the result of the serial correlation (autocorrelation) that was observed and addressed by included a first order auto regression term (AR[1]) in the model. This effect may either be explained by the increasing number of dwellings using electricity for heating purposes, or the impact of solar PV, increasing the difference between average demand in winter periods compared to intermediate seasons (spring and fall).

5.3.11 Latham Zone Substation

The model output for Latham Zone Substation average demand is presented in Table 20. The Latham average demand was estimated using the following independent variables:

- Heating Degree Days;
- Cooling Degree Days;
- Population in Belconnen;
- Residential Price; and
- Residential Energy Efficiency.

All independent variables in the model have the proper signs and are significant. No economic variable was included as it did not improve the model and was not significant. The latter was as expected because the Latham area is predominantly suburban and so residential development (population) was expected to have the most significant impact on average demand.

No significant serial correlation was detected after residual analysis, and therefore no auto regression or moving average terms were included in the model.

Table 20: Model Output for Latham Zone Substation Average Demand

Dependent Variable: LOG(LATHAM)
 Method: Least Squares
 Date: 10/19/17 Time: 18:13
 Sample (adjusted): 12/01/2005 6/01/2017
 Included observations: 47 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000618	1.39E-05	44.40642	0.0000
CDD	0.000665	4.18E-05	15.90331	0.0000
LOG(BELCONNEN_POP)	0.314280	0.021069	14.91668	0.0000
LOG(RESIDENTIAL_PRICE_N)	-0.103794	0.047916	-2.166181	0.0360
EE_RESIDENTIAL_N	-0.000163	8.37E-05	-1.947082	0.0582
R-squared	0.987129	Mean dependent var		3.412166
Adjusted R-squared	0.985903	S.D. dependent var		0.178440
S.E. of regression	0.021186	Akaike info criterion		-4.770639
Sum squared resid	0.018852	Schwarz criterion		-4.573815
Log likelihood	117.1100	Hannan-Quinn criter.		-4.696573
Durbin-Watson stat	1.873395			

Figure 25 provides us with the model fit and forecast. The model shows excellent fit with the historical data, providing significant confidence for the accuracy of the forecast. The forecast shows a somewhat declining average demand as a result of price and energy efficiency impact, supported by a relatively stable population in this area.

Figure 25: Latham Zone Substation Average Demand – Forecast and Historic Values

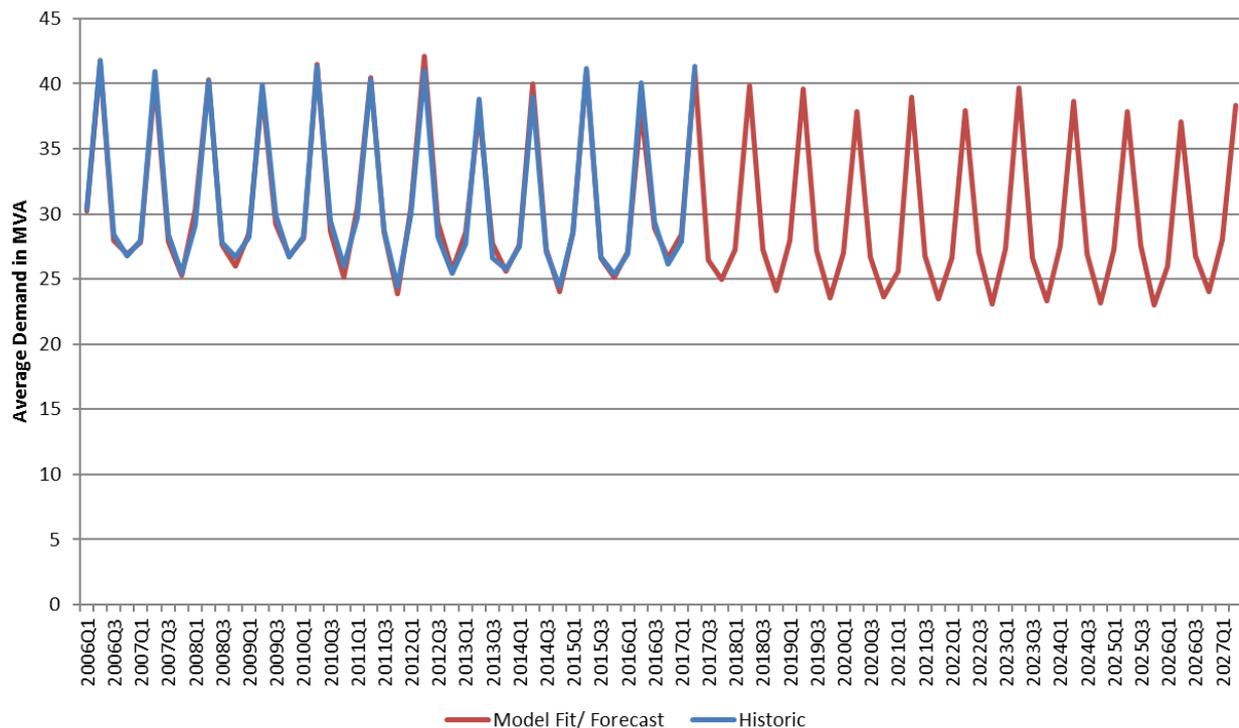
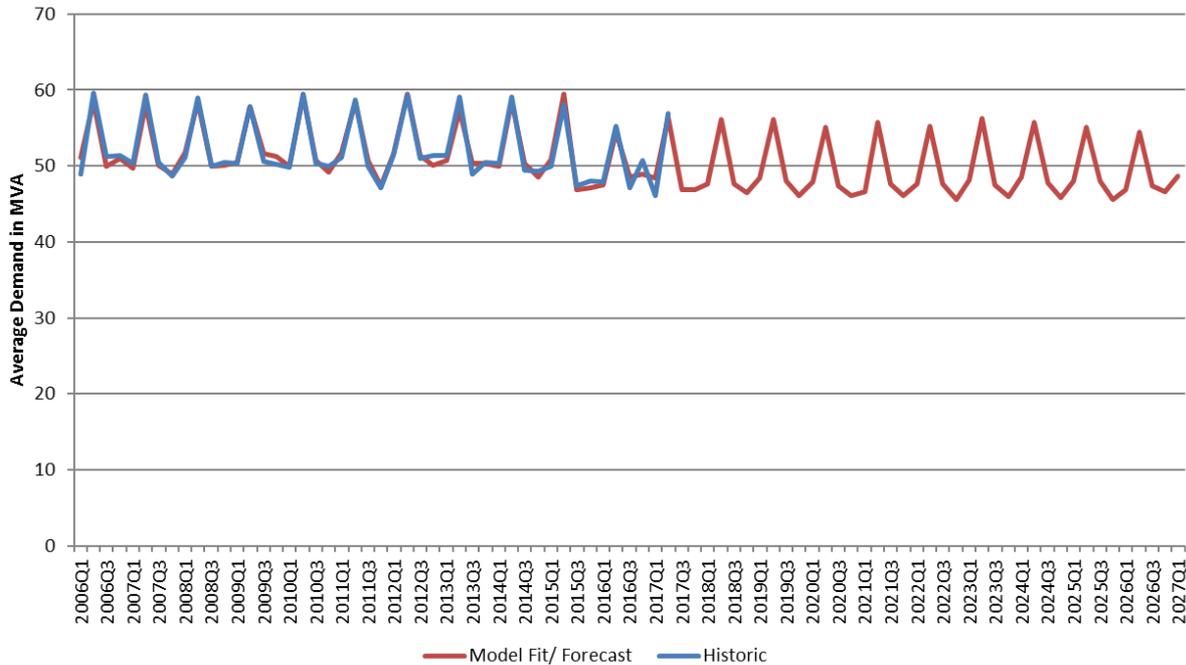


Table 21: Model Output for Telopea Zone Substation Average Demand

Dependent Variable: LOG(TELOPEA)
 Method: ARMA Maximum Likelihood (OPG - BHHH)
 Date: 09/14/17 Time: 13:19
 Sample: 12/01/2005 6/01/2017
 Included observations: 47
 Convergence achieved after 95 iterations
 Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000270	1.59E-05	16.96890	0.0000
CDD	0.000413	4.16E-05	9.930948	0.0000
LOG(SOUTH_CANBERRA_POP)	0.370907	0.001824	203.3973	0.0000
EE_RESIDENTIAL_N	-0.000191	2.99E-05	-6.387362	0.0000
D_TELOPEA	0.053437	0.006395	8.356082	0.0000
MA(3)	-0.542889	0.151005	-3.595180	0.0009
SIGMASQ	0.000315	8.68E-05	3.636297	0.0008
R-squared	0.943968	Mean dependent var		3.948542
Adjusted R-squared	0.935563	S.D. dependent var		0.075847
S.E. of regression	0.019253	Akaike info criterion		-4.903375
Sum squared resid	0.014828	Schwarz criterion		-4.627822
Log likelihood	122.2293	Hannan-Quinn criter.		-4.799683
Durbin-Watson stat	2.201344			

Figure 26: Telopea Zone Substation Average Demand – Forecast and Historic Values



5.3.13 Theodore Zone Substation

Table 22 provides an overview of the modelling results for Theodore zone substation. The Theodore average demand was estimated using the following independent variables:

- Heating Degree Days in Tuggeranong;
- Cooling Degree Days in Tuggeranong;
- Population in Tuggeranong; and
- Residential Price (with a 2 period lag).

The Included independent variables all have the proper signs. HDD, CDD, and population are as expected positively correlated with the average demand in Theodore and the residential price is as expected negatively correlated.

A dummy variable (D_THEODORE) was included to address the effect of an outlier in Q2 of 2007.

The serial correlation in this model has been addressed by adding a moving average (MA[1]) to the model.

Table 22: Model Output for Theodore Zone Substation Average Demand

Dependent Variable: LOG(THEODORE)

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 10/19/17 Time: 18:10

Sample: 6/01/2006 6/01/2017

Included observations: 45

Convergence achieved after 18 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD_T	0.000643	1.09E-05	59.13474	0.0000
CDD_T	0.000786	3.21E-05	24.52899	0.0000
LOG(TUGGERANONG_POP)	0.195157	0.005469	35.68230	0.0000
RESIDENTIAL_PRICE_N(-2)	-0.000625	0.000304	-2.052874	0.0470
D_THEODORE	0.109818	0.013574	8.090280	0.0000
MA(1)	0.603473	0.170833	3.532529	0.0011
SIGMASQ	0.000542	0.000124	4.369703	0.0001
R-squared	0.983507	Mean dependent var	2.523214	
Adjusted R-squared	0.980903	S.D. dependent var	0.183248	
S.E. of regression	0.025323	Akaike info criterion	-4.362081	
Sum squared resid	0.024368	Schwarz criterion	-4.081045	
Log likelihood	105.1468	Hannan-Quinn criter.	-4.257314	
Durbin-Watson stat	1.716901			

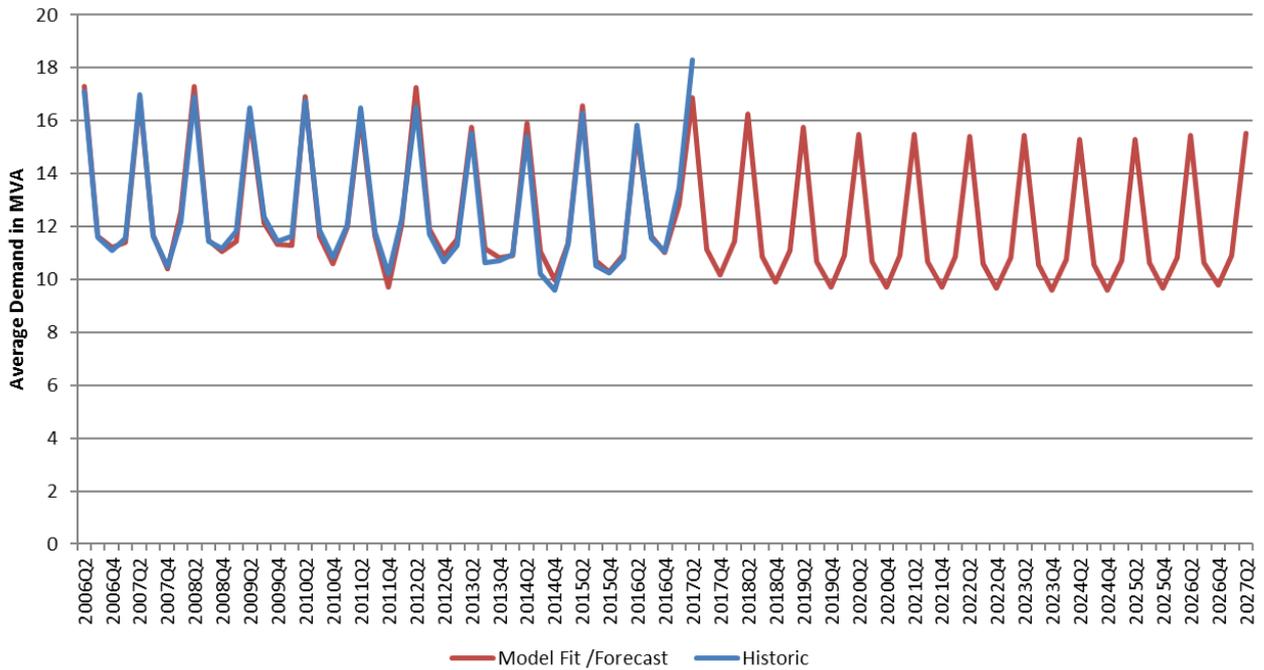
The average demand projections observed in

Figure 27 show a flat, just slightly descending average demand as would be expected in an area of projected decreasing population (Tuggeranong area) and expected increasing retail prices for residential customers.

The model fit can be considered good, except for the final season where the actual average demand seems to have reached its highest point in more than 10 years. After consulting ActewAGL about this anomaly, they noted that since the last quarter the measurements for this substation came from actual metered data as compared to SCADA obtained data, and that this has produced more accurate average demand.¹⁸

¹⁸ Even though this may have resulted in an underestimated average demand forecast, ActewAGL have noted that this should not pose any issues as the capex planning does not include any augmentations to Theodore Zone Substation.

Figure 27: Theodore Zone Substation Average Demand – Forecast and Historic Values



5.3.14 Wanniasa Zone Substation

Table 23 provides an overview of the modelling results for Wanniasa zone substation. The Wanniasa average demand was estimated using the following independent variables:

- Heating Degree Days in Tuggeranong;
- Cooling Degree Days in Tuggeranong;
- Population in Tuggeranong;
- Residential Energy Efficiency; and
- Unemployment.

The Included independent variables all have the proper signs. HDD, CDD, and population are as expected positively correlated, while energy efficiency and unemployment are negatively correlated with the average demand in Wanniasa. The price was not included as it was not significant and did not improve the model.

The Wanniasa zone substation covers a large area of largely residential activity north and south of the Mount Taylor Nature Reserve. In addition, there's also a fair bit of commercial activity around the area and therefore the significance of unemployment in the model is probable.

The serial correlation in this model has been addressed by adding a first order auto regression (AR[1]) and moving average (MA[4]) to the model.

Table 23: Model Output for Wanniasa Zone Substation Average Demand

Dependent Variable: LOG(WANNIASSA)
 Method: ARMA Maximum Likelihood (OPG - BHHH)
 Date: 09/15/17 Time: 17:34
 Sample: 12/01/2005 6/01/2017
 Included observations: 47
 Convergence achieved after 21 iterations
 Coefficient covariance computed using outer product of gradients

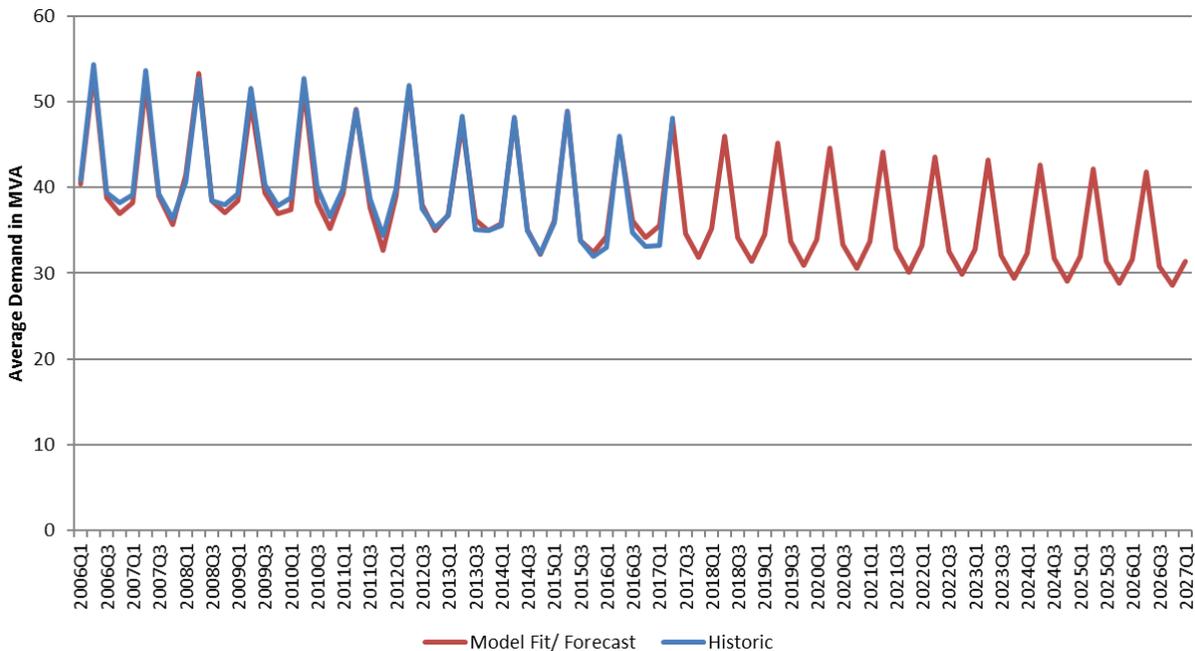
Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD_T	0.000502	1.37E-05	36.64535	0.0000
CDD_T	0.000569	3.73E-05	15.23750	0.0000
LOG(TUGGERANONG_POP)	0.306016	0.002642	115.8388	0.0000
EE_RESIDENTIAL_N	-0.000449	7.95E-05	-5.649428	0.0000
UNEMPLOYMENT	-0.011841	0.006891	-1.718383	0.0937
AR(1)	0.500275	0.135165	3.701218	0.0007
MA(4)	0.674994	0.196003	3.443795	0.0014
SIGMASQ	0.000298	8.06E-05	3.693439	0.0007

R-squared	0.987020	Mean dependent var	3.686835
Adjusted R-squared	0.984690	S.D. dependent var	0.153062
S.E. of regression	0.018939	Akaike info criterion	-4.881706
Sum squared resid	0.013989	Schwarz criterion	-4.566787
Log likelihood	122.7201	Hannan-Quinn criter.	-4.763200
Durbin-Watson stat	2.103240		

The average demand projections observed in Figure 28 show declining average demand, as would be expected in an area of projected decreasing population (Tuggeranong area), and increasing energy efficiency for residential customers.

The model fit can be considered good, except for the slight (structural) overestimation in the summers (Q4's) before 2013. However, over the last few years this effect is no longer observed.

Figure 28: Wanniasa Zone Substation Average Demand – Forecast and Historic Values



5.3.15 Woden Zone Substation

The Woden zone substation covers a large area in the south-west of Canberra. This zone area contains a mixture of mostly established suburban areas with significant commercial activities, and some regional developing zones.

Table 24 includes the model specification for Woden zone substation, it includes the following independent variables:

- Heating Degree Days;
- Cooling Degree Days;
- Population in Woden;
- State Final Demand; and
- Energy Efficiency for Business.

All variables in the model show the proper signs and are significant. A variable for price was not included as it was not significantly correlated with average demand and did not improve the overall model.

State final demand and energy efficiency for business were found to be significantly correlated to the average demand in Woden. This is according to expectations, given the commercial activity, the Canberra Institute of Technology and the Hospital in the Woden Valley.

Lastly, we observed serial correlation in the residuals and addressed this issue by including a first order auto-regression term in the model. The result was a model with a high model fit of 0.95 Adjusted R-squared.

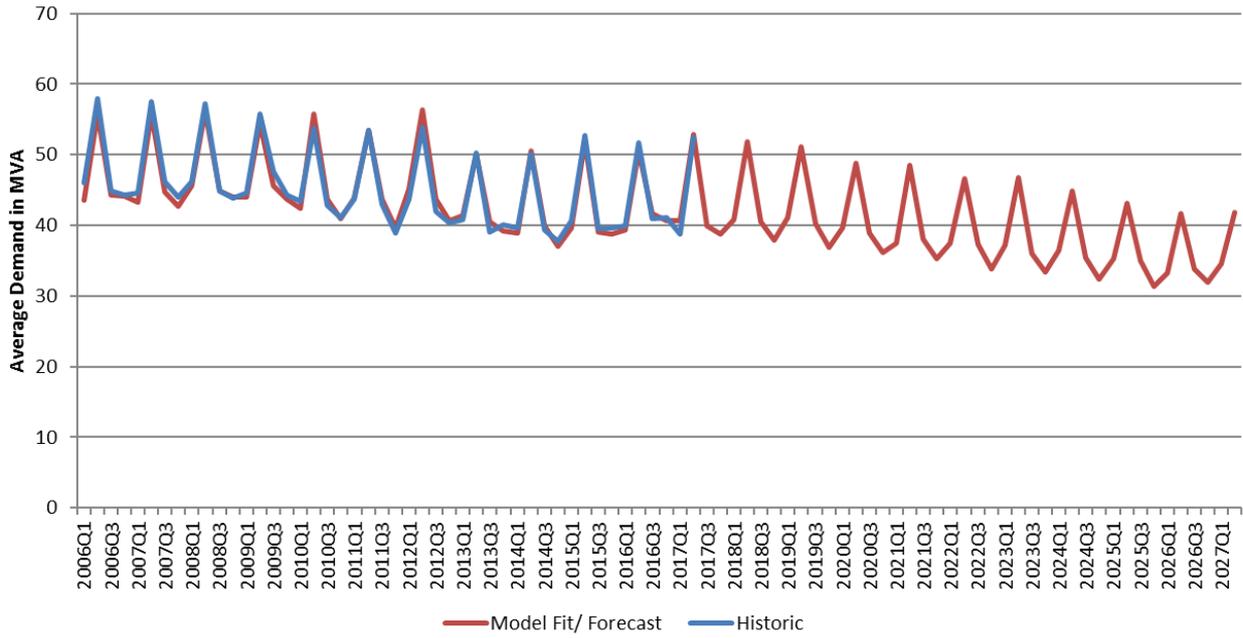
Table 24: Model Output for Woden Zone Substation Average Demand

Dependent Variable: LOG(WODEN)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/15/17 Time: 18:12
Sample: 12/01/2005 6/01/2017
Included observations: 47
Convergence achieved after 103 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000395	1.63E-05	24.29383	0.0000
CDD	0.000486	4.35E-05	11.17882	0.0000
LOG(WODEN_POP)	0.083992	0.013592	6.179573	0.0000
LOG(SFD)	0.348632	0.008900	39.17324	0.0000
EE_BUSINESS_N	-0.003873	0.000195	-19.84019	0.0000
AR(1)	0.379275	0.136482	2.778941	0.0083
SIGMASQ	0.000576	0.000170	3.387946	0.0016
R-squared	0.960188	Mean dependent var		3.805642
Adjusted R-squared	0.954216	S.D. dependent var		0.121624
S.E. of regression	0.026024	Akaike info criterion		-4.319664
Sum squared resid	0.027091	Schwarz criterion		-4.044110
Log likelihood	108.5121	Hannan-Quinn criter.		-4.215971
Durbin-Watson stat	2.012464			

Figure 29 provides a visualisation of the model fit and forecast. The model fit looks good and the forecast is showing a significantly declining trend. The relatively stable population in the area and the strong impact of energy efficiency for business is resulting in declining overall average demand.

Figure 29: Woden Zone Substation Average Demand – Forecast and Historic values



5.4 Forecast Evaluation

We have included the Theil Inequality Coefficient (TIC) and the Theil U2 Coefficient (TU2C) for each of the zone substation average demand forecasts in Table 25 below.

All reported Theil Inequality Coefficients (TIC's) show values very close to zero indicating all models are well fitted and theoretically should also provide good forecasts.

Additionally, the Theil U2 Coefficients included in the below table are all significantly lower than 1, indicating the developed models all perform better than the respective naïve models.

However, we do observe that for some zone substations the TU2C values are higher, primarily: City East, Fyshwick, East Lake and Gilmore. This is the result of the specified models containing more than one AR and/or MA term in the equation, and are therefore closer to a naïve model (refer to section 5.2.4.3).

Table 25: Forecast Evaluation Information by ZSS

ActewAGL ZSS	TIC	TU2C
System	0.007076	0.084064
Belconnen	0.012717	0.171382
City East	0.013810	0.227373
Civic	0.006998	0.128392
East Lake	0.033036	0.575586
Fyshwick	0.025183	0.683376
Gilmore	0.041904	0.381553
Gold Creek	0.029253	0.255500
Latham	0.010070	0.078341
Telopea	0.009326	0.152154
Theodore	0.014378	0.111816
Wanniassa	0.011243	0.105882
Woden	0.012510	0.137402

5.5 Integration of Average Demand Forecasts in MEFM

This section provides a summary of the main steps taken to run the complete MEFM model and integrate Jacobs' average demand models into the main model at the ZSS level.

Integration of the average demand models into the MEFM firstly required time series back-casts of the historic output of residential PV systems (PVBC) for each zone substation, using the PV model described in Section 3.3. Once the PVBC time series for each ZSS was calculated, it was aligned with the observed demand time series.

Jacobs created a macro to assist in this process which is adequately dynamic for future use. The user defines the location of the input files applicable to the specific ZSS of interest. The macro then calculates 15-minute energy and reactive power time series for each of the defined meters and saves the results. The calculated time series data for each meter were then imported into excel and aggregated to the ZSS level to produce a half-hourly MVA time-series of observed demand for each ZSS.

The sum of the observed demand and PVBC at each time-step was calculated to yield the underlying demand time series. Underlying demand was then aggregated by season and year to produce a seasonal average underlying demand series, and the Average Daily Demand (ADD) for each ZSS. These time series were plotted and checked for anomalies. Daily plots of the ADD, Demand, PVBC and UL Demand time series were also inspected. Anomalies were either corrected or removed from the data set.

After verification that the input data was all acceptable, the data were converted to a form suitable to be input to ActewAGL's existing forecasting process in R. An additional adjustment to the summer demand files produced in the previous modelling period had to be made to correct the issue whereby the observed demand data was aligned to daylight savings time rather than AEST.

Following data processing, the underlying demand series and solar back-casts, as well as a number of predefined formulae to calculate battery storage and PV capacity time series were delivered as inputs to the R forecasting code, and the forecasts run from the top.

Appendix A. Description of Steps Taken to Select Final Model

When different models with multiple regressors are compared against each other, the AIC (or Schwarz or Hannan-Quinn criterion) is generally used as selection criteria. These criteria apply penalties for over-fitted models, with the Schwarz and Hannan-Quinn criterion being more restrictive than the AIC.

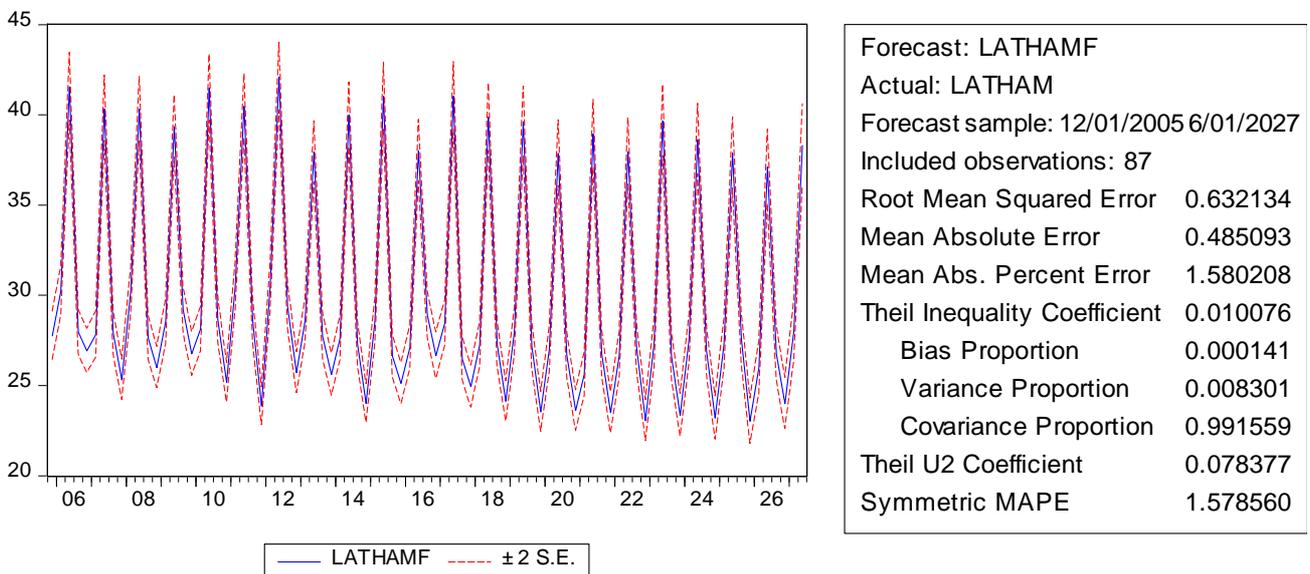
Furthermore, EViews has an automatic dynamic forecasting function that produces a forecast time series based on the model that has been specified. It includes ARMA (dynamic) terms by default, calculates and reports forecasting evaluation criteria including a forecast output graph. The forecast output graph for Latham substation. On the left hand side, the Theil Inequality Coefficient is published, this output provides a quick evaluation of the forecasting model. The Coefficient always lies between 0 and 1, where 0 indicates a perfect fit. The coefficient is based on the observed bias, variance, and covariance:

- The bias proportion tells us how far the mean of the forecast is from the mean of the actual series;
- The variance proportion tells us how far the variation of the forecast is from the variation of the actual series; and
- The covariance proportion measures the remaining unsystematic forecasting errors.

In a good model, the bias and variance proportions should be small so that most of the bias is concentrated on the covariance proportion (note from the figure below that three coefficients add up to 1).

The model output for the Latham zone substation displayed below in shows a low Theil Inequality coefficient with most of the variance attributable to unsystematic forecasting error, implying that the model shown is well fitted and theoretically should also provide a good forecast.

Figure 30: Forecast Output Graph for Latham Zone Substation



The Theil U2 coefficient is also a useful indicator for forecast evaluation purposes. A Theil U2 coefficient greater than one ($TU2 > 1$) indicates the forecasting model performs worse than the “naïve model”¹⁹, while a Theil U2 coefficient smaller than one ($TU2 < 1$) indicates that the specified model performs better than the naïve model. A Theil U2 coefficient of zero ($TU2 = 0$) indicates a perfect fit.

The final step in the selection process was the analysis of the graphical representation of the forecasting model against the actual historic data, including how the projections relate to the historically observed average demand patterns. This is especially important when structurally different models have to be compared; including

¹⁹ A naïve model simply estimates the future value (Y_{t+1}) to be equal to the current value (Y_t)

models with log-transformed or differenced dependent variables versus models with dependents that are not transformed, as these cannot be selected on the basis of AIC.

In addition, even though a reported AIC may look favourable for a certain model, in practise (visually) this may not look reasonable (e.g. this may occur when using auto ARIMA functions only). Determining whether the models look visually correct is mostly dependent on checking whether the model outputs make sense given its specification, e.g. if the zone substation is in a development area and a population variable is included, we expect to see a growth of average demand as compared to a flatter development of average demand in stable suburban areas. If there were any unexpected developments observed, we would look for a specific explanation or if none exist tried to re-specify or select an alternative model.