Demand Forecasting Update and Support

Evoenergy

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5	27/11/2018	Revised Final Draft – Demand Forecast Updates	MFS	LP	MFS
6	28/11/2018	Revised Final Report	MFS	LP	MFS/LP

Contents

Executive Summary

Evoenergy engaged Jacobs to assist with the development of the demand forecast for the Evoenergy distribution network. Jacobs assisted Evoenergy in two phases. The first phase included a detailed review of Evoenergy's existing demand forecasting methodology and draft results, providing recommendations for improvement. The second phase comprised support and collaboration between Evoenergy 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 Evoenergy's demand forecasting approach, methodology and report. Nearly all the recommendations put forward have been implemented by Evoenergy.

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 Evoenergy'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 Evoenergy'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 Evoenergy has in Jacobs' opinion vastly improved from both a structural perspective as well as from an explanatory view as compared to Evoenergy's initial draft. The methodology and approach currently used by Evoenergy 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.

Evoenergy'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

Evoenergy = Evoenergy 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 Evoenergy that will improve existing approaches for demand forecasting. During the preparation of this report Jacobs has relied upon information provided by Evoenergy, as well as information in the public domain. If Evoenergy 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 Evoenergy and no liability is accepted for any use or reliance on the report by third parties.

1. Introduction

Evoenergy 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 Evoenergy'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 a challenge to predict 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 consider 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 Evoenergy Distribution (Evoenergy) 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 Evoenergy'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 Evoenergy 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	**Invest in forecasting** 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.	Regular meetings between the Evoenergy 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.
2a	**Incorporate structural change other than PV** 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.	Jacobs provided historical data and projections on EV, energy efficiency and batteries based on published AEMO reports. The modifications were: The energy efficiency data was used to develop the seasonal average Zone Substation (ZSS) demand forecast (ref section 5) Electric vehicles and battery uptake were treated as post modelling adjustments in the final demand model (ref Evoenergy demand forecasting report)
2b	**Directly integrate structural change due to solar PV in the projections** 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.	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.
3	**Improve model parsimony** 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.	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. 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 Evoenergy 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.
5a	**Daylight saving** Check if daylight saving has been handled properly in the ZSS time-series.	The handling of daylight saving has been assessed and corrected by the Evoenergy forecaster.

No.	Description of critique/recommendation	Addressed as
5b	**Solar profile** 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.	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.
5c	**Retail price projections** Update the retail price projections. We understand that the current forecast is indexed with AEMO 2015/16 projections and Evoenergy 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).	Jacobs provided these projections for three different scenarios: • Neutral Economic Growth • Weak Economic Growth • Strong Economic Growth The above scenarios and the retail price projections methodology are described in detail in section 4.
6a	**Document data preparation** Document approach to cleaning zone substation data, including the nature and reason for any outliers removed.	Jacobs has supported this process by providing resources to assist Evoenergy'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.
6b	**Document models and assumptions** Jacobs has recommended that Evoenergy 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.	Jacobs supported Evoenergy in providing this documentation. This report will be an important input for Evoenergy 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 where taken.
7a	**Improve ex-ante and ex-post assessment** 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: 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? It is generally best practice to have forecasts reviewed by someone who did not do the work. 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.	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. 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. Additionally, Evoenergy included forecast evaluation by means of ex-ante and ex-post assessments of the system forecast for both summer and winter peak demand.

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 methodology that 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.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 Evoenergy'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).

Evoenergy 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.

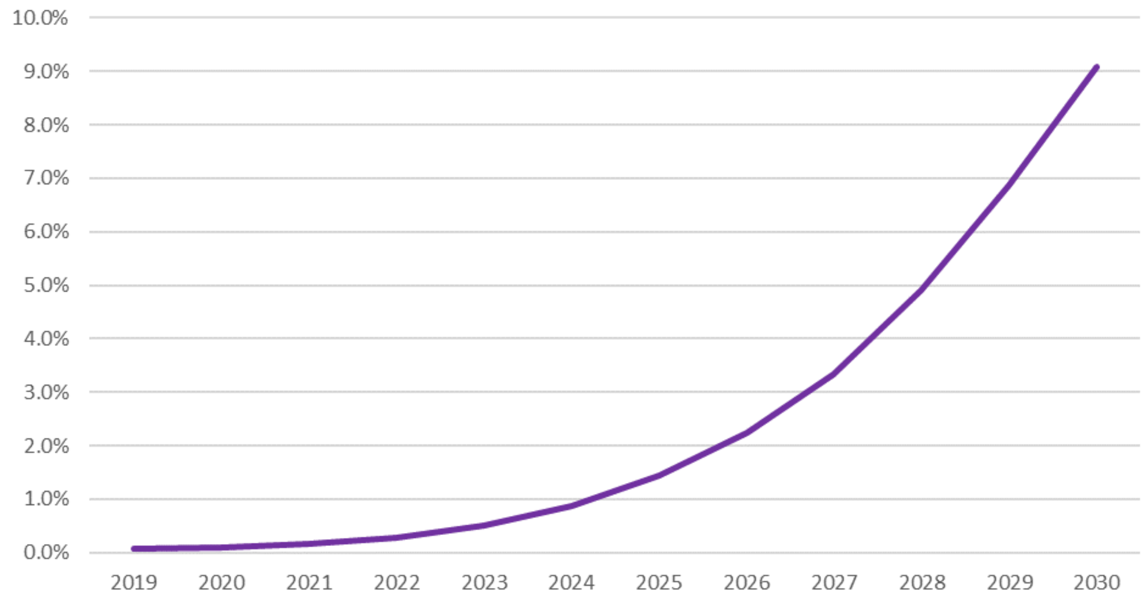
3. Structural Change

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 ESOO 2018

3.2 Energy Efficiency

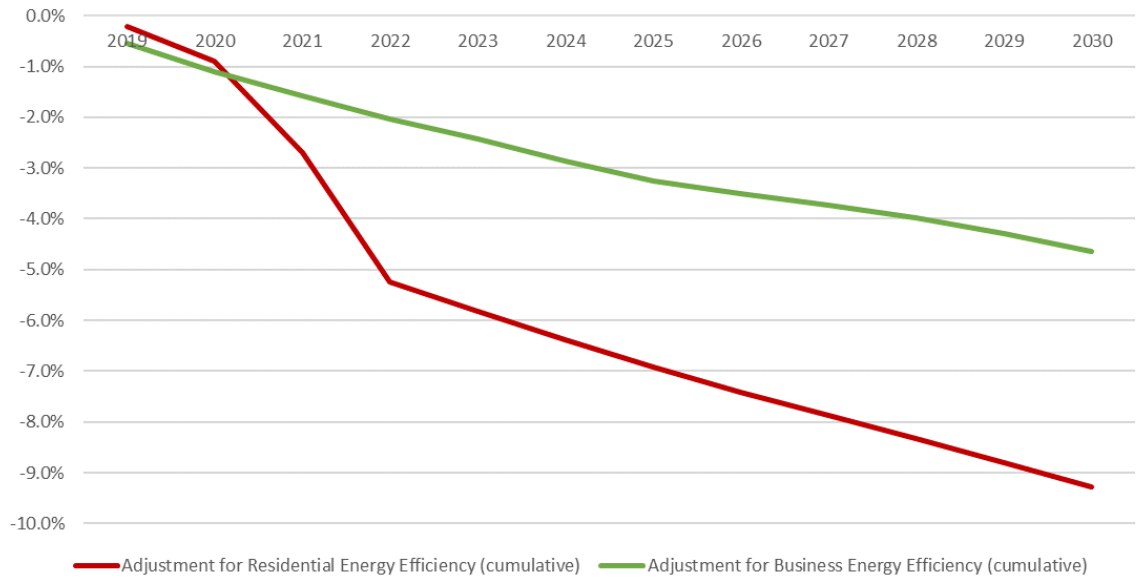
Energy efficiency has made a significant impact on energy consumption in recent years and is expected to have a continuing and ongoing impact.

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 Evoenergy. 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 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 ESOO 2018

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 Evoenergy. 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

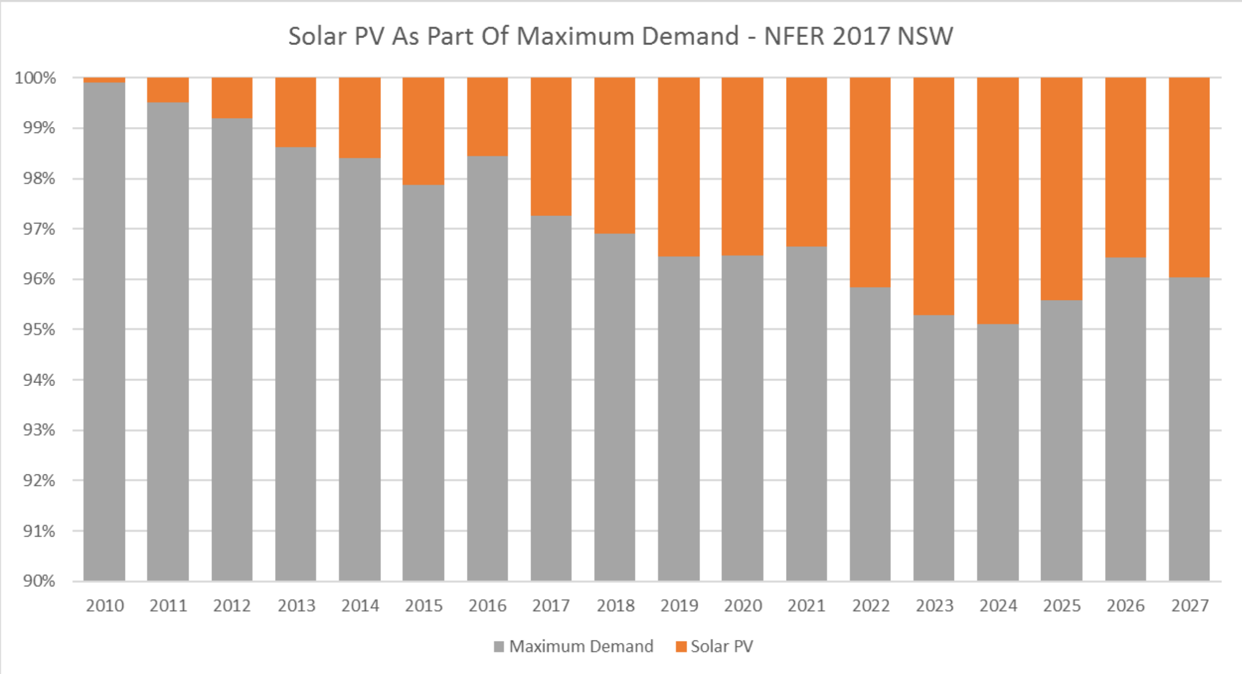
Adequately understanding the PV load and its impact on average demand and demand profiles is an essential part of a distribution utility's forecasting toolkit.

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 underlying[1] 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)



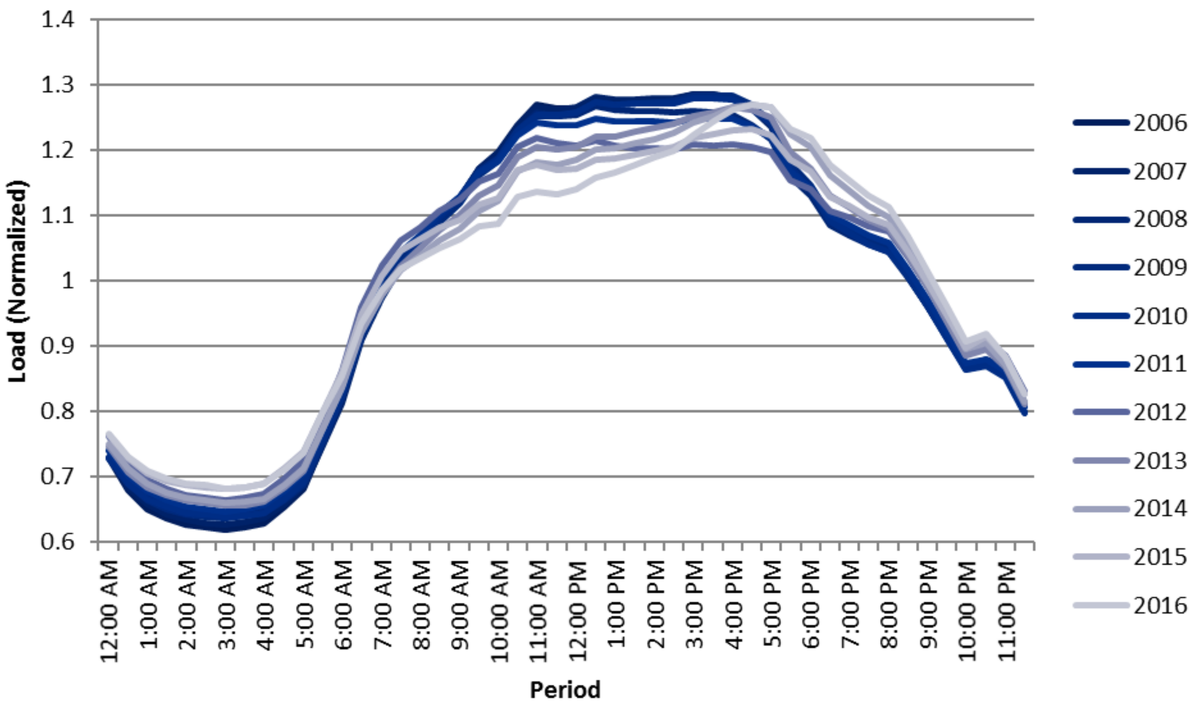
3.3.2 How PV Impacts Electricity Demand

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 correct for general load growth – the result of this correction is the 'normalized' load shape, which is shown in Figure 4.

Figure 4: Normalised 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.

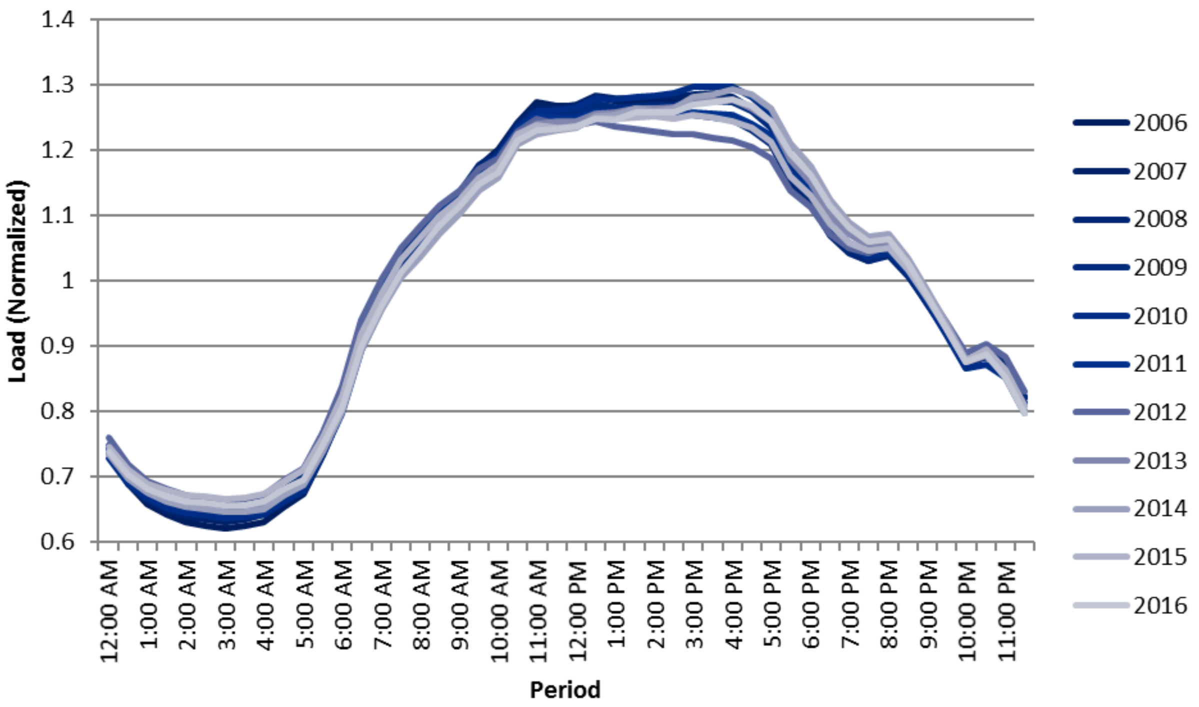
The MEFM approach blends a long-term model that captures growth in overall demand over years with a short-term model that predicts how temperature and other short-term phenomena affect the half-hourly load shape. The MEFM approach assumes that the normalized demand profile used does not change in any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

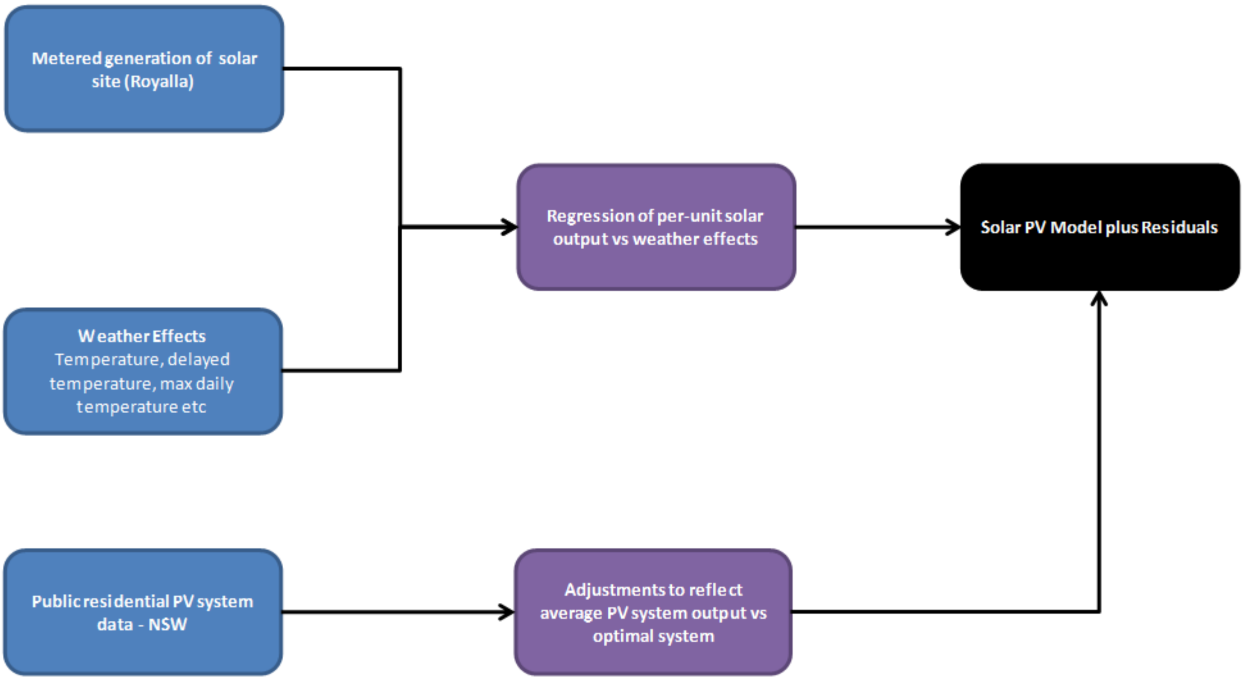
- There is significant uncertainty as to how the behaviour of groups of PV systems spread over a large geographic area compares with single systems. During days of consistent cloud cover the majority of all systems in the ACT may experience reduced production, while intermittent cloud cover may affect 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 publicly 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 to better integrate with Evoenergy's existing approach, with the code provided to Evoenergy 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.

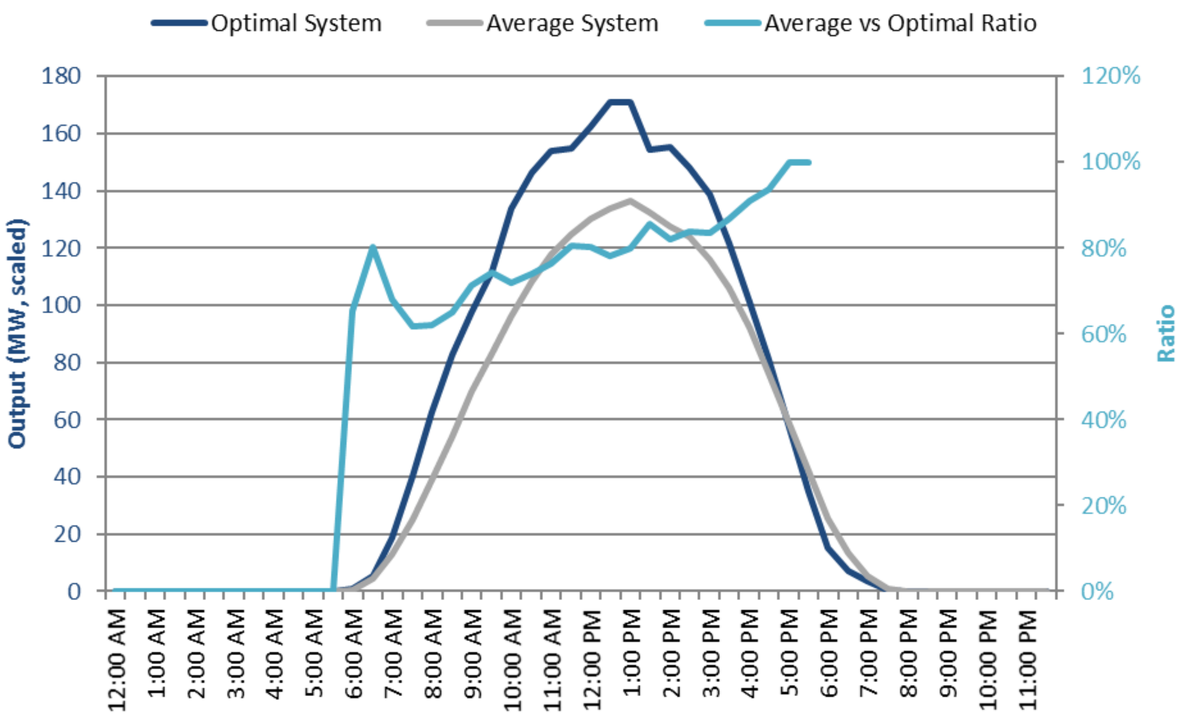
We have used Royalla to develop the solar model because this is a site for which there is interval metered data available, and which can be assumed to have panels oriented in an optimal way for solar exposure and to be free from shading effects. While Evoenergy has several series of gross metered residential 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 Evoenergy'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 Evoenergy will test to select the optimal solar model using the same criteria as in the demand forecasting – an AIC[2] 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 form 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 through 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.

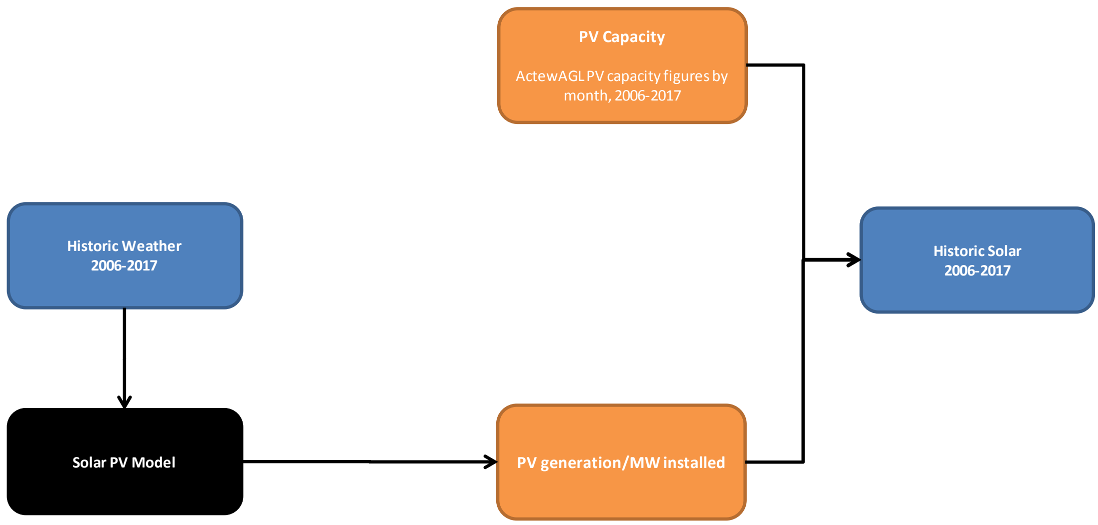
The result of this process is a statistical model that predicts the output of small-scale PV systems on a half-hourly basis as a function of weather and temperature variables (which are used as a proxy for solar exposure). The model produces results on a per-MW basis, which lets us adjust the results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



Evoenergy 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 Evoenergy.

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 Evoenergy is developing its forecasts using underlying demand, we need to subtract our forecast of solar PV from these results 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 Evoenergy 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.

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 Evoenergy's existing forecasting methodology to create a demand model using the MEFM.
3) When Evoenergy 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

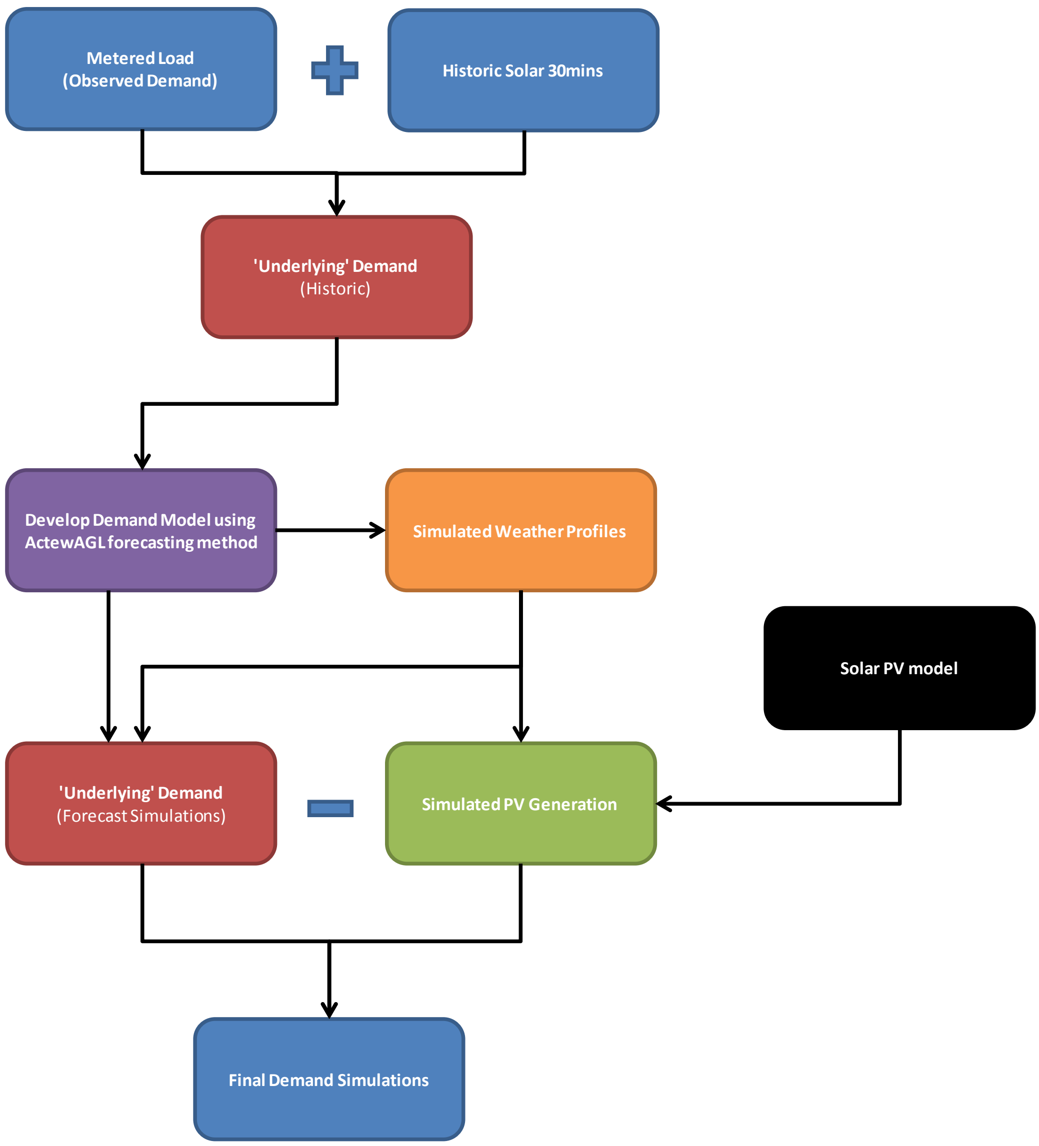
The lack of available, reliable metered data for residential PV systems means that there is no way to completely validate the models of residential PV generation. We also make several assumptions in our PV models, such as how the average ACT system performs compared with optimal systems, and how well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

Figure 9: Illustration of Solar PV Integration Into Demand Forecasting



- 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.

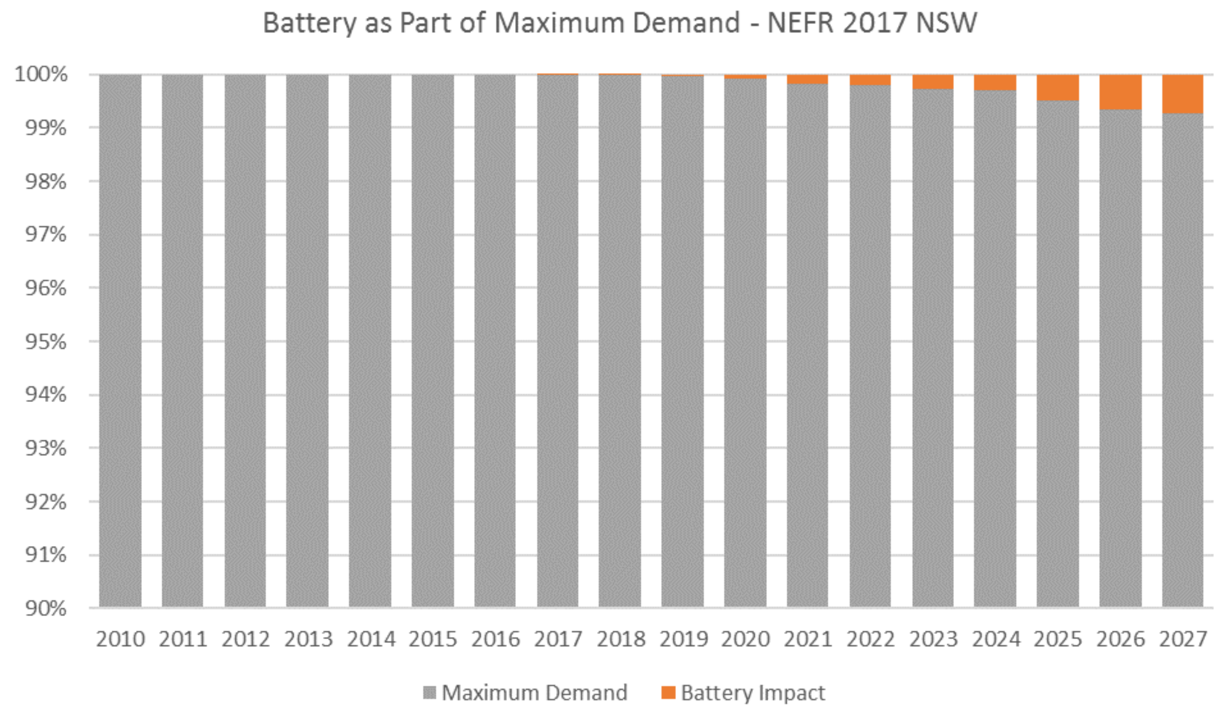
All forecasting models contain some level of simplification, assumptions and error, and we consider that the PV forecasting approach we have used captures the significant impacts of small scale PV on the system load profile without compromising the accuracy or confidence range of the demand forecasts.

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

In October 2018 Evoenergy requested Jacobs to update their zone substation demand forecasts utilising the latest historical demand data. At the same time Jacobs has taken the opportunity to update the retail price forecast for the ACT by applying the same methodology as described in section 4.3.

Apart from some relatively minor changes to network tariffs, larger changes have been implemented as a result of the revised wholesale price forecasts developed by Jacobs in 2018. Jacobs has used recent wholesale steady state price forecasts developed for our clients to inform their project's revenue projections to reach financial close. The updated price projections used in the new retail forecasts will provide more accurate retail price projections going forward.

For the update we have only developed one retail price forecast scenario.

[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 in section 4.3. The key features of the graph are as follows:

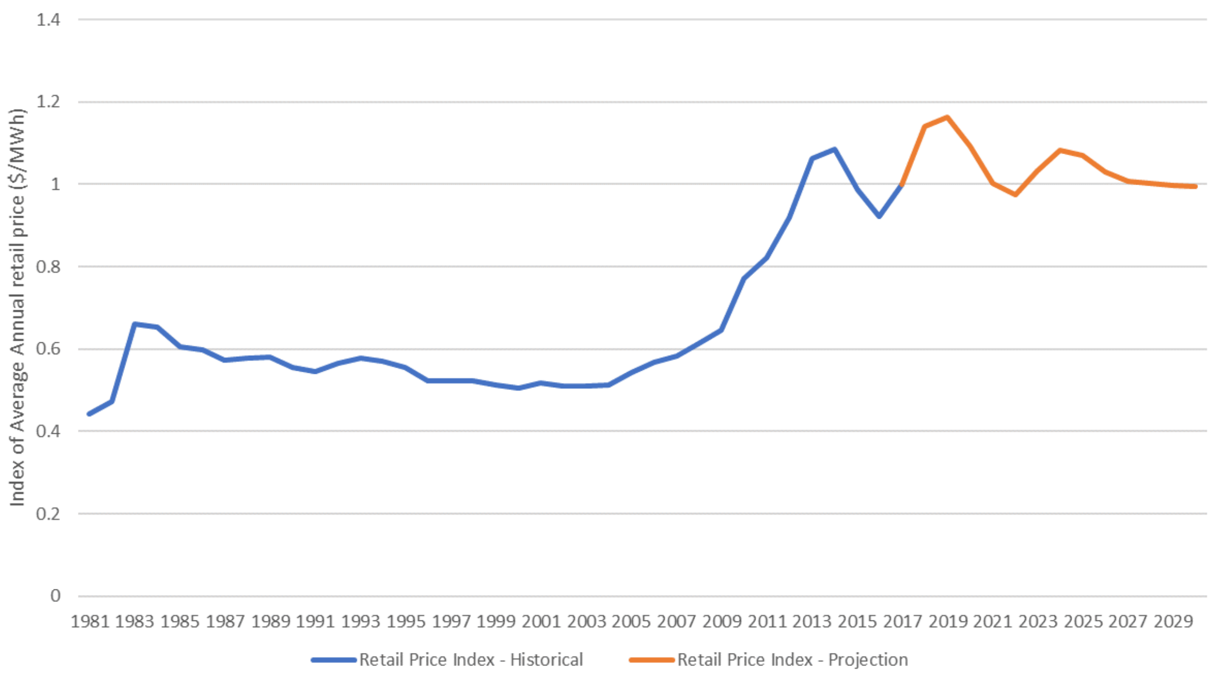
- Residential retail prices exhibited relatively little movement in real terms from 1983 until 2003.
- Prices increased from 2003 until the present, and this increase was mostly driven by rising network charges. A price bump is evident in 2013 and 2014 with the introduction and subsequent repeal of the 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 because of increases to forward contract prices.
- Retail price forecasts exhibit three distinct behaviours across all markets and scenarios:

  (i) increasing trend between 2017 and 2019 of approximately 8% per annum on average;

  (ii) declining trend between 2019 and 2022 of around 6% per annum as several renewables come online; a slight rise in 2023 resulting from Liddell PS retirement, and

  (iii) levelling out from 2027 onwards to 2017 price levels, when new renewable generation enters the market.

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



Source: Jacobs' analysis

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 Commission[5]. 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 several 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).

4.3.2 **Wholesale contract portfolio mix**

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 for the purpose of the retail price forecasts for NSW and ACT are 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.

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-Repor.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.

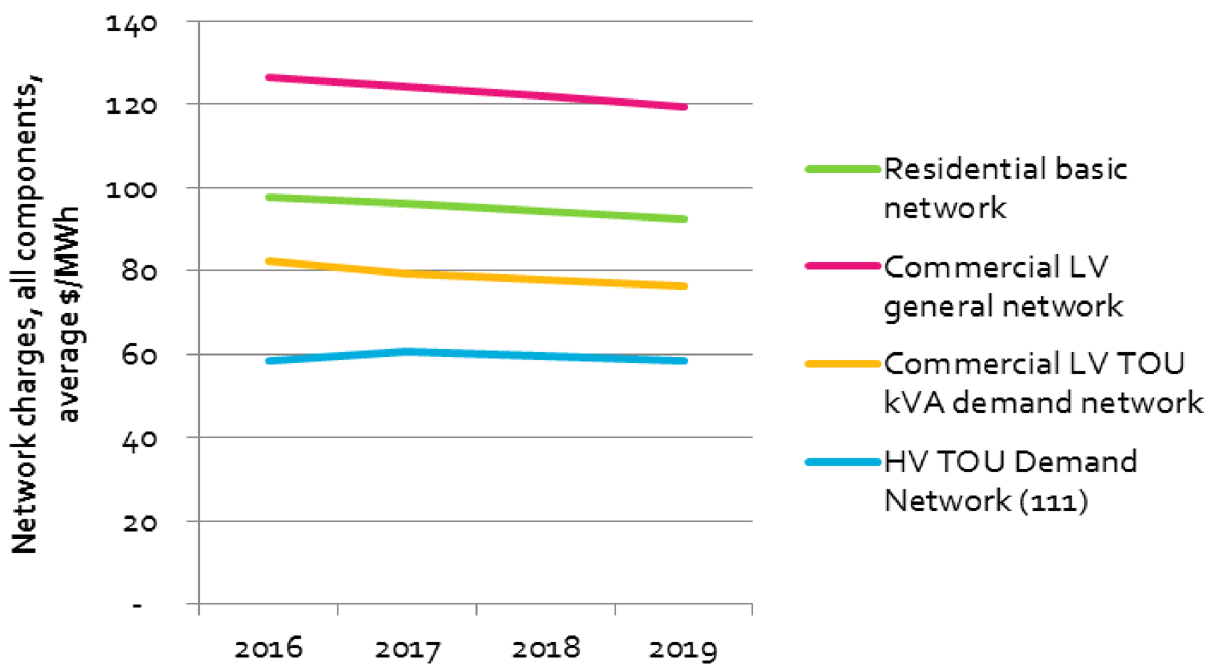
The individual network tariff is made up of different cost components. Fixed charges such as standing charges and prescribed metering service charges are the charges applying to all the connected retailers in the distribution zone irrespective of their network usage. There are also variable charge components 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. Representative[6] 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 Evoenergy, 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
Annual usage, kWh/customer/year					
ACT	Evoenergy	6,811	32,257	480,319	13,474,139
Representative tariff					
ACT	Evoenergy	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. 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:

Average cost of SRES and LRET = (RPP * LGC + STP * STC) * 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 website[7], 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 higher than 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 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 can 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:

Retailer feed-in tariff x % share of solar PV generation

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

Feed-in tariff	Cost recovery
ACT feed-in tariff (large scale) 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. *ACT feed-in tariff (small scale, legacy)* 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.	Network tariffs include provision for feed-in tariffs. Assume 5.5 c/kWh over projection period to cover retailer benefit (based on NSW estimates)

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 statement[8] 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 budget[9]. 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

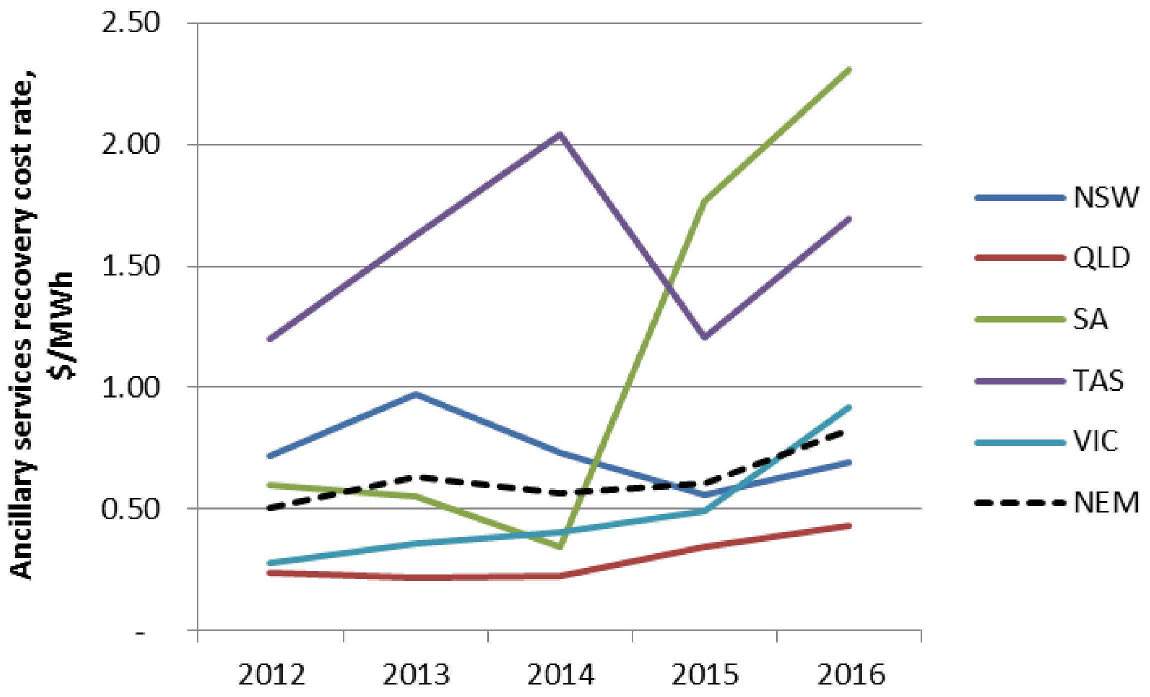
Year ending June	NEM Fees, Nominal	NEM Fees, Real	Full Retail Contestability	National Transmission Planner	Energy Consumers Australia	Total
2017	0.39	0.39	0.06	0.02	0.01	0.48
2018	0.40	0.39	0.06	0.02	0.01	0.49
2019	0.41	0.39	0.06	0.02	0.01	0.48
2020	0.42	0.39	0.06	0.02	0.01	0.49
Post 2020 assumption		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-Satement-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 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 Evoenergy in the development of the monthly average daily demand forecasts for each of their 12 zone substations.[10] In particular, we assisted with the following tasks:

- Verification of historical demand data from the Evoenergy 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 Evoenergy 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 Evoenergy 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, Wanniassa and Gilmore.

Table 8: Zone Substations in the Evoenergy Distribution Network

Evoenergy 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	Wanniassa	ACT South
Gilmore	ACT South	Woden	ACT South-west

[10] In the previous version of this document we used

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, Wanniassa. 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 Evoenergy 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 structure[11], 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 where 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 where 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
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

[11] Partially the result of Jacobs modelling the average demand forecasts by ZSS with Eviews.

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 Evoenergy

The above steps will be briefly discussed in the following subsections

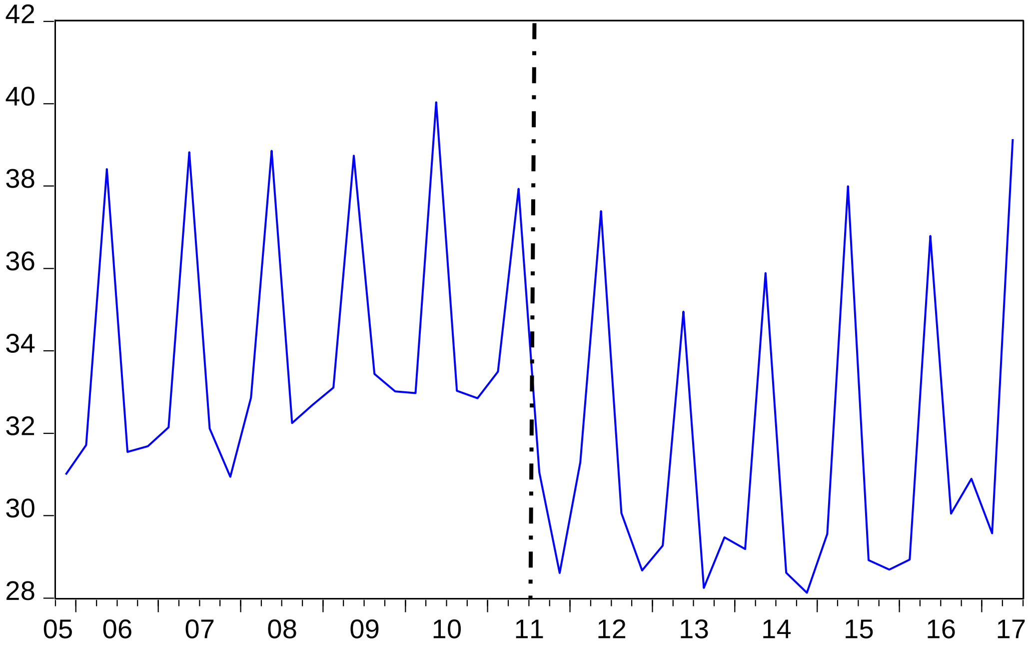
5.2.4.1 Visual Inspection of Historic Data

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 Evoenergy'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 Evoenergy. 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 structural change did not provide any clear answer. Evoenergy noted that this could have been the result of several smaller load transfers to another substation.

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

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

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. Within each of the models we therefore included seasonal independent variables (regressors) to account for seasonality. Quarterly models rather than annual models provided a larger data set for model development improving the robustness of the approach. The seasonal variables used 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 also enable weather correction of the time-series as they provide a means to correct historical data for very warm or very cool summers and winters.

The models also incorporated general regressors for average demand including 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 several variables available representing country wide and state level economic development over time. These variables are Australian Real GDP[12], 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 provide the expected impact, we substituted with the country wide GDP regressor. However, sometimes none of these economic variables had any significant impact and demographic factors were found to be 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 based on historical actuals	2006Q1- 2029Q1	Evoenergy/ BOM (2018)
Seasonal	Cooling Degree Days – historic and simulations based on historical actuals	2006Q1- 2029Q1	Evoenergy/ BOM (2018)

[12] 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.

Class	Independent Variable	Series	Source – Year Published
Economic	Australian Real GDP – historic and projections	2006Q1- 2029Q1	ABS/ Jacobs (2018)
Economic	ACT State Final Demand – historic and projections	2006Q1- 2029Q1	ABS/ Jacobs (2018)
Demographic	ACT Population – historic and projections	2006Q1- 2029Q1	ACT Treasury (2018)
Demographic	ACT Spatial Population – historic and projections	2006Q1- 2029Q1	ACT Treasury (2018)
Price	Residential Retail Prices – historic and projections	2006Q1- 2029Q1	ABS/ AEMO/ Jacobs (2018)
Price	Commercial Retail Prices – historic and projections	2006Q1- 2029Q1	ABS/ AEMO/ Jacobs (2018)
Price	Industrial Retail Prices – historic and projections	2006Q1- 2029Q1	ABS/ AEMO/ Jacobs (2018)
Efficiency	Total Energy Efficiency – historic and projections	2006Q1- 2029Q1	AEMO/ Jacobs (2018)
Efficiency	Total Energy Efficiency – historic and projections	2006Q1- 2029Q1	AEMO/ Jacobs (2018)

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 (2018). 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
Gilmore	Tuggeranong
Gold Creek	Gungahlin
Telopea	South Canberra
Theodore, Wanniassa	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 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 applied statistical approaches such as data transformation, differencing or lagging 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 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 Auto Correlation Function (ACF) and Partial Auto Correlation Function (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 choses the best model (e.g. based on the Akaike info criterion, discussed in next section).[13]

5.2.4.4 Tests for Multicollinearity

Jacobs also tested for potential multicollinearity and associated impact on the developed models.[14] EViews has 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.

First, there are a number of model selection criteria which 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

[13] 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.

[14] 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.

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 Evoenergy

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

The following outputs were reported to Evoenergy 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 available[15];
- 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 Evoenergy'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.

Most of the developed average demand models use a log-transformed dependent variable. The dependent variables are the average monthly demand at a specific zone substation and one quarterly average system level demand model. Any independent 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.

The projections shown in this chapter are also based on underlying energy use, and therefore do not incorporate the impact of rooftop PV which would further reduce the projections. This approach simplifies review of the projections because changing projections are verified relative to well understood factors such as economic and population growth and weather.

5.3.2 System Level Forecast

The system level forecast has been developed including the following independent regressors:

- Quarterly Heating Degree Days (QHDD);
- Quarterly Cooling Degree Days (QCDD);
- Quarterly ACT Population (QPOP)
- Weekend Days and Public Holidays (WEEKDAYS);
- Quarterly Residential Price (PRICE_RES); and
- Quarterly Energy Efficiency for Residential Customers (EE_RES);

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

We constructed a single variable for price and energy efficiency by simply multiplying them, thus avoiding collinearity issues, as there were indications that 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 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 QPOP, QCDD, QHDD and energy efficiency-price regressors with system demand, and all with the correct expected sign for each coefficient. We also recognised that demand is not only influenced by weather but by structural factors such as business hours, and this was a further source of variation in quarterly data. We therefore included a variable to provide a representation of the number of weekend days and public holidays. This variable has a weak negative effect on average demand, as we expect that demand during weekend and public holidays is lower than weekdays. However, the variable improves the fit in summer and winter quarters so was retained.

Table 12: Model Output for System Average Demand

Dependent Variable: LOG(QDEMAND)
Method: Least Squares
Date: 10/22/18 Time: 15:05
Sample (adjusted): 6/01/2006 6/01/2018
Included observations: 49 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(QPOP)	0.444072	0.004460	99.56693	0.0000
QHDD	0.000404	1.02E-05	39.60753	0.0000
QCDD	0.000532	2.88E-05	18.46580	0.0000
EE_RES(-1)*PRICE_RES	-1.12E-06	9.64E-08	-11.66923	0.0000
WEEKEND	-0.298811	0.172208	-1.735182	0.0897

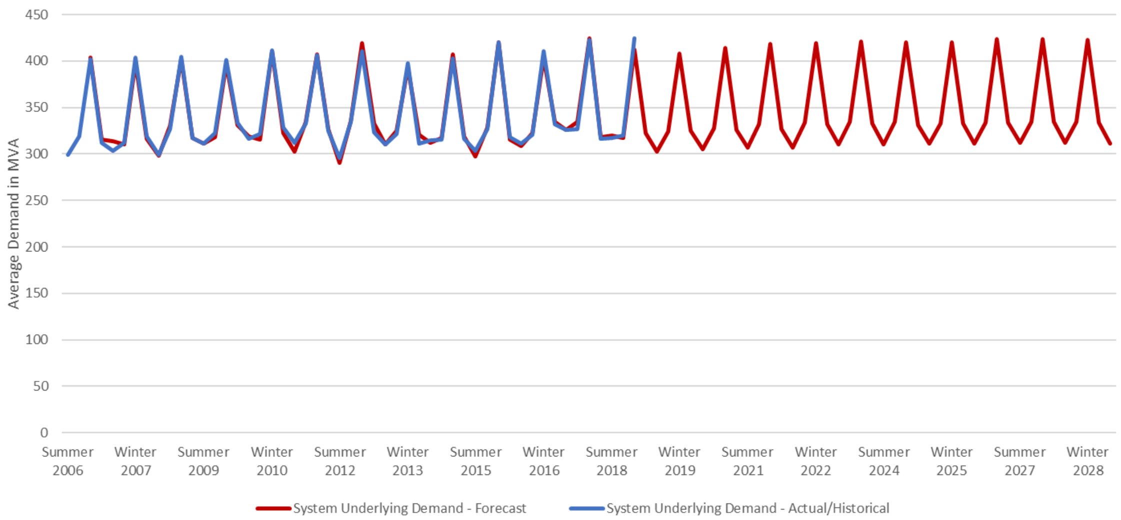
R-squared	0.985187	Mean dependent var	5.828646
Adjusted R-squared	0.983840	S.D. dependent var	0.115643
S.E. of regression	0.014701	Akaike info criterion	-5.505380
Sum squared resid	0.009509	Schwarz criterion	-5.312337
Log likelihood	139.8818	Hannan-Quinn criter.	-5.432140
Durbin-Watson stat	1.769352		

Analysis of the residuals revealed that they were most likely normally distributed, and therefore the model was statistically adequate in this regard.

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 2018, mainly because of expected high electricity prices over the last few quarters[16] (residential and commercial) as well as continuing energy efficiency, offsetting the effects of the moderate population growth in the ACT.

[16] As described in the methodology the wholesale price impact on the retail price is lagged.

Figure 15: Evoenergy System Average Demand - Model Fit and Forecast



5.3.3 Summary of Results Individual Zone Substation Forecasts

Jacobs developed individual average demand forecasts for 11 of the 12 zone substations in the Evoenergy electricity distribution network.[17]

The forecasting results for the zone substations of East Lake, Gilmore and Gold Creek show clearly increasing average demand projections, mostly resulting from growing local population projections and lower projected retail prices.

The developed forecasts for Belconnen, City East, Civic, Latham, Telopea, Theodore and Woden show a stable outlook for demand, while Wanniassa is the only zone substation with a declining average demand trend.

A detailed discussion of the developed models and the average demand projections for each of the zone substations is provided in the sections below.

5.3.4 Belconnen Zone Substation

The model output for Belconnen Zone Substation average demand is presented in

Table 13. The Belconnen average monthly demand was estimated using the following independent variables:

- Heating Degree Days (HDD);
- Cooling Degree Days (CDD);
- Residential Price (PRICE_RES) with a 3-period lag, combined with Residential Energy Efficiency (EE_RES);
- Population in Belconnen (BELC_POP);
- A variable representing the number of working days (WEEKDAYS);
- A winter demand peak trend starting from July-2016 (D_2016M7B*@TREND); and
- Auto Regression (AR) and Moving Average (MA) terms.

[17] The demand forecast for Fyshwick zone substation was developed by Evoenergy.

All variables show the right signs for coefficients in the regression model and all variables are statistically significant. We have also observed an increasing trend of winter demand, in particular July, which is the coldest month of the year.

First order autocorrelation was addressed by the inclusion of an AR[1] term, and (seasonal) moving averages where observed for 12 and 24 month periods aligned with the frequency of the data points (monthly).

Presented in Figure 16 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).

Table 13: Model Output for Belconnen Zone Substation Average Demand

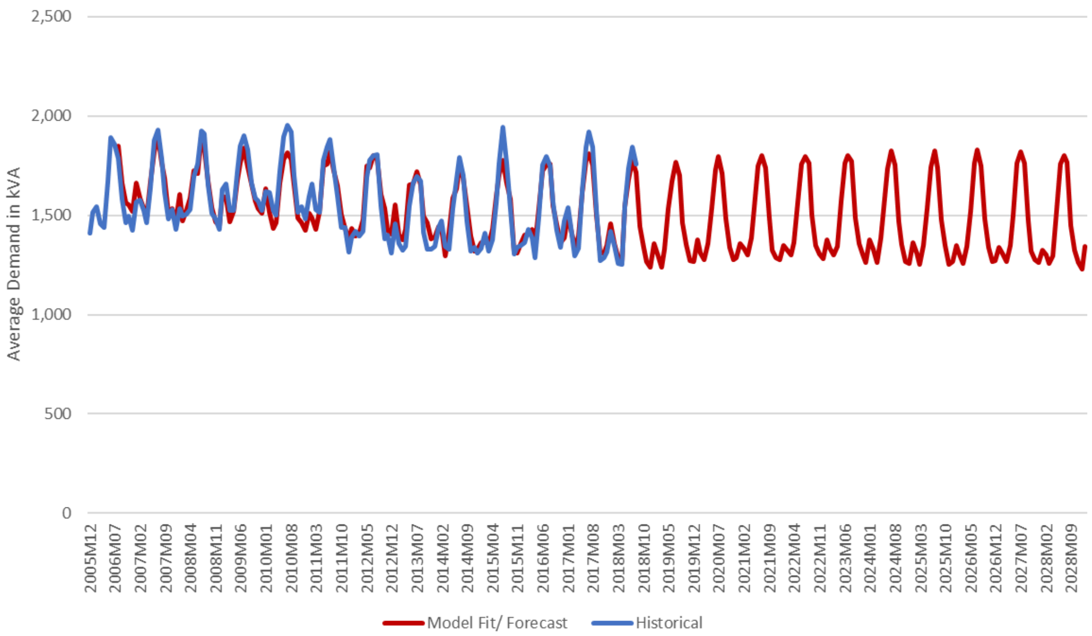
Dependent Variable: BELC_UAD
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/05/18 Time: 19:12
Sample: 2006M03 2018M08
Included observations: 150
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	1.228413	0.072288	16.99328	0.0000
CDD	1.784133	0.161109	11.07409	0.0000
LOG(BELC_POP)	111.1850	7.056196	15.75707	0.0000
WEEKDAYS	420.7595	79.25451	5.308966	0.0000
PRICE_RES(-3)	-1.532998	0.337559	-4.541415	0.0000
D_2016M7B*@TREND	0.570559	0.218000	2.617244	0.0098
AR(1)	0.614892	0.068063	9.034105	0.0000
MA(12)	0.508098	0.081115	6.263944	0.0000
SMA(24)	0.372296	0.111506	3.338788	0.0011
SIGMASQ	1553.060	196.0278	7.922653	0.0000

R-squared	0.956002	Mean dependent var	1561.176
Adjusted R-squared	0.953174	S.D. dependent var	188.5088
S.E. of regression	40.79207	Akaike info criterion	10.35546
Sum squared resid	232959.0	Schwarz criterion	10.55617
Log likelihood	-766.6594	Hannan-Quinn criter.	10.43700
Durbin-Watson stat	2.017572		

For the forecast a slight reduction of the average demand from winter 2018 until winter 2019 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 higher prices for electricity continuing into the current year, some energy efficiency and a relatively stable customer base in the Belconnen area.

Figure 16: 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 Figure 14.

The City East average demand was estimated using the following independent variables:

- Heating Degree Days (HDD);
- Cooling Degree Days (CDD);
- Population in North Canberra (NORT_POP)
- Residential Price (PRICE_RES), combined with Residential Energy Efficiency (EE_RES);
- A variable representing the number of working days (WEEKDAYS)
- Dummies to control for some model outliers; and
- Auto Regression (AR) and Moving Average (MA) terms.

The included independent variables all have appropriate coefficient signs in the regression model and were each statistically significant. HDD, CDD and population are as expected positively correlated to the average demand in City East and price and energy efficiency are as expected negatively correlated. We dropped the independent variable for economic development as it did not improve the model through the AIC and R^2 and showed insignificant coefficients (t-statistics). All remaining independent variables have significant coefficients.

The serial correlation in this model has been addressed by adding a first order autoregression term AR[1] and a seasonal autoregression SAR[12] term, as well as seasonal moving average term SMA[12] consistent with the monthly granularity of demand data we used for the modelling.

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

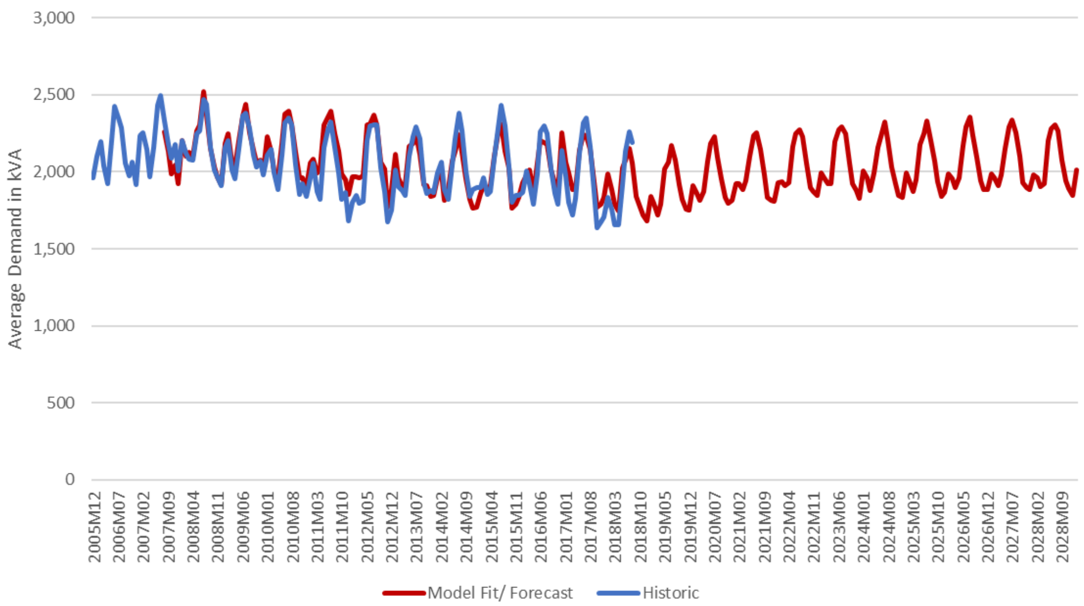
Dependent Variable: LOG(CITY_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/17/18 Time: 16:27
Sample: 2006M07 2018M04
Included observations: 142
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CDD	0.001129	9.65E-05	11.69621	0.0000
HDD	0.000683	5.75E-05	11.88771	0.0000
LOG(NORT_POP)	0.685901	0.005599	122.5132	0.0000
PRICE_RES(-2)*EE_RES	-2.02E-07	4.48E-08	-4.515176	0.0000
WEEKDAYS	0.277851	0.049067	5.662717	0.0000
D_2016M12	0.179537	0.032171	5.580644	0.0000
D_2012M11	-0.084005	0.028426	-2.955186	0.0037
AR(1)	0.689041	0.068600	10.04438	0.0000
SAR(12)	0.854414	0.068755	12.42693	0.0000
MA(11)	0.512609	0.080331	6.381197	0.0000
SMA(12)	-0.331634	0.136871	-2.422965	0.0168
SIGMASQ	0.000475	6.53E-05	7.281192	0.0000

R-squared	0.952827	Mean dependent var	7.617278
Adjusted R-squared	0.948835	S.D. dependent var	0.100730
S.E. of regression	0.022785	Akaike info criterion	-4.552185
Sum squared resid	0.067489	Schwarz criterion	-4.302396
Log likelihood	335.2051	Hannan-Quinn criter.	-4.450681
Durbin-Watson stat	2.125018		

Figure 17 illustrates the model fit and forecast for City East zone substation. The graph shows a reasonably good fit throughout history. In the first few projected years 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 a history of relatively stable populations. Thus, even though there is 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 and prices have impacted the average demand over the last decade or so. Further, retail price projections are expected to decline after 2019, so that the average demand projections recover slightly towards 2029, as shown in the figure below.

Figure 17: 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 (HDD);
- Cooling Degree Days (CDD);
- Population in North Canberra (NORT_POP)
- Commercial Price with a 2-period lag (PRICE_COM), combined with Business Energy Efficiency (EE_COM);
- A variable representing the number of working days (WEEKDAYS)
- Dummy to control for a model outlier; and
- Auto Regression (AR) and Moving Average (MA) terms.

The included independent variable coefficients are each of the appropriate sign. HDD, CDD, and population are as expected positively correlated to average demand in Civic and business energy efficiency and commercial price are as expected negatively correlated. State final demand did not show a significant effect and therefore the decision was taken to drop this regressor as it did not improve the model through the AIC and R^2. All remaining model coefficients were statistically significant.

The serial correlation in this model has been addressed by adding a first and second order moving average MA[1,2] to the model, as well as an seasonal autoregression AR[12] and seasonal moving average SMA[12].

The model fit and forecast for Civic are included in Figure 18 below and shows a good fit with the historic data. Historically the demand has slightly reduced over time as a result of energy efficiency and retail price increases, however going forward the projections show a slight increase of demand from 2019 onwards due to reduction in commercial retail price levels, before levelling-out around 2025.

The area connected to Civic zone substation is dominated by retail-commercial activity with some smaller residential areas, therefore a relatively stable forecast seems reasonable.

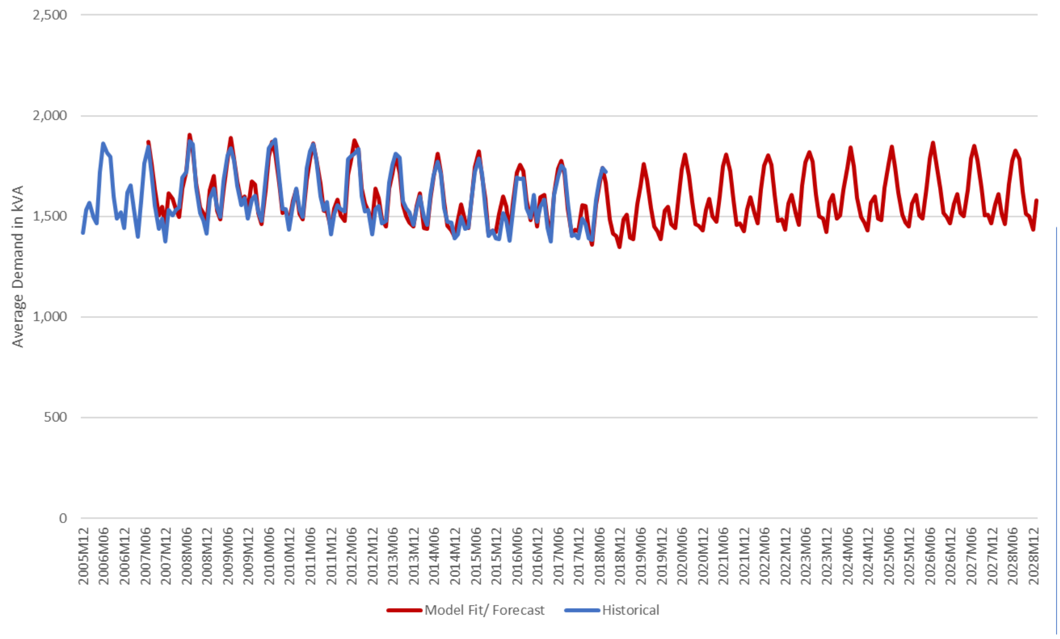
Table 15: Model Output for Civic Zone Substation Average Demand

Dependent Variable: LOG(CIVI_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/17/18 Time: 16:07
Sample: 2006M07 2018M08
Included observations: 146
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000437	4.85E-05	9.001038	0.0000
CDD	0.000831	8.24E-05	10.08078	0.0000
PRICE_COM(-2)*EE_BUS	-3.39E-07	1.87E-08	-18.11742	0.0000
LOG(NORT_POP)	0.665951	0.002772	240.2030	0.0000
D_2016M11	0.065728	0.016991	3.868323	0.0002
WEEKDAYS	0.234794	0.034153	6.874817	0.0000
AR(12)	0.990836	0.008790	112.7253	0.0000
MA(1)	0.665757	0.087528	7.606219	0.0000
MA(2)	0.305128	0.088825	3.435172	0.0008
SMA(12)	-0.756937	0.103790	-7.292946	0.0000
SIGMASQ	0.000299	4.73E-05	6.320585	0.0000

R-squared	0.958411	Mean dependent var	7.366621
Adjusted R-squared	0.955330	S.D. dependent var	0.085097
S.E. of regression	0.017986	Akaike info criterion	-4.951689
Sum squared resid	0.043670	Schwarz criterion	-4.726896
Log likelihood	372.4733	Hannan-Quinn criter.	-4.860350
Durbin-Watson stat	1.922461		

Figure 18: 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 using 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 (HDD);
- Cooling Degree Days (CDD);
- Residential Price with a 3-period lag (PRICE_COM);
- Population in Fyshwick (FYSH_POP); and
- A variable representing the number of working days (WEEKDAYS);

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 0.75 this model can still provide a very reasonable forecast.

For this small, mostly residential area we found a significant correlation with population for Fyshwick, which includes East Lake and the Fyshwick commercial area. Furthermore, the residential retail prices (with a lag of three months) displays a weaker, but still significant, negative impact on demand.

The historical data for East Lake shows a weaker and more inconsistent seasonal pattern compared to what is historically observable for many other zone substations. The latter is one of the main reasons it is more difficult to estimate a more closely fitting model for this zone substation.

The demand forecast for East Lake is first flat, depressed by the current high retail prices, but is projected to recover from 2020 onwards to outgrow historical demand levels due to population growth.

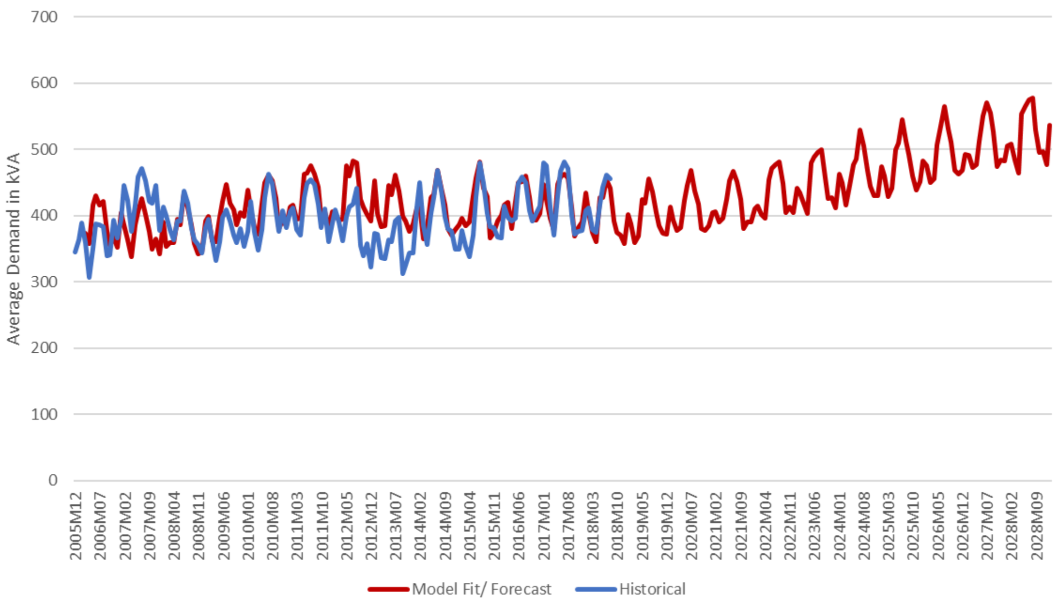
Table 16: Model Output for East Lake Zone Substation Average Demand

Dependent Variable: LOG(EAST_UAD)
Method: Least Squares
Date: 11/05/18 Time: 21:14
Sample (adjusted): 2015M08 2018M08
Included observations: 37 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000637	8.23E-05	7.737372	0.0000
CDD	0.001429	0.000228	6.274515	0.0000
WEEKDAYS	0.530696	0.181413	2.925354	0.0063
PRICE_RES(-3)	-0.000989	0.000460	-2.148231	0.0394
LOG(FYSH_POP)	0.783080	0.020764	37.71386	0.0000

R-squared	0.749301	Mean dependent var	6.026973
Adjusted R-squared	0.717963	S.D. dependent var	0.085844
S.E. of regression	0.045589	Akaike info criterion	-3.213201
Sum squared resid	0.066508	Schwarz criterion	-2.995509
Log likelihood	64.44421	Hannan-Quinn criter.	-3.136454
Durbin-Watson stat	1.477206		

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



5.3.8 Gilmore Zone Substation

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

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

- Heating Degree Days in Tuggeranong (HDD_T);
- Cooling Degree Days in Tuggeranong (CDD_T);
- Population in Tuggeranong (TUGG_POP)
- A variable representing the number of weekend and public holidays (WEEKENDDAYS);
- Dummies to control for model outliers; and
- Auto Regression (AR) and Moving Average (MA) terms.

All regressors have the expected signs and are all significant.

We estimated models by adding variables state economic development, commercial and residential price and energy efficiency, but they did not improve the AIC and where not significant and were therefore dropped from the equation.

Furthermore, in the Gilmore ZS average demand model, the main driving factor for growth in this area is the population in Tuggeranong, while heating degree days and cooling degree days providing for most of the seasonal (summer, winter) variation.

Two moving average terms for 12 months MA[12] and 24 months MA[24], and a first order autoregression term AR[1] were included in the model to address the serial correlation issues.

Table 17: Model Output for Gilmore Zone Substation Average Demand

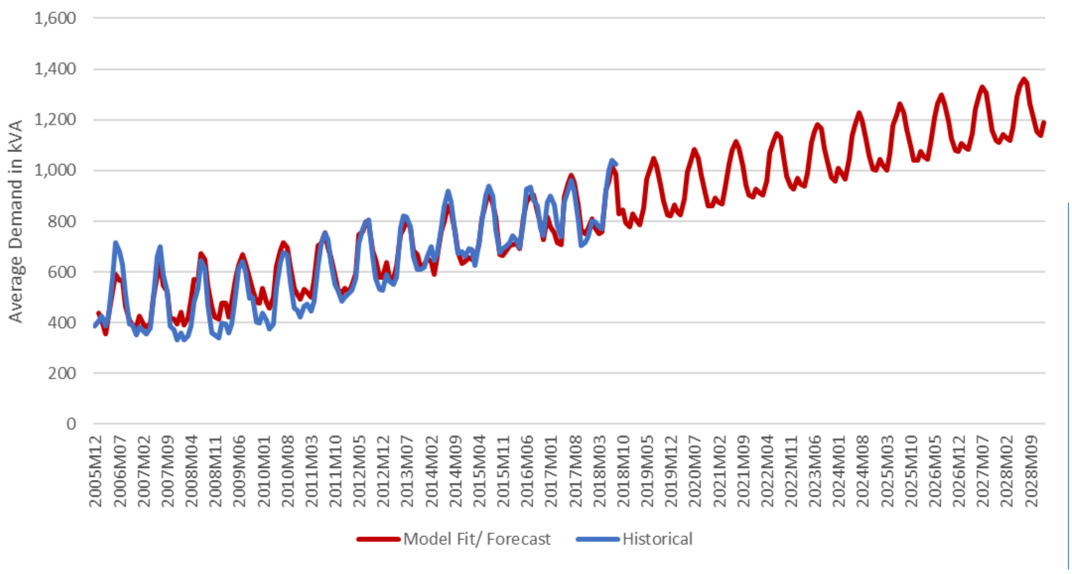
Dependent Variable: GILM_UAD
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/05/18 Time: 19:14
Sample: 2005M12 2018M08
Included observations: 153
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD_T	0.758083	0.045010	16.84245	0.0000
CDD_T	0.799077	0.098143	8.141934	0.0000
LOG(TUGG_POP)	25.14923	2.675146	9.401068	0.0000
D_2016M12	83.25793	10.09518	8.247293	0.0000
D_2017M4	-70.51262	18.53249	-3.804811	0.0002
@TREND	3.019194	0.272330	11.08652	0.0000
WEEKENDDAYS	-130.0131	48.54614	-2.678134	0.0083
AR(1)	0.792206	0.058296	13.58932	0.0000
MA(12)	0.307515	0.085314	3.604509	0.0004
MA(24)	0.307132	0.112840	2.721851	0.0073
SIGMASQ	703.0980	93.31866	7.534378	0.0000

R-squared	0.978322	Mean dependent var	626.5599
Adjusted R-squared	0.976796	S.D. dependent var	180.6860
S.E. of regression	27.52387	Akaike info criterion	9.563886
Sum squared resid	107574.0	Schwarz criterion	9.781761
Log likelihood	-720.6373	Hannan-Quinn criter.	9.652390
Durbin-Watson stat	2.125434		

As shown below in Figure 20 the historical data depicts significant growth from 2009/2010 onwards. This effect is picked up by the model and a similar level of growth is projected forward.

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



Overall this model tracks reasonably well to the historical data except for the summer load in the first few years of the historical data. However, given the model more accurately tracks the recent historical data, Jacobs believes it should provide a very reasonable forecast for input to the MEFM model.

5.3.9 Gold Creek Zone Substation

The model output for Gold Creek Zone Substation average demand is presented in Table 18.

The Gold Creek average demand was estimated using the following independent variables:

- Heating Degree Days (HDD);
- Cooling Degree Days (CDD);
- Residential Price with a 3-period lag (PRICE_COM);
- Population in Gungahlin (GUNG_POP);
- A variable representing the number of working days (WEEKDAYS); and
- Auto Regression (AR) and Moving Average (MA) terms.

The Included independent variables all have the proper signs. HDD, CDD, and population are as expected positively correlated with the average demand in Gold Creek. The residential price is as expected negatively, but only weakly correlated. Nevertheless, it was not removed from the equation as it clearly improved the AIC and R^2.

The serial correlation in this model has been addressed by adding a first order autoregression term AR[1] a half-yearly moving average MA[6] and a twelve month seasonal moving average SMA[12] term to the model.

Figure 21 depicts the average demand in historical and projected kVA for Gold Creek zone substation. The model seems to track the historical demand very well, especially the more recent years where it picks-up the increasing difference between summer and winter demand. Therefore, this model can be considered a very good fit, just as the R-squared of .98 in the table above suggests.

The forecast shows significant increasing average demand up to 2029. This is due to the expected strongly growing population in this area resulting from 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] and moving average terms for 6 and 12 months MA[6,12] 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).

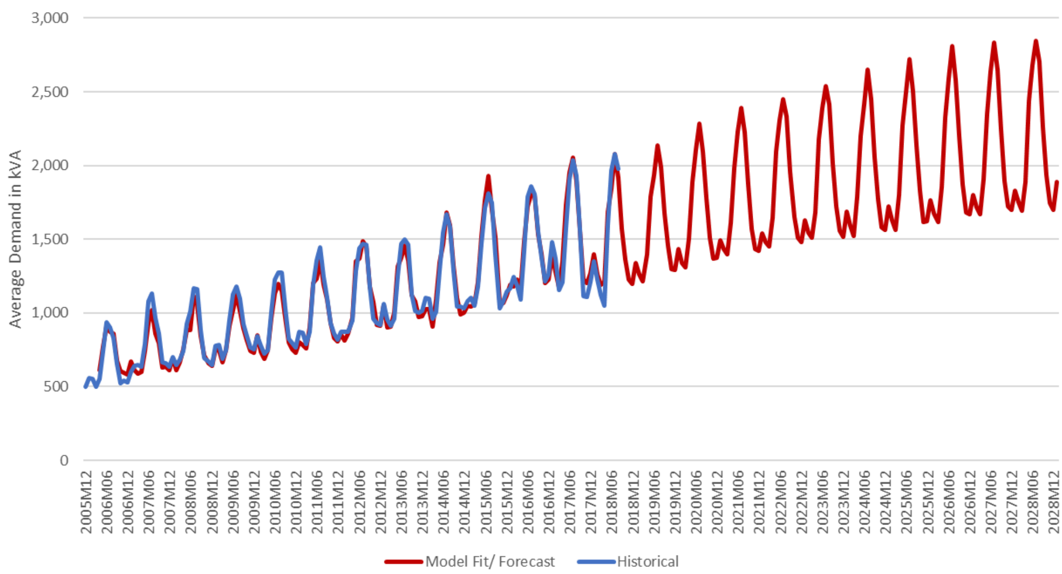
Table 18: Model Output for Gold Creek Zone Substation Average Demand

Dependent Variable: LOG(GOLD_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/05/18 Time: 19:03
Sample: 2006M03 2018M08
Included observations: 150
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.001664	5.80E-05	28.69396	0.0000
CDD	0.001904	0.000174	10.91878	0.0000
LOG(GUNG_POP)	0.985490	0.086947	11.33438	0.0000
PRICE_RES(-3)	-0.000888	0.000524	-1.695130	0.0923
WEEKDAYS	0.248892	0.083428	2.983311	0.0034
C	-4.089114	0.864768	-4.728566	0.0000
AR(1)	0.614592	0.062611	9.816091	0.0000
MA(6)	0.232206	0.085855	2.704642	0.0077
SMA(12)	0.402132	0.092321	4.355805	0.0000
SIGMASQ	0.001795	0.000219	8.211179	0.0000

R-squared	0.982348	Mean dependent var	6.949923
Adjusted R-squared	0.981213	S.D. dependent var	0.319966
S.E. of regression	0.043856	Akaike info criterion	-3.333521
Sum squared resid	0.269267	Schwarz criterion	-3.132812
Log likelihood	260.0140	Hannan-Quinn criter.	-3.251979
F-statistic	865.6885	Durbin-Watson stat	2.057159
Prob(F-statistic)	0.000000		

Figure 21: Gold Creek Zone Substation Average Demand – Forecast and Historic Values



5.3.10 Latham Zone Substation

The model output for Latham Zone Substation average demand is presented in Figure 19.

The Latham average demand was estimated using the following independent variables:

- Heating Degree Days (HDD);

- Cooling Degree Days (CDD);
- Residential Price with a 3-period lag (PRICE_COM);
- Residential Energy Efficiency;
- Population in Belconnen (BELC_POP);
- Dummy to control for a model outlier; and
- Auto Regression (AR) and Moving Average (MA) terms.

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.

Significant serial correlation was detected after residual analysis, and therefore several moving average terms were included in the model, representing seasonal moving averages for 6, 12 and 24 months. This adjustment was sufficient to improve the statistical adequacy of the model.

Table 19: Model Output for Latham Zone Substation Average Demand

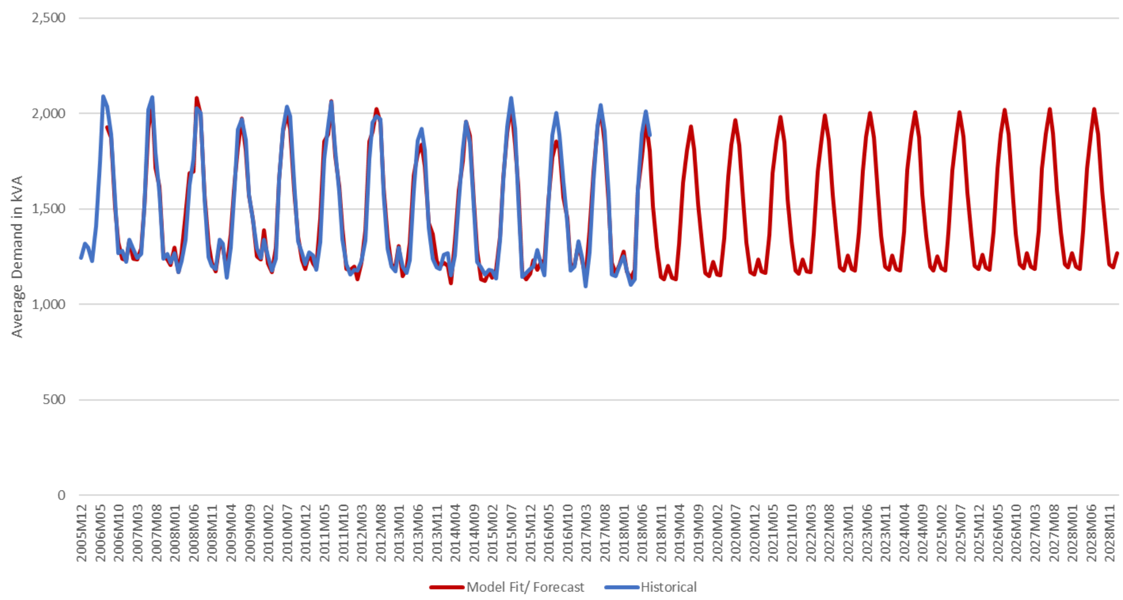
Dependent Variable: LOG(LATH_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/28/18 Time: 01:50
Sample: 2006M07 2018M08
Included observations: 146
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.001655	4.34E-05	38.17851	0.0000
CDD	0.001463	0.000130	11.25331	0.0000
LOG(BELC_POP)	0.619234	0.002451	252.6277	0.0000
PRICE_RES(-3)	-0.000545	0.000187	-2.919609	0.0041
EE_RES	-1.36E-05	5.25E-06	-2.588465	0.0107
D_2012M10	-0.068442	0.022339	-3.063749	0.0026
MA(1)	0.250072	0.093203	2.683081	0.0082
SMA(12)	0.383094	0.098746	3.879602	0.0002
SMA(24)	0.225481	0.097942	2.302178	0.0229
SMA(6)	0.258183	0.092237	2.799135	0.0059
SIGMASQ	0.000840	0.000108	7.797399	0.0000

R-squared	0.979517	Mean dependent var	7.275953
Adjusted R-squared	0.978000	S.D. dependent var	0.203254
S.E. of regression	0.030147	Akaike info criterion	-4.072061
Sum squared resid	0.122697	Schwarz criterion	-3.847268
Log likelihood	308.2604	Hannan-Quinn criter.	-3.980722
Durbin-Watson stat	1.994246		

Figure 22 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 historical data shows declining average demand from price and energy efficiency impact, supported by a relatively stable population in this area. Projections show some recovery of demand to 2016 levels from expected retail price reductions.

Figure 22: Latham Zone Substation Average Demand – Forecast and Historic Values



5.3.11 Telopea Zone Substation

The model output for Telopea Zone Substation average demand is presented in Figure 20.

The Telopea average demand was estimated using the following independent variables:

- Heating Degree Days (HDD);
- Cooling Degree Days (CDD);
- Population in South Canberra (SOUT_POP)
- Residential Price with a 3-period lag (PRICE_RES), combined with Residential Energy Efficiency (EE_RES);
- A variable representing the number of working days (WEEKDAYS)
- Dummy to control for a model outlier; and
- Auto Regression (AR) and Moving Average (MA) terms.

All independent variable coefficients in the model have the appropriate signs and are significant.

Telopea covers a large part of the Australian Federal Departmental offices, museums and other (local) Government related activities, therefore this would largely support the outcome that average demand is significantly influenced by population development and the number of working days in a month.

Finally, to address the serial correlation in the model a first order autoregression term AR[1], a moving average term MA[1] and seasonal moving average terms for 12 and 24 months SMA[12,24] were included.

Figure 23 provides an overview of the model fit and forecast. The model shows overall good fit with the historical data but is not always able to track some of the seasonal variability given it is not always as consistent as observed at other zone substations.

The graph shows a somewhat declining average demand over the last few years of historical data. This is likely the result of increasing energy efficiency and higher retail price levels. The demand projections display a fairly stable forecast going forward, as projected population growth in South Canberra and easing retail prices are balancing out the negative impact of the future energy efficiency on demand.

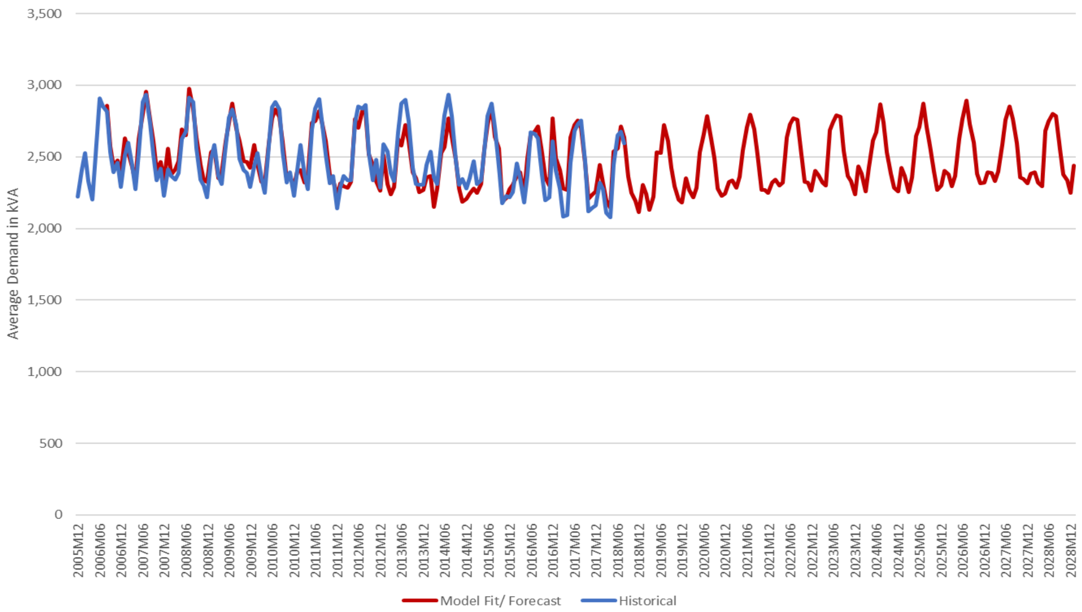
Table 20: Model Output for Telopea Zone Substation Average Demand

Dependent Variable: LOG(TELO_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 10/17/18 Time: 16:43
Sample: 2006M07 2018M02
Included observations: 140
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000661	3.78E-05	17.48075	0.0000
CDD	0.001078	9.71E-05	11.10051	0.0000
LOG(SOUT_POP)	0.737502	0.005308	138.9299	0.0000
EE_RES*PRICE_RES(-3)	-1.23E-07	2.63E-08	-4.679235	0.0000
D_2016M12	0.179688	0.037110	4.842003	0.0000
WEEKDAYS	0.410227	0.061597	6.659895	0.0000
AR(1)	0.843769	0.074022	11.39885	0.0000
MA(1)	-0.486994	0.126960	-3.835819	0.0002
SMA(12)	0.591116	0.088241	6.698920	0.0000
SMA(24)	0.436506	0.107061	4.077159	0.0001
SIGMASQ	0.000547	7.78E-05	7.035474	0.0000

R-squared	0.928609	Mean dependent var	7.815805
Adjusted R-squared	0.923075	S.D. dependent var	0.087859
S.E. of regression	0.024368	Akaike info criterion	-4.459229
Sum squared resid	0.076600	Schwarz criterion	-4.228100
Log likelihood	323.1460	Hannan-Quinn criter.	-4.365305
Durbin-Watson stat	1.903005		

Figure 23: Telopea Zone Substation Average Demand – Forecast and Historic Values



5.3.12 **Theodore Zone Substation**

The model fit can be considered very good with an R-squared of .98, which is also noticeable in Figure 24. The dummy that was included in the model captures the higher than usual peak in winter 2017 and a clear and consistent seasonal pattern with high winter demands and lower summer peaks are projected going forward.

Table 21 provides an overview of the modelling results for Theodore zone substation. Theodore average demand was estimated using the following independent variables:

- Heating Degree Days in Tuggeranong (HDD_T);
- Cooling Degree Days in Tuggeranong (CDD_T);
- Population in Tuggeranong (TUGG_POP)
- Residential Price with a 3-period lag (PRICE_RES);
- Dummy to control for model outliers;
- A trend (@TREND); and
- Auto Regression (AR) and Moving Average (MA) terms.

The included independent variable coefficients all have the appropriate positive or negative signs. HDD, CDD, and population in Tuggeranong are as expected positively correlated with the average demand in Theodore and the residential retail price from three months back (coinciding a typical quarterly billing rate) is as expected negatively correlated.

Furthermore, a positive overall trend was found to be significant, although with a small coefficient. Any observed serial correlation in this model has been addressed by adding a first order autoregression term, a moving average term MA[1] and seasonal moving average terms for 12 and 24 months to the model.

The model fit can be considered very good with an R-squared of .98, which is also noticeable in Figure 24. The dummy that was included in the model captures the higher than usual peak in winter 2017 and a clear and consistent seasonal pattern with high winter demands and lower summer peaks are projected going forward.

Table 21: Model Output for Theodore Zone Substation Average Demand

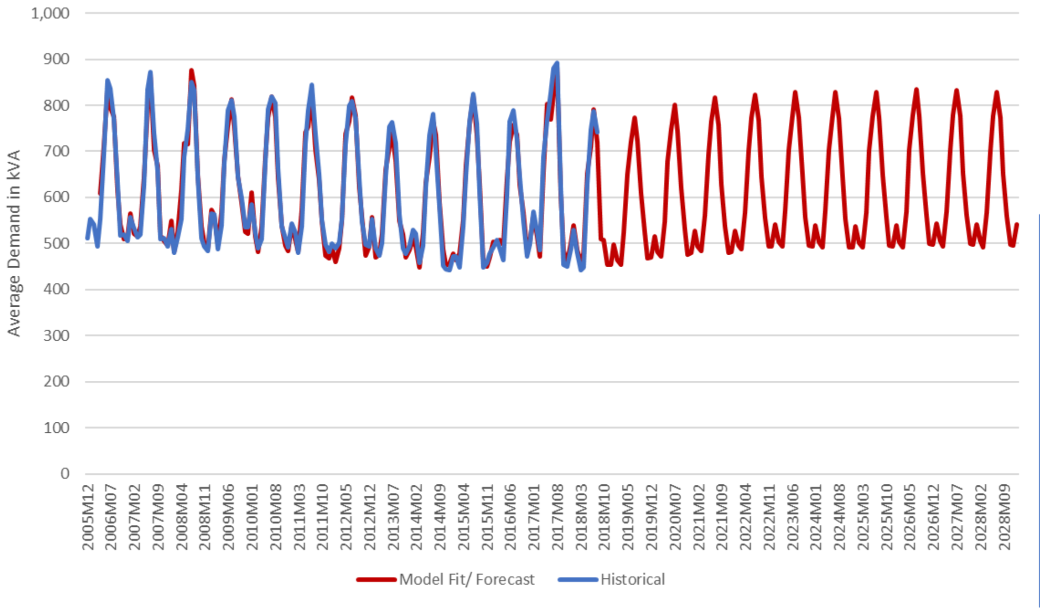
Dependent Variable: LOG(THEO_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/28/18 Time: 02:28
Sample: 2006M03 2018M08
Included observations: 150
Convergence achieved after 18 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD_T	0.001659	4.55E-05	36.48225	0.0000
CDD_T	0.001865	0.000127	14.73429	0.0000
LOG(TUGG_POP)	0.542861	0.002590	209.6373	0.0000
PRICE_RES(-3)	-0.001111	0.000189	-5.880259	0.0000
D_2017M4_5_8	0.161742	0.016465	9.823600	0.0000
@TREND	0.000662	0.000188	3.511150	0.0006
AR(1)	0.229447	0.103414	2.218721	0.0281
MA(12)	0.275671	0.091913	2.999260	0.0032
SMA(24)	0.511623	0.095094	5.380191	0.0000
SIGMASQ	0.000828	0.000109	7.565842	0.0000

R-squared	0.980346	Mean dependent var	6.383577
Adjusted R-squared	0.979082	S.D. dependent var	0.205935
S.E. of regression	0.029784	Akaike info criterion	-4.076203
Sum squared resid	0.124195	Schwarz criterion	-3.875494
Log likelihood	315.7152	Hannan-Quinn criter.	-3.994661
Durbin-Watson stat	2.030690		

The average demand projections observed in Figure 27 show a slight increase in the next few years levelling out in 2021 for a flat long-term forecast.

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



5.3.13 Wanniassa Zone Substation

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

- Heating Degree Days in Tuggeranong (HDD_T);
- Cooling Degree Days in Tuggeranong (CDD_T);
- Population in Tuggeranong (TUGG_POP)
- Residential Price with a 3-period lag (PRICE_RES), combined with residential energy efficiency (EE_RES);
- Dummies to control for model outliers; and
- Moving Average (MA) terms.

The included independent variable coefficients all have the appropriate positive or negative signs. HDD, CDD, and population in Tuggeranong are as expected positively correlated, while energy efficiency and residential retail price is negatively correlated with the average demand in Wanniassa.

The Wanniassa 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, but the inclusion of an economic variable provided insignificant correlation and did not improve the model and was therefore dropped.

The serial correlation in this model was addressed by adding a moving average MA[1] and seasonal moving averages for 12 and 24 months SMA[12,24] to the model.

Based on the R-squared of .98 and visually inspecting Figure 25, the model fit can be considered very good.

The historical demand has shown a consistent seasonal pattern with a steady overall decline since 2005, driven by decreasing population.

The average demand projections in Figure 25 shows a continuing decline, but less significant as historically observed. This is likely due to the forecasted reduction in retail electricity prices after 2019 and the slower decrease of population in the Tuggeranong area.

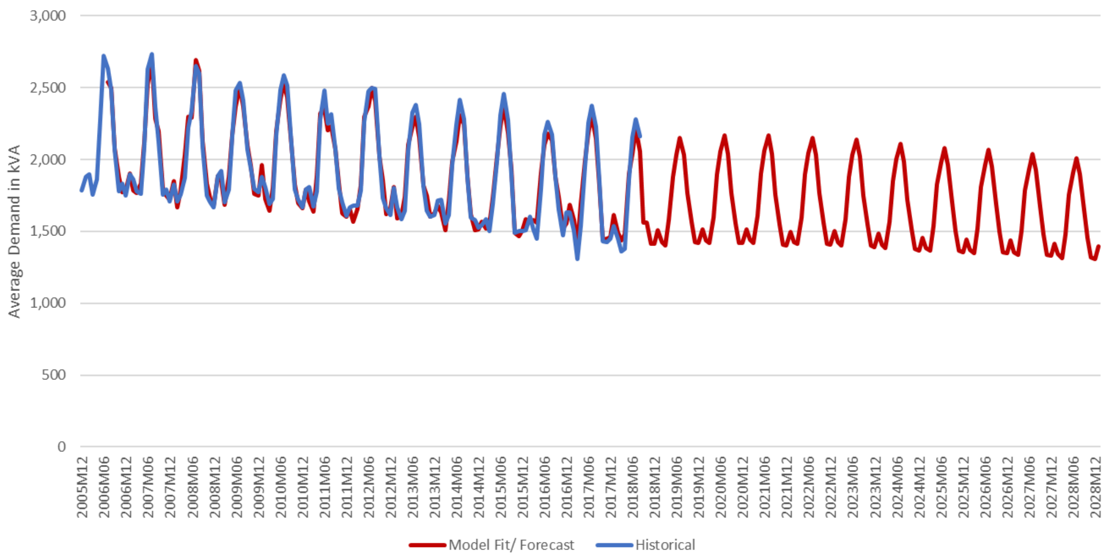
Table 22: Model Output for Wanniassa Zone Substation Average Demand

Dependent Variable: LOG(WANN_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/28/18 Time: 02:28
Sample: 2006M07 2018M08
Included observations: 146
Convergence achieved after 35 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD_T	0.001341	4.45E-05	30.15184	0.0000
CDD_T	0.001404	0.000100	14.00392	0.0000
LOG(TUGG_POP)	0.645113	0.001218	529.7592	0.0000
EE_RES*PRICE_RES(-3)	-1.10E-07	1.04E-08	-10.58940	0.0000
D_2011M7	-0.135405	0.049872	-2.715073	0.0075
D_2017M12	-0.045188	0.014012	-3.224828	0.0016
MA(1)	0.253865	0.084505	3.004141	0.0032
SMA(12)	0.524480	0.093317	5.620396	0.0000
SMA(24)	0.420136	0.110664	3.796507	0.0002
SIGMASQ	0.000640	8.90E-05	7.197167	0.0000

R-squared	0.979230	Mean dependent var	7.541083
Adjusted R-squared	0.977856	S.D. dependent var	0.176185
S.E. of regression	0.026218	Akaike info criterion	-4.334269
Sum squared resid	0.093485	Schwarz criterion	-4.129912
Log likelihood	326.4016	Hannan-Quinn criter.	-4.251234
Durbin-Watson stat	2.019560		

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



5.3.14 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 23 includes the model specification for Woden zone substation, it includes the following variables:

- Heating Degree Days (HDD) and Cooling Degree Days (CDD);
- Population in Woden (WODE_POP)
- Residential Price with a 3-period lag (PRICE_RES);
- Residential energy efficiency (EE_BUS);
- Dummies to control for model outliers; and
- Moving Average (MA) terms.

All variable coefficients in the model show the correct positive or negative signs and are significant. Monthly HDD and CDD explain most of the seasonal variation in the demand at Woden zone substation. Residential price levels with a 3-month lag, coinciding with the quarterly billing cycle, are significantly negatively correlated to Woden demand. Moreover, energy efficiency for business was found to be significantly negatively correlated to the average demand in Woden. This is according to expectations, given the commercial activity, the presence of the Canberra Institute of Technology and presence of a hospital in the Woden Valley.

Lastly, we observed serial correlation in the residuals and addressed this issue by including a first order moving average term MA[1] and seasonal moving average terms for 12 and 24 months SMA[12,24] in the model. The result is a model with a high model fit of 0.96 R-squared.

Table 23: Model Output for Woden Zone Substation Average Demand

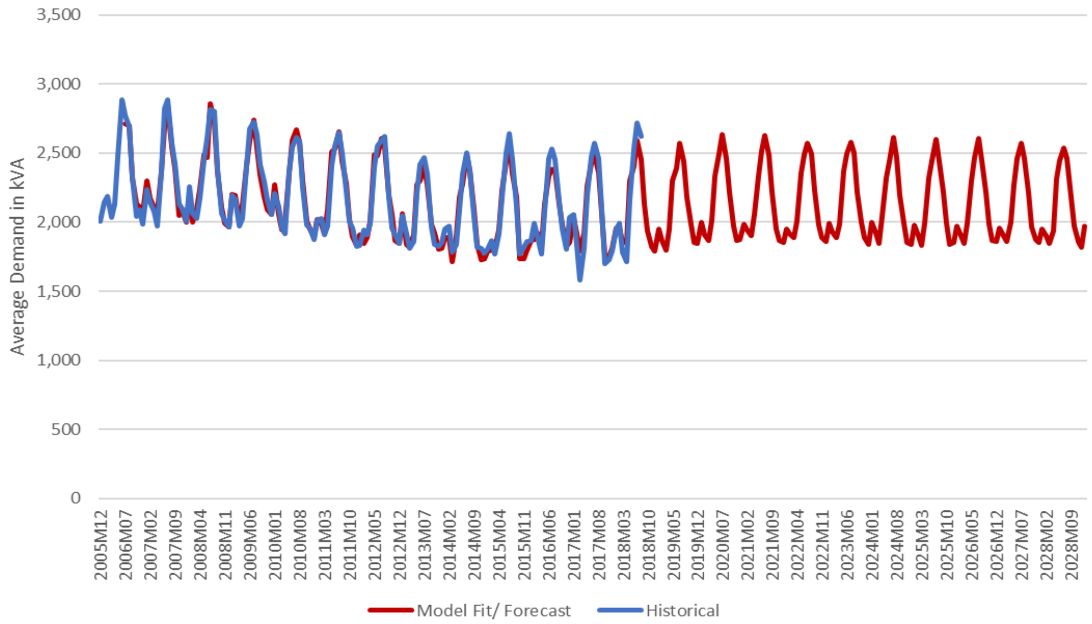
Dependent Variable: LOG(WODE_UAD)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/28/18 Time: 02:32
Sample: 2006M07 2018M07
Included observations: 145
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.001045	4.23E-05	24.73687	0.0000
CDD	0.001367	0.000114	11.99351	0.0000
PRICE_RES(-3)	-0.001021	0.000181	-5.635484	0.0000
EE_BUS	-3.10E-05	7.80E-06	-3.971260	0.0001
D_NEWDEV_WODEN_I	0.074278	0.012816	5.795868	0.0000
LOG(WODE_POP)	0.719448	0.005009	143.6299	0.0000
WEEKDAYS	0.255902	0.069061	3.705454	0.0003
MA(1)	0.263561	0.092666	2.844214	0.0052
SMA(12)	0.366708	0.085862	4.270910	0.0000
SMA(24)	0.372336	0.102669	3.626562	0.0004
SIGMASQ	0.000719	8.88E-05	8.096384	0.0000

R-squared	0.962095	Mean dependent var	7.667157
Adjusted R-squared	0.959266	S.D. dependent var	0.138174
S.E. of regression	0.027887	Akaike info criterion	-4.217153
Sum squared resid	0.104210	Schwarz criterion	-3.991332
Log likelihood	316.7436	Hannan-Quinn criter.	-4.125394
Durbin-Watson stat	2.005851		

Figure 26 provides a visualisation of the model fit and forecast. The model fit looks good and the forecast is showing a stable outlook for Woden. The negative impact of continuing energy efficiency for business, balanced with a stable population outlook and reducing electricity prices, results in an overall flat projection of average demand.

Figure 26: 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 he zone substation average demand forecasts in Table 24 below. Use of these statistics provides an independent validation of the quality of the forecasting models derived.

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

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

However, we do observe that for some zone substations the TU2C values are higher, primarily: City East, East Lake, Telopea and Gilmore. This is a 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 24: Forecast Evaluation Information by ZSS

Evoenergy ZSS	TIC	TU2C
System	0.006894	0.081294
Belconnen	0.019224	0.445730
City East	0.021011	0.575901
Civic	0.013327	0.409747
East Lake	0.042182	1.086935
Gilmore	0.037954	0.837582
Gold Creek	0.026623	0.386427
Latham	0.017538	0.268562
Telopea	0.018665	0.508926
Theodore	0.017807	0.252015
Wanniassa	0.016757	0.307447
Woden	0.015928	0.345344

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 Evoenergy'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 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 Hanna-Quinn criterion being more restrictive than the AIC.

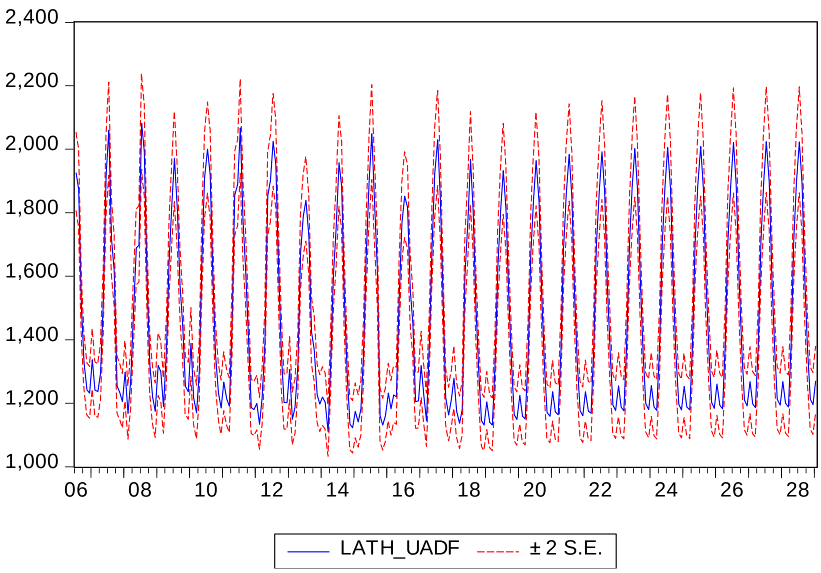
Furthermore, EViews has an automatic dynamic forecasting function that produces a forecast time series based on the model that has been specified. It includes ARMA (dynamic) terms by default, and calculates and reports forecasting evaluation criteria including a forecast output graph. For example, Figure 27 displays 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 Figure 27 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 27: Forecast Output Graph for Latham Zone Substation



Forecast: LATH_UADF
Actual: LATH_UAD
Forecast sample: 2005M12 2029M12
Adjusted sample: 2006M07 2029M01
Included observations: 271

Root Mean Squared Error	52.82396
Mean Absolute Error	41.89995
Mean Abs. Percent Error	2.852868
Theil Inequality Coefficient	0.017538
Bias Proportion	0.000619
Variance Proportion	0.104725
Covariance Proportion	0.894656
Theil U2 Coefficient	0.268562
Symmetric MAPE	2.843752

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"[18], 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

[18] A naïve model simply estimates the future value (Yt+1) to be equal to the current value (Yt)

demand patterns. This is especially important when structurally different models are compared; including models with log-transformed or differenced dependent variables versus models with dependents that are not transformed, as these cannot be selected using 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.