



Energy and Customer Forecasting

ActewAGL

ActewAGL - Energy and Customer Forecasting

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Appendix A. Data Tables

Glossary

ACT = Australian Capital Territory

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

CDD = Cooling Degree Days

DNSP = Distribution Network Service Provider

EV = Electric Vehicle

HDD = Heating Degree Days

HV = High Voltage

LV = Low Voltage

MEFM = Monash Electricity Forecasting Model

NEFR = National Electricity Forecasting Report

NEM = National Electricity Market

MA = Moving Average

MWh = Megawatt Hour

NSW = New South Wales

SCADA = Supervisory Control and Data Acquisition

SFD = State Final Demand

TWh = Terawatt Hour

ZSS = Zone Substation

Important note about your report

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

1. Introduction

Jacobs assisted ActewAGL in the development of the energy and customer number forecasts for the following four customer groups:

1. Residential Customers
2. Commercial Low Voltage Customers
3. Commercial High Voltage Customers
4. Unmetered Customers, including Public Lighting Connections

Together with ActewAGL's Regulatory Affairs and Energy Network teams we have determined the most appropriate set of historical data for projecting the energy volumes and customer numbers of the above customer categories.

Jacobs received a number of spreadsheets with historical data, explanatory comments and clarifications of the data addressing some gaps, uncertainties and potential data glitches.

In particular, Jacobs undertook the following tasks:

- Verification of historical energy and customer data from the ActewAGL billing system for each of the four customer categories;
- Development of econometric seasonal (quarterly) energy volume and customer number models and projections for each of the customer categories, using an econometric time-series modelling tool (EViews);
- Verification of the developed projections with a system wide energy volume forecast; and
- The breakup of the energy volume projections and customer numbers in the different applicable tariff categories.

The next section will discuss the forecasting approach and underlying methodology in detail, followed by an outline of the forecasting results. The final section will provide a summary of the framework for breaking up the tariff classes (plus unmetered) in the different applicable (future) tariff components.

2. Approach

2.1 Tools

The energy volume and customer number forecasting models were developed using EViews. EViews is a Windows based statistical package used mainly for time-series oriented econometric analysis. It can be used for general statistical analysis and econometric analyses, such as cross-section and panel data analysis and time series estimation and forecasting. It is a flexible and transparent tool to build, validate and forecast hybrid econometric models. EViews can handle regular multi-year to intraday time-series data, panel (dated, cross-section) and unstructured data and can import and export data sets to Excel and other highly used formats.

In addition, EViews has a great forecasting tool that automatically reports useful forecast evaluation metrics. Because of its flexibility, diversity and transparency, Jacobs has chosen to prepare the energy volume and customer number forecasts using EViews.

2.2 Objective

The objective for the energy volume and customer number forecasts is to create 10-year projections to support the development of the ActewAGL regulatory pricing proposal for the FY2019-2024 regulatory submission.

2.3 Development, Cleaning and Verification of Historic Energy and Customer Data

Jacobs received a number of sales reports containing monthly historical data on energy sales and customer numbers over the period 2005 – 2017. The historical energy and customer numbers time-series data formed the main input or dependent variables for the energy volumes and customer number forecasts. We started a verification process which involved checking historic data from end of 2005 to June 2017 for gaps and inconsistencies and reported back to ActewAGL on our findings. Afterward we received updates for the energy volumes and customer numbers that addressed most of the identified issues. The final updates were received on 7 September 2017. As of this date we have checked and verified the figures and found that the dataset is now complete and without significant inconsistencies.

Subsequently we developed classes for customer numbers and energy volumes, these categories are defined in Table 1 below.

Table 1: Energy Volume and Customer Number Categories

Category Number	Energy Volume/ Customer Number Tariff Classes	Main Tariffs
1	Residential	Residential Basic, Residential Off-peak Night, Residential Off-peak Day and Night, Residential kW Demand Network, Residential kW Demand Network XMC, Residential Basic XMC, Residential TOU, Residential TOU XMC, Residential 5000, Residential 5000 XMC, Residential with Heat Pump, Residential with Heat Pump XMC, Net Generation Energy, Generation Energy (Gross)
2	Commercial LV	General, General XMC, General TOU, General TOU XMC, LV TOU kVA Demand, LV TOU Capacity, LV TOU kVA Demand XMC Network, LV TOU Capacity XMC, Net Generation Energy, Generation Energy (Gross), LV kW Demand Network, LV kW Demand Network XMC
3	Commercial HV	HV TOU Demand Network, HV TOU Demand Network – Customer LV, HV TOU Demand Network – Customer HV and LV
4	Unmetered	Street Lighting, Street Lighting XMC, Small Unmetered Load

From the final set of historical data, we then developed the following time-series:

- **Customers¹**; quarterly time-series (2005 Q3 to 2017 Q2) such that 2011 Q1 refers to data for (Jan 2011 + Feb 2011 + Mar 2011)/3.
- **Energy Volumes**; quarterly time-series (2005 Q3 to 2017 Q2) such that 2005 Q1 refers to data for (Energy for Jan 2005 + Feb 2005 + Mar 2005).

Furthermore, energy volumes are calculated as gross underlying energy volumes such that:

- **Gross Energy Volumes²** = Net Metered Energy Volumes + Gross Metered Solar PV Generation (Residential/Commercial LV only) + Net Metered Solar PV Generation (Residential/Commercial LV only); and then
- **Gross Energy Volumes per customer (TC)_x** = Gross Energy Volumes for TC_x / Customer Numbers TC_x

The developed and verified historic gross energy volumes per customer and customer number time-series for each category are then used to develop eight individual models (4 energy forecasts and 4 customer number forecasts) and two summary or system models for all energy volumes and all customers (for verification purposes). The methodology for the development of these models is discussed in the following sections of this report.

2.4 Development of Energy and Customer Forecasting Models

The volume and customer number forecasts are developed using EViews econometric time-series software following a multi-step approach summarised as follows:

1. Visual inspection of data for each category to check for potential anomalies, breakpoints and outliers
2. Development of potential models to be tested for each category for energy and customer numbers
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
7. Selection of the best model based on:
 - a. Model evaluation criteria (e.g. AIC, appropriate sign of coefficients, discussed in detail in section 2.4.6);
 - b. Forecast evaluation criteria (e.g. Theil Inequality Coefficient, discussed in detail in section 2.4.6); and
 - c. Visual inspection against historic data and development expectations for the different categories.
8. Development of system level volume model (for verification)
9. Development of solar PV generation forecast
10. Post model adjustments

¹ The calculation of customer numbers in Jacobs' approach differs slightly from the formula used in AAD's previous pricing proposal. ActewAGL used annual average customer numbers weighted by number of days in the month, rather than by number of months.

² The Gross Energy Volumes used in the forecast will differ from the total volumes used in the pricing proposal as the AAD's method adds Gross PV Generation to the Gross Energy for pricing purposes. However, Jacobs will forecast the Gross PV Generation separately so that it can be added for this purpose.

The above steps will be briefly discussed in the following subsections.

2.4.1 Visual Inspection of Historic Data

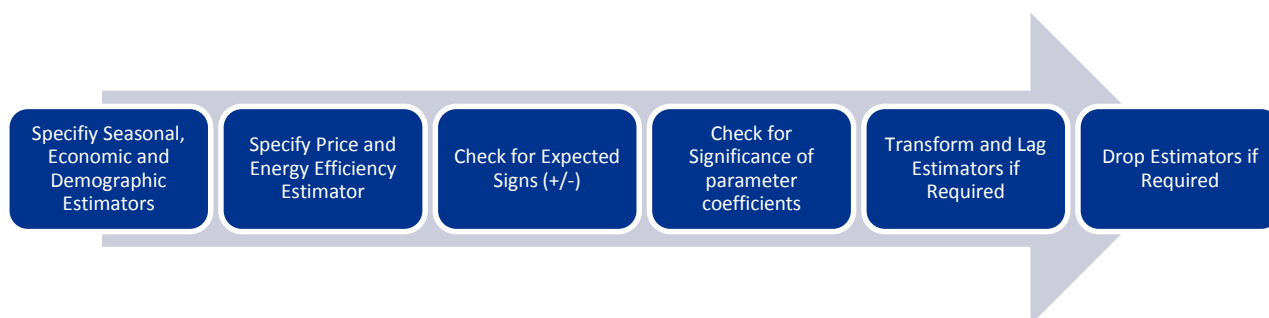
A visual analysis of historic data is a powerful tool to identify any issues or structural changes in time-series data. Therefore, for each of the categories we have plotted the data and analysed the output.

In several cases we identified irregularities in the historical data and have discussed the observations with ActewAGL to seek the necessary clarifications.⁴

In other cases, the analysis resulted in inclusion of dummy variables to control for outliers and/or structural changes in the historical data.

2.4.2 Specification of Energy Volume Models

The following process-chart provides a high-level summary of the steps we have followed to specify the energy volume models for each customer category. The steps are discussed in more detail in the remainder of this section.



Jacobs is specifying quarterly models of energy volumes per customer, therefore for each of the models we are including seasonal independent variables (regressors). The most important seasonal variables are the Heating Degree Days (HDD) and Cooling Degree Days (CDD), which have traditionally been used in electricity models for decades. These variables include the daily number of degrees the average minimum and maximum temperature is above or below a certain threshold ($>18^{\circ}\text{C}$ for CDD and $<19^{\circ}\text{C}$ for HDD). Thus the variable measures the number of degree days heating or cooling load significantly impacts the average demand. These variables essentially 'weather correct' the time-series as they will pick up a significant part of the seasonal variety in average demand.

The further specification of the models is determined on general estimators for energy volumes such as geographic, demographic, economic and other specific variables. We would initially specify a model that contains at least one independent variable that proxies the impact of the economy on energy volumes. For this we have a number of variables available representing country wide and state level economic development over time. These variables are Australian Real GDP, State Final Demand (SFD) and the Unemployment Rate and are included in below. For each model we would initially test the inclusion of one of the two local economic variables and if they do not provide the expected impact, we can substitute those for the country wide GDP regressor. However, it can be that none of these economic variables have any significant impact and that demographic factors are more relevant.

Furthermore, when modelling the above regressors, the best results will be obtained when measuring these against gross energy volumes as they represent the 'uncompromised' underlying demand.

Finally, we have included other independent variables that could estimate the potential impact of price levels and energy efficiency. Both variables are applied on the basis of what we are modelling. For example, for commercial energy volumes we test a model using the energy efficiency times-series for business and the

⁴ For example, one of the explanations to irregularities in historical data may be resulting from revenue meters being read at different times during the year. Thus estimating annual or seasonal consumption of energy involves allocation of revenue metering data into respective time periods (e.g. calendar years). This process may produce some anomalies for individual years which are likely to be corrected through over-and under adjustments over a longer period.

commercial price time-series. Alternatively, for residential energy volumes we will specify the model based on residential time-series. A full list of potential variables is supplied in below.

As we also model the energy volumes for unmetered, mostly public lighting connections, we have made use of an independent variable that is considered as a proxy for the amount of daylight or in other words should be inversely related to the energy volumes for public lighting connections (more daylight = lower energy volumes).

2.4.3 Specification of Customer Number Models

For the modelling of customer numbers, we will only use economic and demographic regressors.as other regressors do not have any (meaningful) theoretical relationship with the number of customers.

Table 2: Independent Variables Used in Energy and Customer Modelling

Class	Independent Variable	Series	Source – Year Published	Energy Volumes	Customer Numbers
Seasonal	Heating Degree Days – historic and simulations	2005Q3-2027Q2	ActewAGL/ BOM (2017)	✓	
Seasonal	Cooling Degree Days – historic and simulations	2005Q3-2027Q2	ActewAGL/ BOM (2017)	✓	
Seasonal	Quarterly Instrumental Variables (Dummies for Q1, Q2, Q3 and Q4)	2005Q3-2027Q2	Jacobs	✓	
Economic	Australian Real GDP – historic and projections	2005Q3-2027Q2	ABS/ Jacobs (2016)	✓	✓
Economic	ACT State Final Demand – historic and projections	2005Q3-2027Q2	ABS/ Jacobs (2016)	✓	✓
Economic	ACT Unemployment Rate – historic and projections	2005Q3-2027Q2	ACT Gov./ Jacobs (2016)	✓	✓
Demographic	ACT Population – historic and projections (used to forecast customer numbers only)	2005Q3-2027Q2	ACT Treasury (2017)		✓
Price	Residential – historic and projections – strong/neutral/weak scenarios forecast ⁵	2005Q3-2027Q2	ABS/ AEMO/ Jacobs (2017)	✓	✓
Price	Commercial Retail Prices – historic and projections - strong/neutral/weak scenarios forecast ⁶	2005Q3-2027Q2	ABS/ AEMO/ Jacobs (2017)	✓	
Efficiency	Total Residential Energy Efficiency – historic and projections - strong/neutral/weak scenarios forecast	2005Q3-2027Q2	AEMO	✓	
Efficiency	Total Business Energy Efficiency – historic and projections - strong/neutral/weak scenarios forecast	2005Q3-2027Q2	AEMO	✓	
Daylight	Sunshine Hours ACT – Long-term Average	2005Q3-2027Q2	Livinginaustralia.com	✓	

⁵ The historic prices have been crossed checked with the ICRC numbers and found that the price series used for the projections in this report align with the ICRC indexed change.

⁶ The historic prices have been crossed checked with the ICRC numbers and found that the price series used for the projections in this report align with the ICRC indexed change.

2.4.4 Analysis of Model Coefficients

When specifying the models in the time-series forecasting tool, one initial step is to assess whether the coefficients have the proper sign (e.g. population is expected to be positively correlated with the number of customers) and/or are significant estimators (by means of analysing the t-Statistic). In case the coefficients of the specified independent variables do not show the appropriate sign, one could transform, difference or lag the independent variables to see if there's any improvement.

However, the above steps should only be taken if it makes sense to do so. For example, the retail price of electricity could have a lagged impact of several periods as most customers do not receive (near) real-time invoices and therefore the volume adjustment could very well take effect a few periods later. Also, the impact of severe price shock can have longer term impacts as consumers invest in more energy efficient equipment or housing.

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

2.4.5 Residual Analysis

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 helpful tools to perform a residual analysis. The most important tools are discussed in this section.

The first step in a proper residual analysis is a visual check for serial correlation in the residuals, after the model is specified and run in EViews. The visual check for serial correlation can be undertaken by reviewing Autocorrelation function (ACF) and Partial autocorrelation function (PACF) plots.

The above information is 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 provides an optimal level of fit for the specified model.

In some cases, it is helpful to use the automatic ARMA modelling function (available in EViews and R) to verify if you have chosen a reasonable model. The automatic ARMA function selects the best model by trialling a predetermined set of ARMA order terms and lagged terms and chooses the best model (e.g. based on the Akaike info criterion, discussed in next section). However, in many cases the best model includes multiple (insignificant) ARMA terms reducing the model's explanatory value and usefulness for the purpose of energy and customer 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 therefore a manual process taking into account different selection criteria. This process will be described in the next section.

2.4.5.1 Tests for Multicollinearity

Jacobs has also tested for potential multicollinearity and associated impact on the developed models. Multicollinearity is a phenomenon in which one independent variable in a multiple regression model can be linearly predicted from the others 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.

EViews has a number of tests available to check for the existence and the impact of collinearity. We have used the Variance Inflation Factors (VIF) to determine the significant existence of collinearity and the Coefficient Variance Decomposition tests whether identified multicollinearity issues have a significant impact on the forecasts. In case multicollinearity was present and significant we have re-specified the model to address the issue.

2.4.6 Selection of Best Performing Model

After specification of complete models including potential ARMA terms (if necessary, based on residual analysis), there are usually several models with slight differences we can select (e.g. dropping or including specific independent variables). For the selection of the best model we have several tools available.

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

- R-squared
- Adjusted R-squared
- Akaike Information Criterion (AIC)
- 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 , which is very similar) is a very useful tool to determine your model's fit, where an R^2 of 1 would constitute as a perfect fit and an R^2 of 0 as the opposite. However, the R^2 statistic does not adequately penalise over-fitted models and is therefore not the most practical option for model selection.

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.

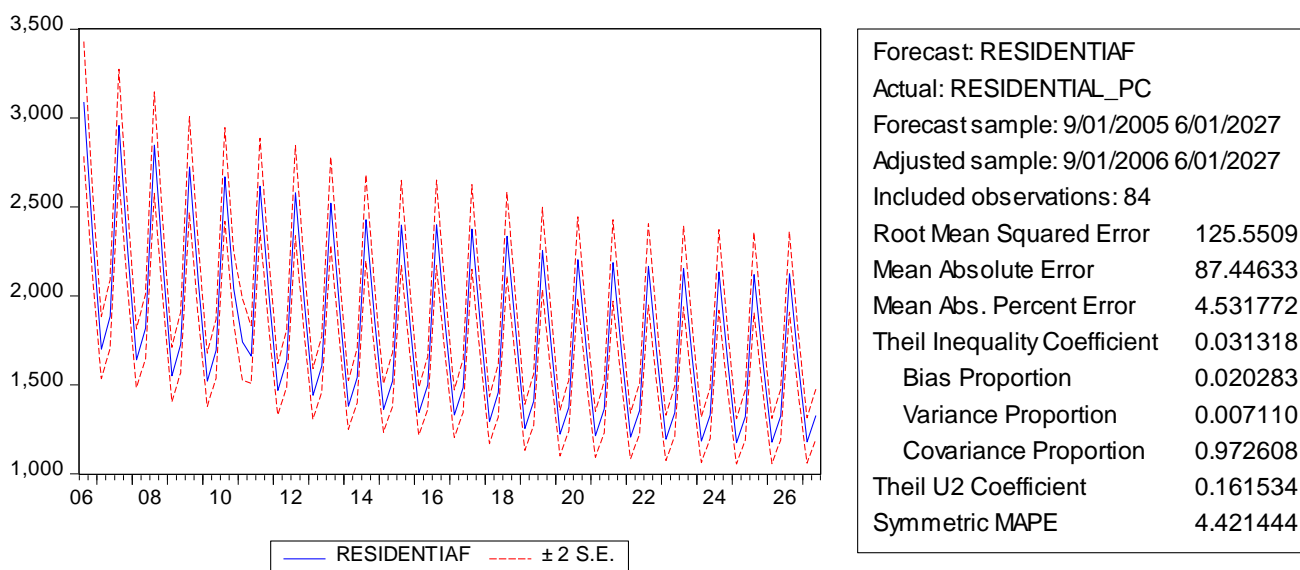
Furthermore, EViews has an automatic dynamic forecasting function that produces a forecasted time series based on the model that has been specified. It includes ARMA (dynamic) terms by default, calculates and reports forecasting evaluation criteria including a forecast output graph. Figure 1 displays the forecast output graph for residential energy volumes. 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 1 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 1: Forecast Output Graph for Residential Energy Volumes



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”⁷, 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.

A final step in the selection process is the analysis of the graphical representation of the forecasting model against the actual historic data including how the projections relate to the historically observed average demand patterns. This is especially important when structurally different models have to be compared; including models with log-transformed or differenced dependent variables versus models with dependents that are not transformed, as these cannot be selected on the basis of AIC.

In addition, even though a reported AIC may look favourable for a certain model, in practise (visually) this may not look reasonable (e.g. this may occur when using auto ARIMA functions only). Determining whether the models look visually correct is mostly dependent on checking whether the model outputs make sense given its specification, e.g. if the projected population numbers are rising significantly, we expect to also see a growth of residential customers as compared to a declining development. If there are any unexpected developments observed, we should look for a specific explanation or if none exist try re-specifying or select an alternative model.

2.4.7 Development of System Model

After the individual models for each of the categories were specified and selected, Jacobs also developed a model for the energy volumes per connection of the entire system (summary of the energy volumes for all customer categories) and a model for total customers. For these models we have used all the independent variables we have used across all category models (except for the instrumental regressors like dummies⁸).

These models are developed for verification purposes: the system level models and resulting total energy volumes projections (customer*energy per customer) should closely align with the summation of all four customer category volume models.

The results of this verification step are discussed in section 3.

⁷ A naïve model simply estimates the future value (Y_{t+1}) to be equal to the current value (Y_t)

⁸ Dummy variables are instrumental binary variables that can only have the value 1 or 0. These variables are generally included in a regression to indicate the absence or presence of some categorical or one-off effect that may be expected to shift the outcome.

2.4.8 Solar PV Energy Generation Forecast

From the demand forecasting work stream, we used the solar PV capacity forecast to project the energy volumes for total gross and net metered solar PV generation for residential and commercial LV customers separately. This helps to ensure consistency between the two forecasts.

These projections were then split in two parts:

- The energy volumes (residential/ commercial LV) for Gross Solar PV Metered Generation⁹
- The energy volumes (residential/ commercial LV) for Net Solar PV Metered Generation

As the gross metering scheme is closed, the Gross Solar PV Metered generation was fixed based on the average output over the last 2 years or 8 periods and projected forward without any change. Subsequently the remaining Solar PV Metered Generation was designated as Net Solar PV Metered Generation.

The historic and forecast Net Solar PV Metered Generation (residential/ commercial LV) were then subtracted from the forecast energy volumes to create the Gross Energy Volumes as specified in section 2.3.

⁹ For tariff purposes the energy generated by gross metered PV is added to gross energy volumes by ActewAGL. This is because AAD needs to recover revenue to pay customers with gross metered PVs.

3. Modelling Results

This section contains the modelling results starting with a summary of the result, working down to the detailed results.

3.1 Scenarios

Jacobs developed three scenarios based on AEMO's 'Strong/Neutral/Weak' scenarios for retail prices and energy efficiency projections. The base scenario uses the 'Neutral' projections for retail prices and energy efficiency. Summary results for the other two scenarios will be provided in a separate subsection at the end of section 3.

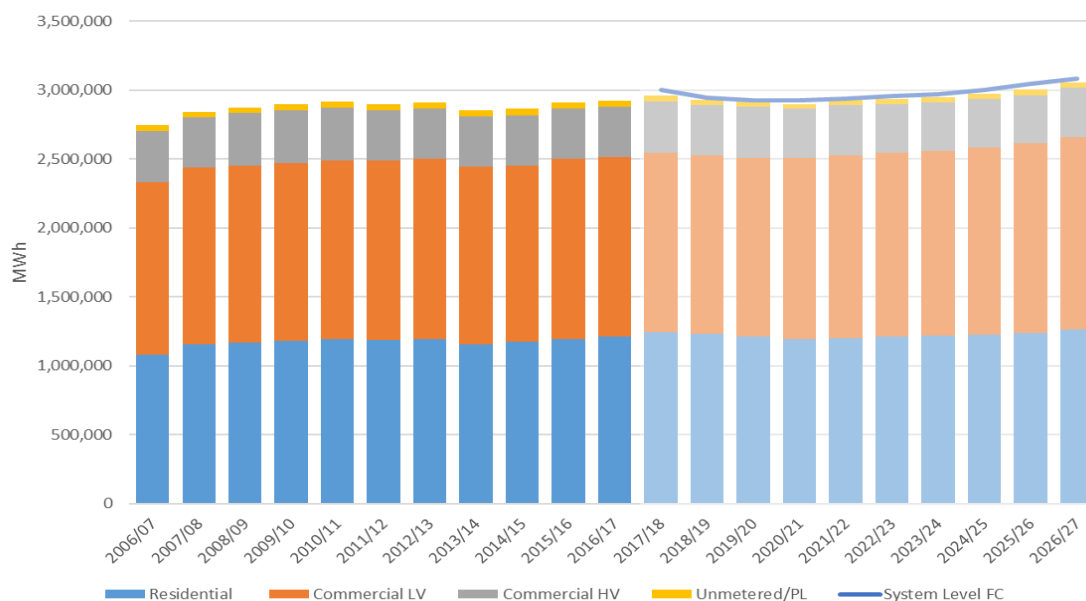
3.2 Summary of Results

Figure 2 below offers an overview of the total energy volume historical development over time and the forecast for the period FY2018-2027 (shaded area). For this 10-year projection period an overall increase in gross energy volumes to approximately 3.1 TWh annually is projected.

Following from the below graph a slight increase in volumes is projected for the running year (FY2018), following from the historical increasing trend Starting in FY2014). However, for FY2019 a decline in total energy volumes is expected as a correction to the announced increasing retail prices for electricity¹⁰, ongoing energy efficiency increases, and solar PV generation behind the meter. Consequently, the volume decline per customer has a larger negative impact than the growth of energy volumes as a result of the increasing customer base. After FY2020 the energy volumes are increasing again resulting from the growth in customer base and the fading effects of price response.

The figure also displays a blue line representing the results of the system model projections that show a very similar outcome. This is confirming and validating that we are able to accumulate the results of the individual customer category models to form the total gross energy volume forecast (i.e. we may conclude from the below representation that no significant bias is observable).

Figure 2: ActewAGL Total Gross Energy Volumes by Customer Type – Historic & Projections FY18-27¹¹

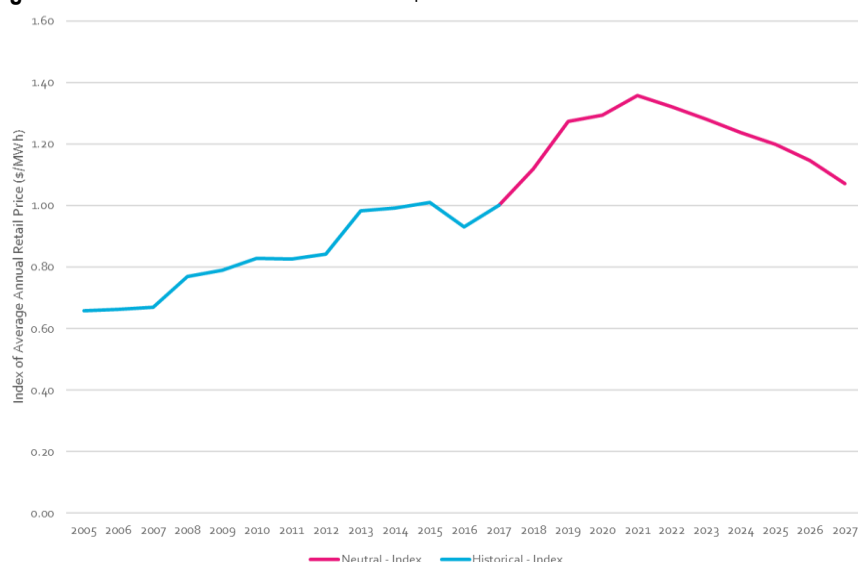


¹⁰ The effect of increasing prices is slightly lagged as customers tend to adjust their behaviour (demand) after they received their first bill (bill shock effect).

¹¹ This chart includes Gross Metered PV up to FY2020.

Figure 3 shows the historical and projected residential retail price development. A strong rise in real retail price levels is expected for the 2018/19 financial year and after that we see stabilisation of retail real price levels, and decreasing retail prices again from 2025 onwards. These price projections coincide largely with the gross energy volumes in Figure 2 above, where a decrease in volumes can be observed in FY2019 and FY2020, followed by a relatively small increase in the next four years, and a steeper increase in the final three years of the projections (coinciding with the decreasing retail price levels in the figure below).

Figure 3: Residential Retail Price in 2017\$/MWh - Neutral Scenario



The projected customer numbers show a moderate increase for residential, commercial (HV/LV) and unmetered (incl. public lighting) customers. The increase for residential customers is mainly driven by the most recent published population projections (ACT Treasury – 2017), as well as state (ACT) economic activity and long-term positive trends. The result of the accumulated historic and projected customers for ActewAGL are displayed in Figure 4 and Figure 5 below.

Figure 4: ActewAGL Total Customers by Type (Residential and Commercial LV) – Historic & Projections FY18-27

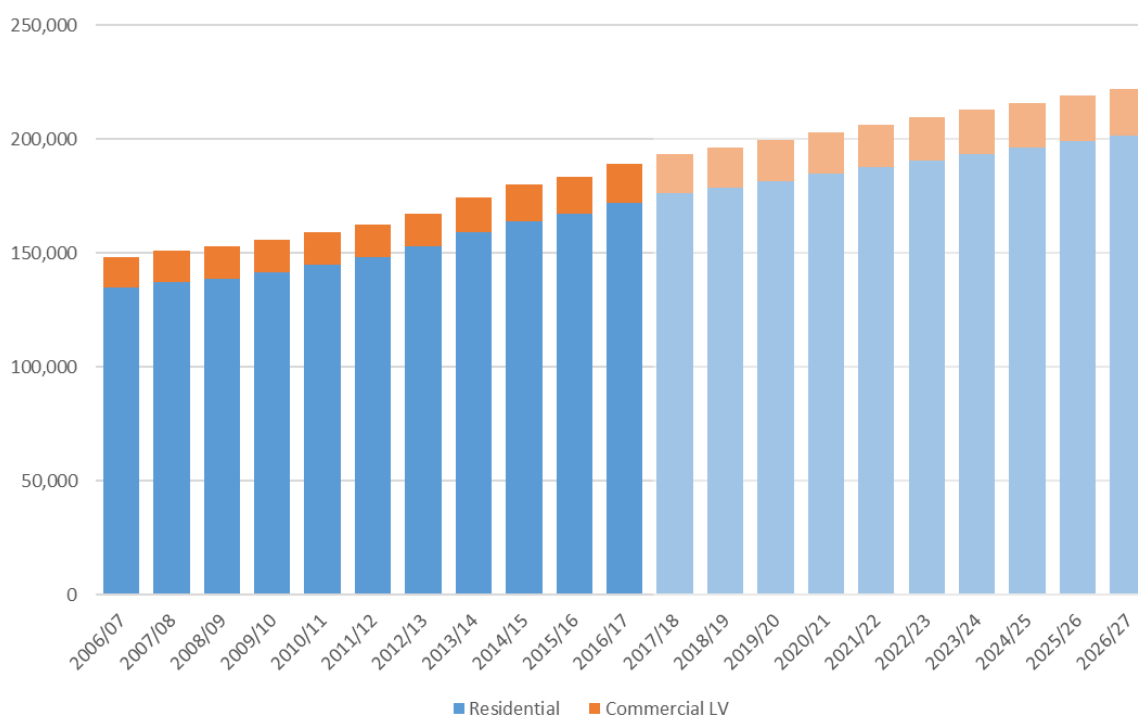


Figure 5: ActewAGL Total Customers by Type (Unmetered/SL and Commercial HV) – Historic & Projections FY18-27

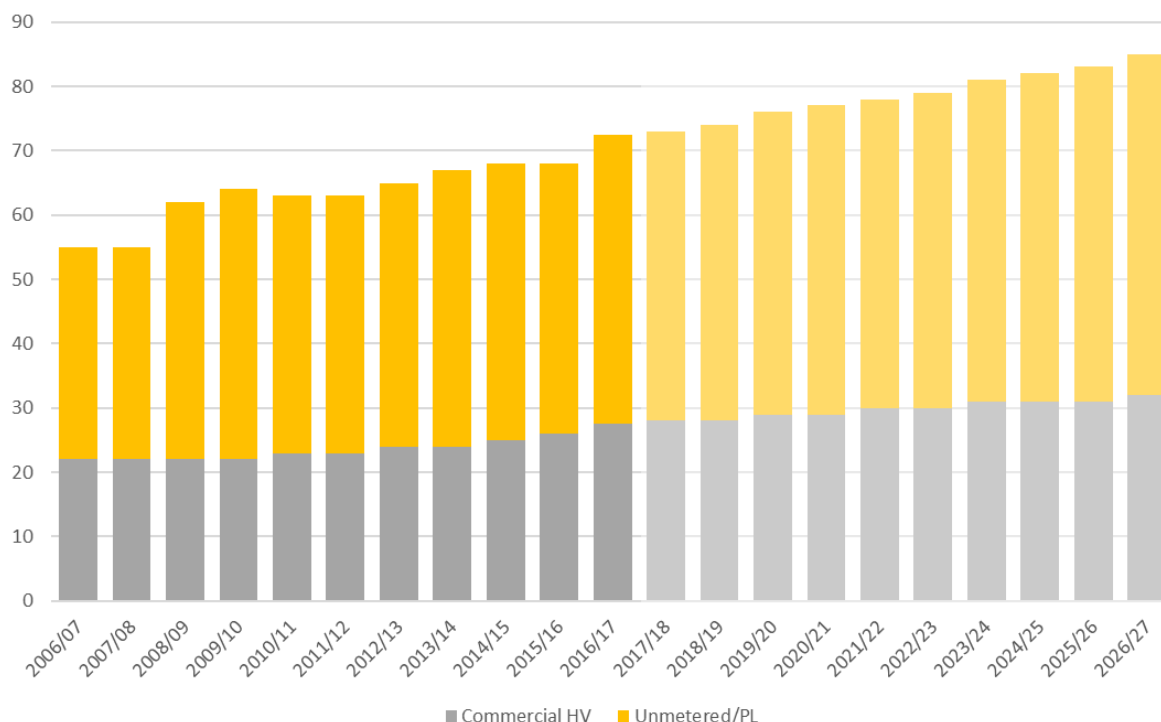


Figure 6 includes the per connection historical and projected energy volumes for each of the four customer tariff classes. The blue bar diagram represents the residential energy volumes per connection, the green bar chart shows the Commercial LV energy volumes per connection, the purple the Commercial HV energy volumes per connection and the yellow bar chart the Unmetered/ Street Lighting energy volumes per connection.

All projections show a decreasing trend per connection/ customer. However, for all but the Street Lighting forecasts we can observe a flattening of the energy volume projections after FY2023. The decreasing trends are the result of the following effects that have been included in the individual models:

- The Price impact: included in the forecast for Residential, Commercial LV and Unmetered volumes per customer. Since retail prices are projected to rise the volumes will be decreasing from next year onwards for Residential customers (because of the lagged price response effect) and expected immediately for Commercial LV customers (no lagged price response effect).
- The Energy Efficiency impact: per customer volumes for each customer type is negatively impacted by increasing energy efficiency.
- Impact of Economic Development: this impact is significant only in the per customer volumes for Commercial LV and Commercial HV customers. Given the stable forecast on economic development, the impact on the projections will be relatively flat.

A post modelling adjustment has been applied to the forecast for the customer class Unmetered/ Street Lighting as a result of the pending implementation of LED street lighting. It is expected that LED street lighting will reduce the energy volumes by 40%, captured over a three-year implementation period starting in financial year 2018.¹³ The yellow chart in Figure 6 clearly shows this effect with a sharp decline in FY2018-2020 and the final realisation of the full volume decrease in FY2021. The subsequent slight yearly increase after FY2021 is due to lamp intensity adjustments accounting for a 0.5% per annum increase from the date of LED implementation.¹⁴

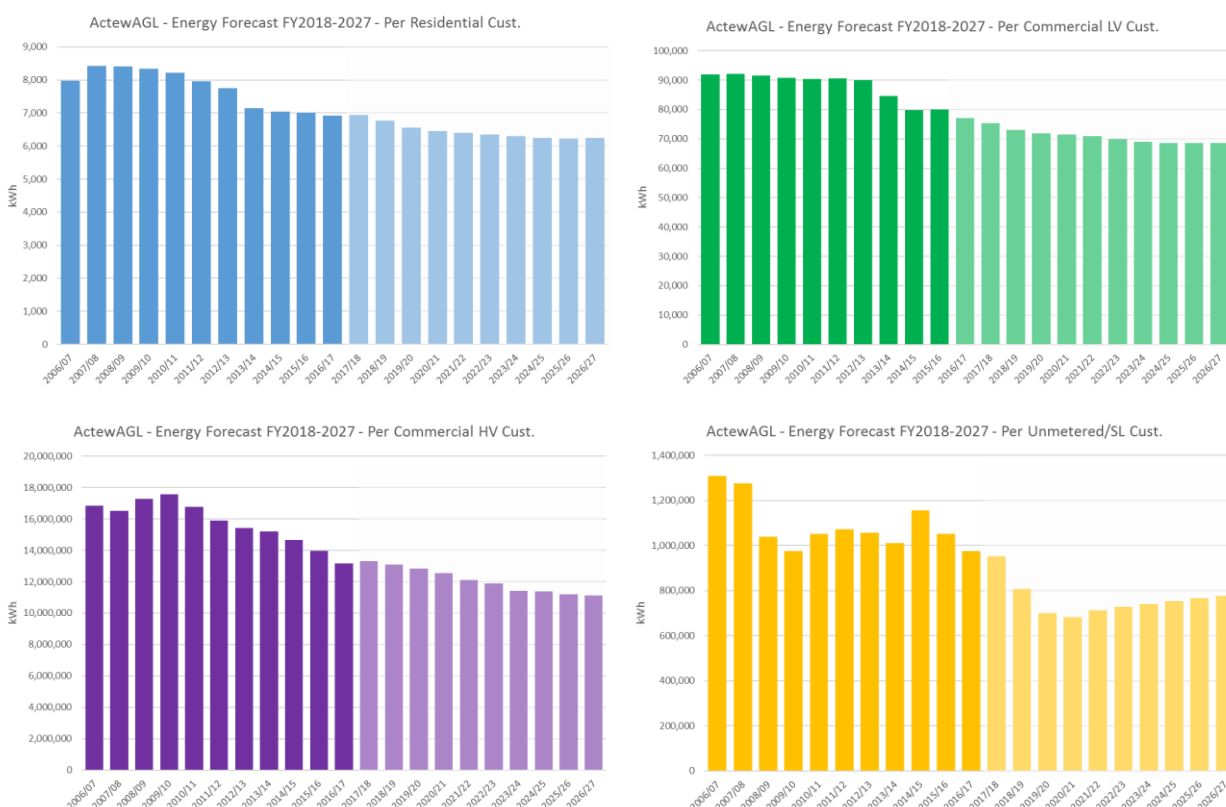
¹³ Since the base forecast already included a decline of energy volumes, we have netted this effect against the decrease as a result of the LED implementation to avoid any double counting of energy efficiency effects.

¹⁴ LED lights slowly lose brightness over time so that the light intensity needs to be adjusted regularly, this adjustment increases the energy consumption slightly.

Furthermore, in regards to Residential and Commercial LV volumes, as a result of closing the gross solar PV generation scheme the take up of the net metered solar PV generation scheme will increase. In addition, given the low retail buy back tariffs of net metered solar PV it is expected that solar PV generation and self-usage behind the meter will significantly rise in the future. This will negatively impact the metered energy volumes per customer¹⁵, specifically in the commercial LV and residential customer groups.

Also note that the historical volumes per customer for Commercial HV and Unmetered/Street Lighting appear more volatile because the number of customers is limited and therefore an individual customer's change in energy volumes is likely to have a more significant impact on the average volume per customer.

Figure 6: Gross Energy Volumes Per Customer/Connection – Historic & Projections FY18-27¹⁶



Fuel Switching

The effects of fuel switching (consumers switching from gas to electric heating and/or hot water) have been considered, but have not been modelled for the following reasons:

- To adequately model this effect, there is a need for detailed historical data on consumers switching from gas to electricity based on relative price changes or other reasons. This type of data was not available at the time of analysis; and
- Currently both gas and electricity retail prices are rising, so that the current relative gap between the price of gas and electricity will most likely not be large enough to encourage consumers to switch fuel sources immediately, as it may take too long to recover the investments to be made in new equipment.
- There may be a growing propensity for new consumers (e.g. in greenfield areas) and customers with gas equipment at end of life to take up electric heating and hot water systems, which could increase the per capita electricity volumes for Residential and Commercial LV in the long term. However, this change would be small and grow slowly, e.g. if the life of gas heating was 15 years only 1/15th of the population would be considering switching in the first year, 2/15 in the second year and so forth.

¹⁵ The self-usage of PV Generation will increase and therefore the demand energy volumes taken from the distribution network is likely to decline.

¹⁶ These charts do not include Gross Metered Solar PV.

Based on the above argumentation, the forecasts in this report do not include any adjustment as a result of potential future fuel switching of consumers.

3.3 Detailed Modelling Results

3.3.1 Residential Energy Volumes & Customers

Table 3 shows the EViews model outputs for the residential energy volume. It includes the seasonal instrumental variables for Q1, Q3 and Q4 (Q2 is the default). Residential energy efficiency is included as an interaction variable with the residential retail price showing a significant negative impact on the energy volumes for residential customers. The latter indicates that there is a strong negative correlation of price and energy efficiency with energy volumes. The interaction variable not only captures the individual effects of price and energy efficiency, but also the interaction between price changes and the resulting energy efficiency effects of these changes. In addition, it helps avoid multicollinearity as compared to including the variables into the equation separately.

Moreover, we found that none of the economic regressors (e.g. GDP, SFD) did have any significant and improving effect on energy volume estimated and therefore we have left them out of the equation.

Finally, the model includes one dummy variable to pick-up an outlier we identified in the historic quarterly energy volume data in 2011 Q1.

Table 3: EViews Model Outputs for Residential Gross Energy Volumes Per Customer

Dependent Variable: LOG(RESIDENTIAL_PC)

Method: Least Squares

Date: 10/27/17 Time: 14:17

Sample (adjusted): 3/01/2007 6/01/2017

Included observations: 42 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.916373	0.152252	58.56324	0.0000
Q1	-0.119551	0.020504	-5.830586	0.0000
Q3	0.473781	0.020495	23.11663	0.0000
Q4	0.204671	0.020497	9.985508	0.0000
LOG(RESIDENTIAL_EE_N*RESIDENTIAL_PRICE_N(-4))	-0.144026	0.014411	-9.994162	0.0000
D_RESIDENTIAL2	0.155928	0.049173	3.170982	0.0031
R-squared	0.964487	Mean dependent var	7.534141	
Adjusted R-squared	0.959555	S.D. dependent var	0.233035	
S.E. of regression	0.046866	Akaike info criterion	-3.151503	
Sum squared resid	0.079070	Schwarz criterion	-2.903264	
Log likelihood	72.18156	Hannan-Quinn criter.	-3.060514	
F-statistic	195.5442	Durbin-Watson stat	1.532322	
Prob(F-statistic)	0.000000			

Table 4: EViews Model Outputs for Residential Customer Numbers

Dependent Variable: RESIDENTIAL_CUST

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 10/04/17 Time: 14:33

Sample: 9/01/2005 9/01/2017

Included observations: 49

Convergence achieved after 47 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(SFD)	824.6427	724.3226	1.138502	0.2614
LOG(POP)	178287.0	33698.02	5.290727	0.0000
C	-2141250.	440844.9	-4.857150	0.0000
AR(1)	0.955566	0.052066	18.35301	0.0000
MA(1)	0.637921	0.128379	4.969042	0.0000
SMA(3)	0.423005	0.163359	2.589426	0.0132
SIGMASQ	284523.7	70163.80	4.055136	0.0002
R-squared	0.998406	Mean dependent var		149969.5
Adjusted R-squared	0.998178	S.D. dependent var		13497.74
S.E. of regression	576.1461	Akaike info criterion		15.79175
Sum squared resid	13941663	Schwarz criterion		16.06201
Log likelihood	-379.8979	Hannan-Quinn criter.		15.89429
F-statistic	4383.832	Durbin-Watson stat		1.948407
Prob(F-statistic)	0.000000			

The EViews output in Table 4 is for the customer number model. The output shows, as was expected, that the number of customers is significantly correlated to the population in ACT.

A number of auto regression (AR), moving average (MA) and seasonal moving average (SMA) terms have been added to the model to address serial correlation.

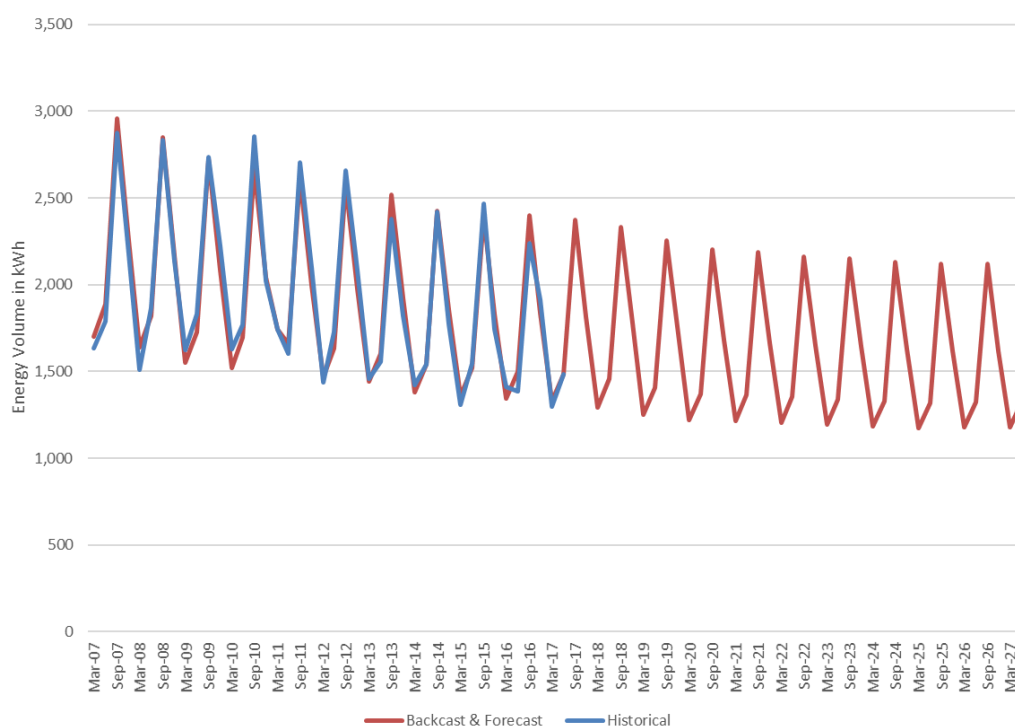
Figure 7: ActewAGL Residential Quarterly Energy Volumes Per Customer Historical, Backcast and Forecast Comparison

Figure 7 shows how the model performs visually¹⁷ against the actual historical data on quarterly energy volumes per customer. As observable, the model shows a very close approximation to the historical data in the back-cast period.

There is a visible declining trend in the historical data and this trend continues to FY2023 in the forecast after the decline seems to level-off. The declining trend is the result of the energy efficiency and price increases (included in the model), and is projected to continue to have a significant impact on the volume of energy per customer until FY2023 as shown below.

3.3.2 Commercial LV Energy Volumes & Customers

The commercial energy volumes per customer are forecasted using the model displayed in Table 5. Again this model includes seasonal instrumental variables for quarter 1, 3 and 4 (default is quarter 2), all indicating significant coefficients with the proper signs.

Commercial energy efficiency has been included only from 2014 as there was no significant correlation observable before that time. The commercial price also was found to have a significant negative correlation with commercial LV energy demand.

The unemployment rate with a lag of three periods provided the best economic estimator (negatively related). The latter makes sense as an increasing unemployment rate in the ACT should negatively impact commercial activity and therefore energy volumes in this segment.

As a result of detected serial correlation we included a second order autocorrelation (AR). Finally, we included a dummy variable to identify an outlier in the data (2014 Q1).

Table 5: EViews Model Outputs for Commercial LV Gross Energy Volumes Per Customer

Dependent Variable: LOG(COMMERCIAL_LV_PC)

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 10/27/17 Time: 14:56

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

Included observations: 45

Convergence achieved after 11 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.11154	0.020229	499.8587	0.0000
Q4	0.024864	0.012767	1.947487	0.0598
Q3	0.052153	0.008164	6.388158	0.0000
Q1	0.052022	0.009159	5.679887	0.0000
COMMERCIAL_EE_N	-0.000767	4.00E-05	-19.15816	0.0000
UNEMPLOYMENT(-3)	-0.008016	0.004143	-1.934857	0.0614
D_COMMERCIAL_LV	-0.058641	0.018641	-3.145866	0.0034
COMMERCIAL_LV_PRICE_N	-0.000599	0.000154	-3.887955	0.0004
AR(2)	-0.409122	0.191069	-2.141225	0.0395
SIGMASQ	0.000195	6.04E-05	3.231817	0.0027
R-squared	0.960523	Mean dependent var		9.986743
Adjusted R-squared	0.950074	S.D. dependent var		0.071106
S.E. of regression	0.015888	Akaike info criterion		-5.241440
Sum squared resid	0.008583	Schwarz criterion		-4.835943
Log likelihood	125.3117	Hannan-Quinn criter.		-5.091062
F-statistic	91.91858	Durbin-Watson stat		2.120581
Prob(F-statistic)	0.000000			

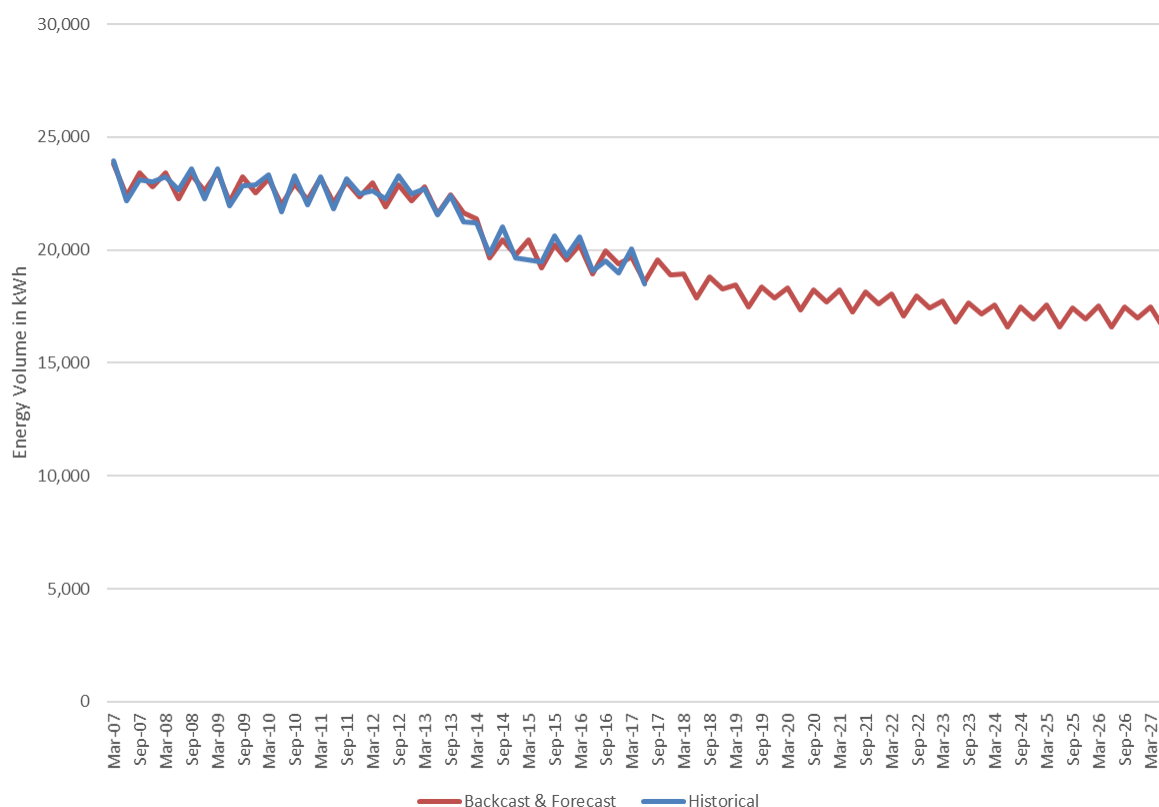
¹⁷ Besides the use of a visual inspection, models are picked based on the best AIC satisfying a number of rigorous adequacy tests.

Table 6: EViews Model Outputs for Commercial LV Customer Numbers

Dependent Variable: COMMERCIAL_LV_CUST
 Method: ARMA Maximum Likelihood (OPG - BHHH)
 Date: 10/04/17 Time: 15:51
 Sample: 9/01/2006 9/01/2017
 Included observations: 45
 Convergence achieved after 26 iterations
 Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D_COMMERCIAL_LV_CUST	402.5759	46.07967	8.736519	0.0000
@TREND	66.01549	16.31872	4.045384	0.0002
LOG(SFD(-4))	1411.790	48.05470	29.37881	0.0000
AR(1)	0.933068	0.084940	10.98505	0.0000
SAR(2)	0.300820	0.169941	1.770139	0.0845
SIGMASQ	15950.03	3911.649	4.077572	0.0002
R-squared	0.986782	Mean dependent var		14912.00
Adjusted R-squared	0.985087	S.D. dependent var		1110.908
S.E. of regression	135.6609	Akaike info criterion		12.84492
Sum squared resid	717751.4	Schwarz criterion		13.08580
Log likelihood	-283.0106	Hannan-Quinn criter.		12.93472
Durbin-Watson stat	1.947032			

Table 6 the EViews output for the customer model is included. The model was initially tested with the ACT Population data, but did not provide a decent model. We did however find the State Final Demand (SFD) to be significantly positively correlated to the number of commercial LV connections, when we applied a lag of four periods (one year).

Figure 8: ActewAGL Commercial LV Per Customer Historical, Back-cast and Forecast Comparison

Moreover, we found a positive trend that improved the model significantly, and we identified a period with data anomalies in commercial customer numbers in commercial LV customer numbers in 2014 (Q1). For the latter we included a dummy variable to improve the model.¹⁸ Coincidentally 2014 Q1 was also identified as an outlier in the volume per capita model (see above) indicating that there was some form of correction to the number of customers in that particular quarter.

Figure 8 depicts how the model performs visually against the actual historical data on energy volumes per connection for the commercial LV category. The back-cast (model-fit) shows a very close approximation to the historical data. A clear continuing drop in energy volumes per connection is visible up to FY2019-2020, resulting from the effects of increasing retail prices and ongoing energy efficiency (including solar PV behind the meter). The energy volumes are stabilising after FY2020 and returning to their long-term average seasonal pattern. Also note here that the seasonal pattern is much less spikey as for the residential energy volumes.

3.3.3 Commercial HV Energy Volumes & Customers

The models for commercial HV energy volumes and customer numbers are included in respectively Table 7 and Table 8. The energy volume model includes seasonal variables specifying the cooling and heating degree days¹⁹. We also found significant negative correlation between energy volume and energy efficiency, and positive correlation between Australian GDP and HV energy volumes. A dummy variable was included for the period 2009Q2 – 2011Q1 as we noticed inflated levels of energy volumes. The latter may be due to data quality issues, e.g. an underspecified number of customers may have a large impact on the energy volumes per customer, as average volumes per customer are very high. It may be worth further investigating the data. Finally, we have included a first order auto regression term to resolve serial correlation issues.

Table 7: EViews Model Outputs for Commercial HV Energy Volumes Per Customer

Dependent Variable: LOG(COMMERCIAL_HV_PC)

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 10/27/17 Time: 15:24

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

Included observations: 45

Convergence achieved after 16 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDD	0.000122	2.49E-05	4.883830	0.0000
CDD	0.000339	7.86E-05	4.317884	0.0001
COMMERCIAL_EE_N	-0.003887	0.000188	-20.65978	0.0000
LOG(GDP)	1.201419	0.002644	454.3178	0.0000
D_COMMERCIAL_HV	0.065858	0.036023	1.828200	0.0754
AR(1)	0.439131	0.175784	2.498131	0.0169
SIGMASQ	0.000959	0.000220	4.353562	0.0001
R-squared	0.894982	Mean dependent var		15.18541
Adjusted R-squared	0.878401	S.D. dependent var		0.096656
S.E. of regression	0.033705	Akaike info criterion		-3.795545
Sum squared resid	0.043169	Schwarz criterion		-3.514509
Log likelihood	92.39977	Hannan-Quinn criter.		-3.690778
Durbin-Watson stat	1.759928			

¹⁸ It might be worth investigating the reason for this large increase in customers at this date, as it may be the result of a re-categorisation of customer types (e.g. customers on residential tariffs moved to commercial tariffs).

¹⁹ This is a different method for applying seasonal adjustments, HDD and CDD provided a better fit for Commercial HV customers than simple quarterly seasonal regressors we used for Commercial LV and Residential volumes.

Table 8: EViews Model Outputs for Commercial HV Customer Numbers

Dependent Variable: COMMERCIAL_HV_CUST

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 11/27/17 Time: 14:00

Sample: 12/01/2005 9/01/2017

Included observations: 48

Convergence achieved after 22 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(POP)	27.51248	4.724034	5.823939	0.0000
C	-328.6945	60.50757	-5.432288	0.0000
AR(1)	0.672499	0.165135	4.072413	0.0002
MA(1)	0.351262	0.198990	1.765224	0.0846
SIGMASQ	0.353335	0.065071	5.430023	0.0000
R-squared	0.878494	Mean dependent var		3.162470
Adjusted R-squared	0.869603	S.D. dependent var		0.083442
S.E. of regression	0.030131	Akaike info criterion		-4.063300
Sum squared resid	0.037224	Schwarz criterion		-3.902708
Log likelihood	95.42425	Hannan-Quinn criter.		-4.003433
F-statistic	98.81043	Durbin-Watson stat		1.836046
Prob(F-statistic)	0.000000			

The lower table above displays the customer number model. In this model we used a lagged GDP per capita and again a first order auto regression term to resolve serial correlation issues.

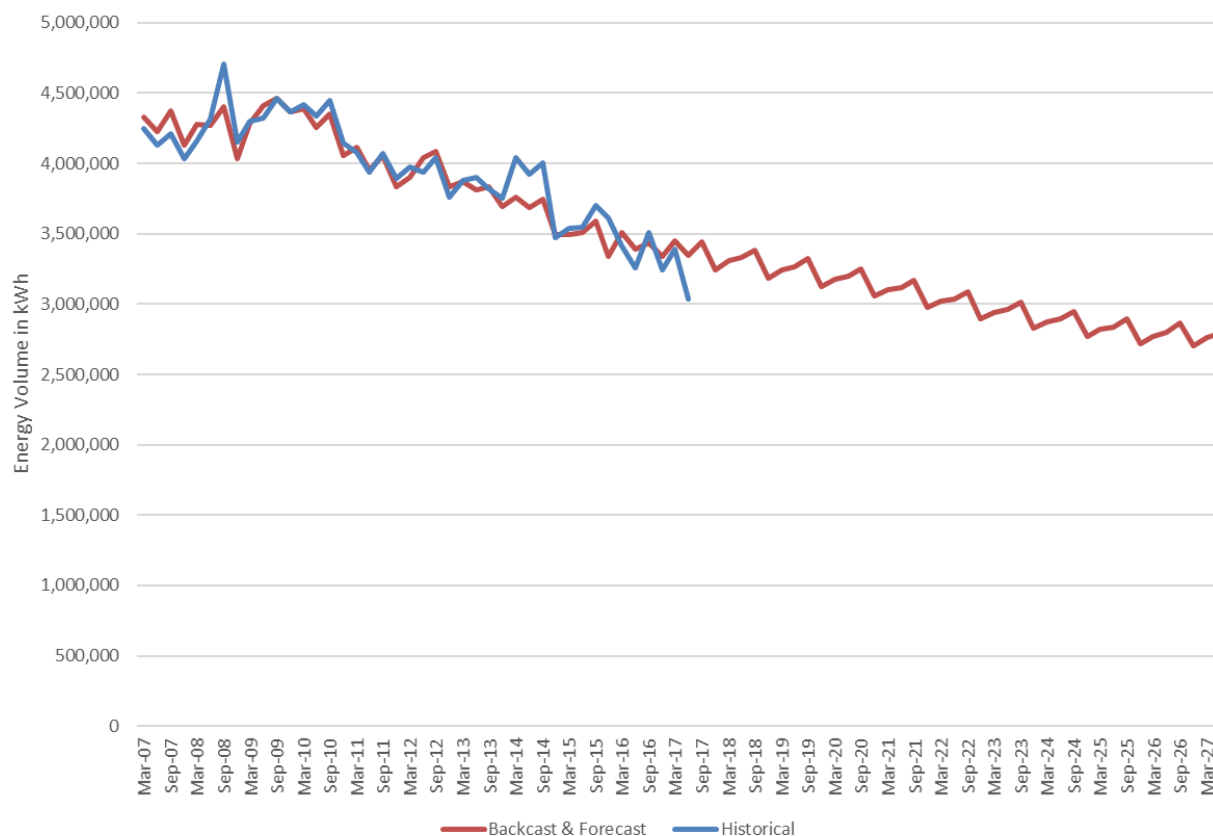
Figure 9: ActewAGL Commercial HV Per Customer Historical, Backcast and Forecast Comparison

Figure 9 provides an overview of the back- and forecast against historical energy volume actuals. Just like the commercial LV energy volumes we observe a less pronounced seasonal effect than observed in the residential energy volumes. In addition, the latest historical data-point (2017Q2) is lower than the model estimates. The overall energy volumes per connection show an ongoing decline in the next ten years, although not as steep as previous years. The decline is the result of the ongoing energy efficiency effect as specified in the model.

3.3.4 Unmetered Energy Volumes & Customers

The unmetered energy volumes and customer numbers are for the largest part built up from public lighting connections and a very small number of other unmetered connections. Therefore, to estimate the energy volume model as displayed in Table 9 we have included the variable "Sunshine" (hours) as the main regressor for volumes. This variable is a proxy for the amount of sunlight in the different seasons. It takes into account both daylight as well as sunshine and has proven to be a better estimator than average number of daylight hours.

Additionally, we included an interaction variable of price and energy efficiency just in the residential model, and found a significant negative correlation based on a 2 period lagged price effect. It is plausible that price has a lagged effect on the volumes, in this case through the result of implementing more energy efficient luminaires or dimming/adjusting the operating time of public lighting to save on energy usage.

A dummy variable was included to account for a spike that was detected in the data. This spike is clearly visible in Figure 10 below (2015Q2), and is most likely the result of a data quality issue. Another observation from the figure below is the difference between the model back-cast and the historical data in the first few years. Apart from these observations, the model's back-cast is a very close match with the actual data.

Table 9: EViews Model Outputs for Unmetered Energy Volumes Per Customers

Dependent Variable: LOG(UNMETERED_PC)

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 10/27/17 Time: 16:23

Sample: 3/01/2006 6/01/2017

Included observations: 46

Convergence achieved after 13 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.16584	0.262744	53.91502	0.0000
SUNSHINE	-0.001151	5.04E-05	-22.84111	0.0000
LOG(COMMERCIAL_HV_PRICE_N(-2)*COMMERCIAL_EE_N)	-0.098978	0.028758	-3.441720	0.0014
D_UNMETERED	0.324403	0.094779	3.422722	0.0015
D_UNMETERED3	-0.024980	0.011035	-2.263768	0.0294
AR(1)	0.747881	0.139361	5.366523	0.0000
MA(1)	0.401133	0.197497	2.031087	0.0493
SIGMASQ	0.001107	0.000232	4.762510	0.0000
R-squared	0.961536	Mean dependent var		12.50445
Adjusted R-squared	0.954450	S.D. dependent var		0.171497
S.E. of regression	0.036602	Akaike info criterion		-3.587638
Sum squared resid	0.050908	Schwarz criterion		-3.269613
Log likelihood	90.51567	Hannan-Quinn criter.		-3.468504
F-statistic	135.7039	Durbin-Watson stat		1.916053
Prob(F-statistic)	0.000000			

Table 10: EViews Model Outputs for Street Lighting and Unmetered Customer Numbers

Method: ARMA Maximum Likelihood (OPG - BHHH)

Dependent Variable: UNMETERED_CUST

Date: 10/03/17 Time: 17:57

Sample: 9/01/2005 9/01/2017

Included observations: 49

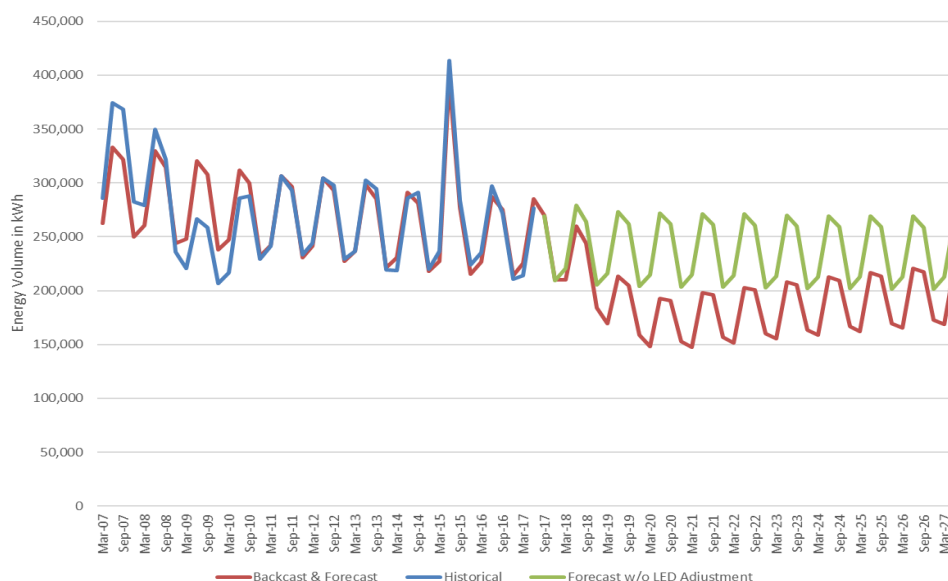
Convergence not achieved after 500 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-534.3994	115.1190	-4.642149	0.0000
LOG(POP)	44.77017	8.973310	4.989259	0.0000
AR(1)	1.742097	0.160900	10.82718	0.0000
AR(2)	-0.839587	0.133264	-6.300183	0.0000
MA(1)	-0.649252	0.260742	-2.490016	0.0168
SIGMASQ	0.752331	0.196562	3.827450	0.0004
R-squared	0.947319	Mean dependent var		39.60417
Adjusted R-squared	0.941047	S.D. dependent var		3.818987
S.E. of regression	0.927257	Akaike info criterion		2.850319
Sum squared resid	36.11187	Schwarz criterion		3.084219
Log likelihood	-62.40766	Hannan-Quinn criter.		2.938710
Durbin-Watson stat	151.0497			

The EViews model output in Table 10 shows the model for the number of customers, which is driven mostly by population as a proxy for development and a number of AR and MA terms to correct for serial correlation.

The green line in Figure 10 shows the forecasting results based on the EViews model, a slight reduction of the volumes per customer before a mostly flat projection from FY2020 onwards is visible. The red line provides the final forecast, taking into consideration the implementation of LED street lighting. It is expected that LED street lighting will reduce the energy volumes by 40%, captured over a three-year implementation period starting in financial year 2018. This is followed by a subsequent slight yearly increase after FY2021, due to lamp intensity adjustments accounting for a 0.5% per annum increase from the date of LED implementation.²⁰

Figure 10: ActewAGL Unmetered Per Customer Historical, Back-cast and Forecast Comparison

²⁰ Since the base forecast already included a decline of energy volumes, we have netted this effect against the decrease as a result of the LED implementation to avoid any double counting of energy efficiency effects.

3.3.5 System Energy Volumes & Customers

Jacobs also built a system model to verify the outcomes of the separate customer class models. The per customer energy volumes were derived by dividing the total energy volumes for each quarter by the average number of customers for each quarter. The models for energy volumes and customer numbers were then estimated as per below in Table 11. The most critical model is the energy volume model. We included seasonal, price and energy efficiency estimators (as an interaction variable). Economic variables were not significant and did not improve the model, so we did not include any.

The residual analysis resulted in applying a moving average and seasonal moving average to address some serial correlation issues. The total energy forecast was then derived by multiplying the number of customers with the energy volumes per customer. The resulting forecast was in line with the accumulated projections of all customer categories as shown above in Figure 2. The latter provides an additional level of confidence to the individual models we estimated for each of the customer categories.

Table 11: EViews Model Outputs for System Energy Volumes Per Customer

Dependent Variable: LOG(SYSTEM_PC)

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 10/27/17 Time: 16:50

Sample: 3/01/2007 6/01/2017

Included observations: 42

Convergence achieved after 13 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.865800	0.158619	62.19798	0.0000
Q3	0.143406	0.011834	12.11830	0.0000
Q1	-0.104613	0.011885	-8.802433	0.0000
Q2	-0.088081	0.014761	-5.967253	0.0000
LOG(RESIDENTIAL_EE_N*RESIDENTIAL_PRICE_N)	-0.140784	0.015134	-9.302418	0.0000
MA(1)	0.357750	0.182314	1.962268	0.0580
SMA(3)	0.485529	0.248867	1.950960	0.0593
SIGMASQ	0.000691	0.000176	3.921593	0.0004
R-squared	0.953814	Mean dependent var		8.363770
Adjusted R-squared	0.944305	S.D. dependent var		0.123818
S.E. of regression	0.029221	Akaike info criterion		-4.034690
Sum squared resid	0.029031	Schwarz criterion		-3.703706
Log likelihood	92.72850	Hannan-Quinn criter.		-3.913371
F-statistic	100.3075	Durbin-Watson stat		1.786077
Prob(F-statistic)	0.000000			

Table 12 shows the model specified for the customer number forecast. The population in the ACT is strongly correlated to the total number of customers in the ActewAGL distribution area (as expected). We have included two auto-regression and three moving average terms to address serial correlation as well.

Table 12: EViews Model Outputs for System Total Customer Numbers

Dependent Variable: SYSTEM_CUST

Method: ARMA Maximum Likelihood (OPG - BHHH)

Date: 11/27/17 Time: 14:26

Sample: 12/01/2005 9/01/2017

Included observations: 48

Convergence achieved after 24 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1936835.	364142.1	-5.318898	0.0000
LOG(POP)	164211.2	28343.16	5.793681	0.0000
AR(1)	0.981864	0.044107	22.26105	0.0000
MA(1)	0.525089	0.166117	3.160947	0.0029
SMA(3)	0.412585	0.178853	2.306841	0.0261
SIGMASQ	392599.1	93248.96	4.210225	0.0001
R-squared	0.998086	Mean dependent var		165241.4
Adjusted R-squared	0.997858	S.D. dependent var		14473.00
S.E. of regression	669.8393	Akaike info criterion		16.08972
Sum squared resid	18844757	Schwarz criterion		16.32362
Log likelihood	-380.1533	Hannan-Quinn criter.		16.17811
Durbin-Watson stat	4379.974			

3.4 Scenarios

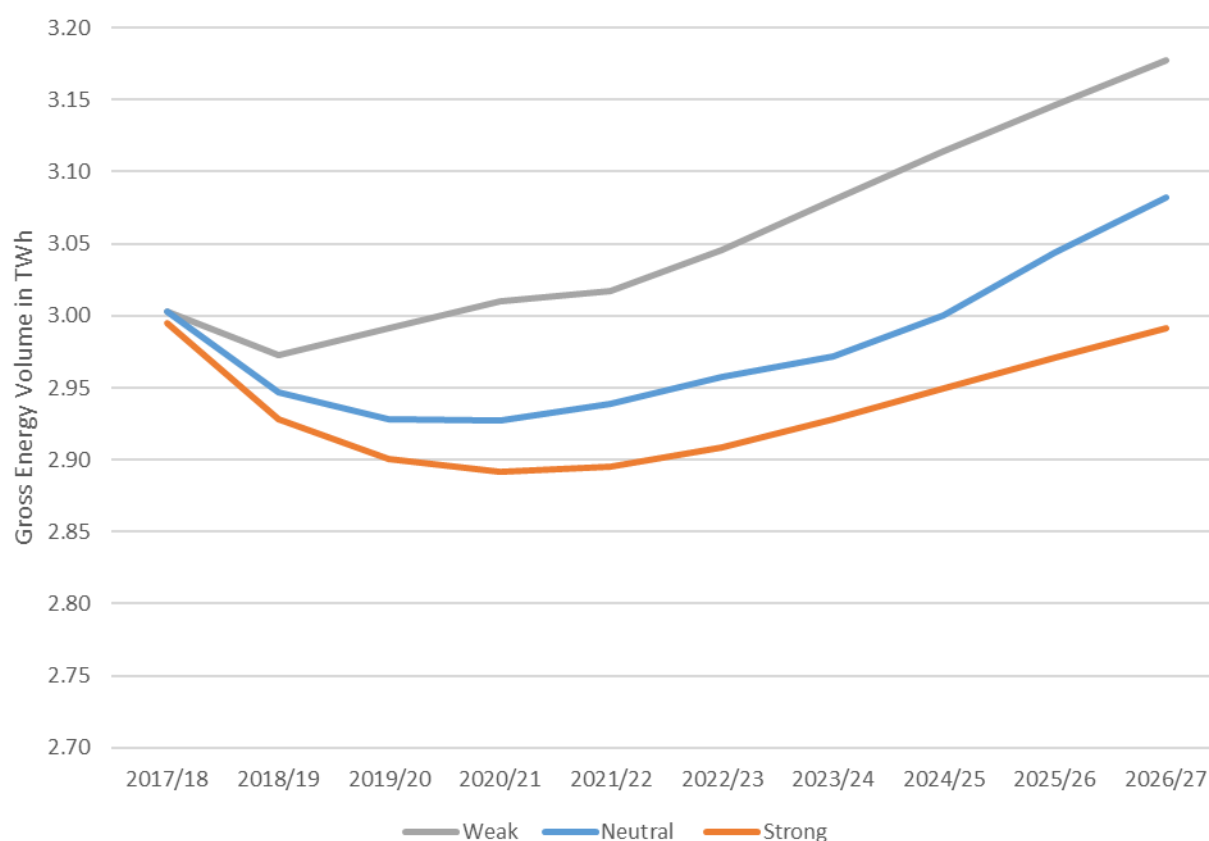
AEMO created three scenarios for future development in the energy market.²¹ These scenarios have an impact on the retail prices and energy efficiency numbers we have used in our models. The details on these scenarios are described in Jacobs' demand forecasting report prepared for ActewAGL in 2017.

We estimated our models using the following three scenarios:

- Weak: low retail prices and low energy efficiency projections
- Neutral: moderate retail prices and moderate energy efficiency projections
- Strong: high retail prices and high energy efficiency projections

All outcomes discussed above are based on the neutral scenario²² and Figure 11 shows the total accumulated energy volumes for each of the scenarios (Weak, Strong and Neutral). The differences between the total energy volumes in FY2027 between the scenarios is approximately 190 GWh.

Figure 11: ActewAGL Total Gross Energy Volumes by Scenario



Since the weak scenario represents low energy retail prices and low energy efficiency projections, the resulting volumes are expected to be higher than the other scenarios and would therefore effect the network tariffs negatively, since higher volumes would spread the network costs over more kWh's (assuming that a substantial part of the network tariffs are kWh based). On the other hand, the Strong Scenario provides for higher than average retail energy prices and higher energy efficiency. This is expected to reduce the energy volumes and drive up the network tariffs as the network costs would be spread over a lower number of kWh's.

²¹ Please refer to Jacobs' 2017 Demand Forecasting Report for more details on AEMO pricing and energy efficiency scenarios.

²² The Neutral Scenario was chosen as the base scenario for volume projections to be consistent with the demand forecast.

3.5 Solar PV Generation

Solar PV Generation was modelled using the solar PV capacity projections developed for the demand forecasting model. Below in Table 13 the models are included. We have used a simple but effective model separating out the different seasons by including quarterly dummies (default is Q3).

Table 13: Solar PV Generation Models for Residential and Commercial LV

Dependent Variable: LOG(RESIDENTIAL_GENPV)

Method: Least Squares

Date: 10/27/17 Time: 17:49

Sample (adjusted): 9/01/2009 6/01/2017

Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.36193	0.086523	142.8739	0.0000
Q1	0.597216	0.070535	8.466893	0.0000
Q2	0.273580	0.070763	3.866144	0.0007
Q4	0.425958	0.070433	6.047693	0.0000
LOG(PV_CAP)	0.770955	0.024261	31.77705	0.0000
D_PV	0.523705	0.054891	9.540748	0.0000
R-squared	0.981822	Mean dependent var		15.27984
Adjusted R-squared	0.978326	S.D. dependent var		0.952312
S.E. of regression	0.140199	Akaike info criterion		-0.924150
Sum squared resid	0.511048	Schwarz criterion		-0.649324
Log likelihood	20.78640	Hannan-Quinn criter.		-0.833053
F-statistic	280.8629	Durbin-Watson stat		2.105419
Prob(F-statistic)	0.000000			

Dependent Variable: LOG(COMMERCIAL_LV_GENPV)

Method: Least Squares

Date: 10/27/17 Time: 18:01

Sample (adjusted): 9/01/2009 6/01/2017

Included observations: 32 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.741110	0.115908	75.41444	0.0000
Q1	0.541362	0.094490	5.729309	0.0000
Q2	0.153539	0.094795	1.619700	0.1174
Q4	0.463740	0.094353	4.914947	0.0000
LOG(PV_CAP)	0.777655	0.032501	23.92724	0.0000
D_PV	0.518331	0.073533	7.048954	0.0000
R-squared	0.967860	Mean dependent var		11.64393
Adjusted R-squared	0.961680	S.D. dependent var		0.959420
S.E. of regression	0.187812	Akaike info criterion		-0.339392
Sum squared resid	0.917105	Schwarz criterion		-0.064566
Log likelihood	11.43027	Hannan-Quinn criter.		-0.248295
F-statistic	156.5942	Durbin-Watson stat		1.465777
Prob(F-statistic)	0.000000			

The forecasts from above models were subsequently divided into gross solar PV generation and net solar PV generation. This was done by assuming the gross solar PV scheme as closed (projecting it forward as a constant) and adding all increase in solar PV generation to the net solar PV generation projections. In addition,

all solar PV gross tariff customers will be transferred to the solar PV net tariff scheme as of FY2021.²³ The results of this transfer are included in Figure 12 and Figure 13.

Figure 12: ActewAGL Residential Solar PV Energy Generation by Type

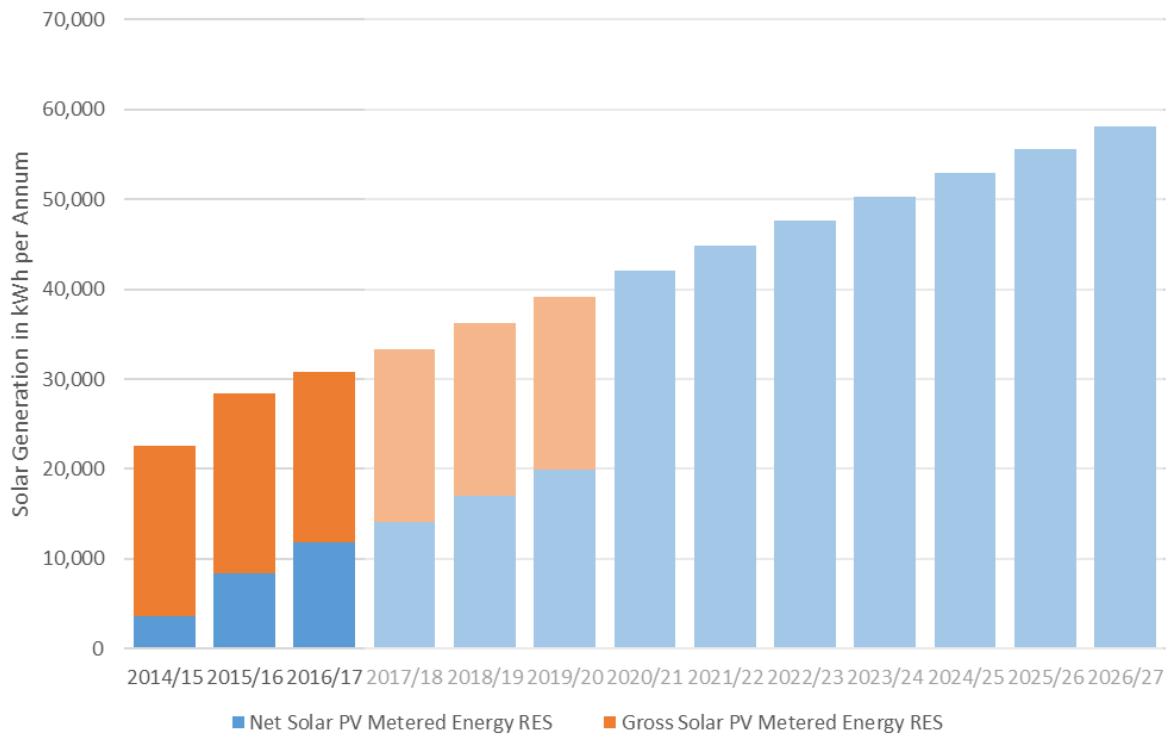
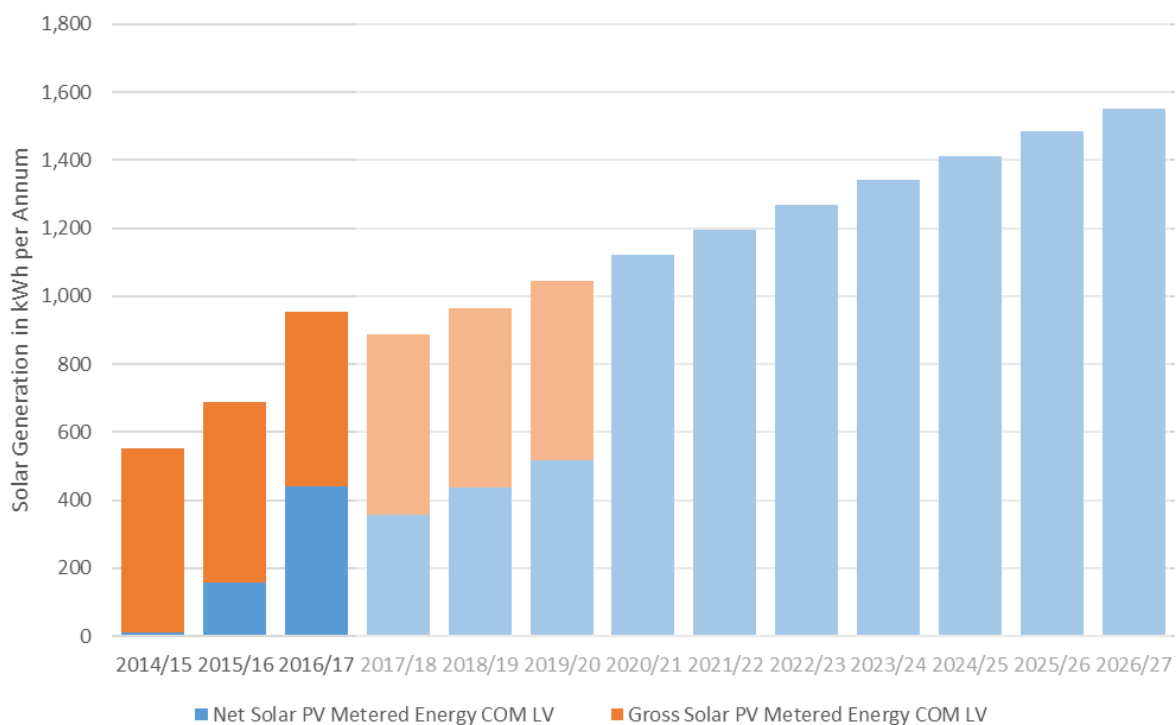


Figure 13: ActewAGL Commercial LV Solar PV Energy Generation by Type



²³ Even though gross metered customers are being transferred to the net metered solar tariffs scheme, they will still retain their gross metering and so no distinction can be made between energy they consume and feed into the grid.

4. Development of Forecasts into Applicable Customer Tariff

This section provides some guidance to ActewAGL on how to disaggregate the forecasted customer classes into applicable customer tariffs.

We propose that ActewAGL follows the below steps to disaggregate the customer tariffs and apply the forecasted energy volumes:

1. Calculate the percentage share of each tariff within a customer class, based on the latest actual energy volumes data (metered data);
2. Take the latest actual customer numbers (residential, commercial LV, commercial HV and unmetered/street lighting) and multiply these with the applicable forecasted energy volumes for the financial years 2018-2027, this will provide ActewAGL with the total energy forecast by customer class, deactivating the impact of customer growth; and
3. Apply the percentages calculated in step 1 to estimate the energy volume forecasts by tariff class, exclusive of customer growth.

The energy volumes based on new customer growth will need separate treatment as these new customers may be broken up (contracted) into different and/or new tariffs classes, not related to any historical disaggregation as calculated in steps 1 and 2 above.

ActewAGL will need to assess how the new customers will be allocated to the different and/or new tariff classes. To calculate the additional customers, simply subtract the number of customers calculated in step 2 above from the forecasted customer numbers by class, so that only the new customers will remain in the forecast.

Appendix A. Data Tables

Gross Energy Forecast in kWh by Customer Type, Per Customer (Financial Years) - Neutral Scenario (AEMO, Energy Efficiency and Price) ²⁴				
FY	Residential	Commercial LV	Commercial HV	Unmetered/SL
2017/18	6,934	75,292	13,313,247	952,400
2018/19	6,768	73,046	13,079,922	807,237
2019/20	6,559	71,933	12,824,694	700,106
2020/21	6,453	71,390	12,526,090	682,379
2021/22	6,407	70,844	12,103,138	712,610
2022/23	6,346	69,952	11,884,861	727,607
2023/24	6,301	68,974	11,419,924	741,304
2024/25	6,249	68,534	11,371,725	753,739
2025/26	6,229	68,513	11,180,898	765,457
2026/27	6,242	68,489	11,120,164	776,316

Customer Number Forecasts (Financial Years)				
FY	Residential	Commercial LV	Commercial HV	Unmetered/SL
2017/18	176,116	17,319	28	45
2018/19	178,871	17,697	28	46
2019/20	181,765	18,034	29	47
2020/21	184,691	18,377	29	48
2021/22	187,612	18,721	30	48
2022/23	190,506	19,066	30	49
2023/24	193,367	19,411	31	50
2024/25	196,193	19,756	31	51
2025/26	198,984	20,100	31	52
2026/27	201,733	20,443	32	53

²⁴ The numbers in this table are rounded to the kWh per customer and do not include Gross Metered Solar PV.

Total Gross Energy Forecast (including Gross Metered Solar PV up to FY2020) in MWh by Customer Type (Financial Years) - Neutral Scenario (AEMO, Energy Efficiency and Price)					
FY	Residential	Commercial LV	Commercial HV	Unmetered/SL	Total
2017/18	1,240,428	1,304,496	372,771	42,858	2,960,553
2018/19	1,229,791	1,293,216	366,238	37,133	2,926,378
2019/20	1,211,388	1,297,768	371,916	32,905	2,913,978
2020/21	1,191,813	1,312,462	363,257	32,754	2,900,286
2021/22	1,201,940	1,326,266	363,094	34,205	2,925,505
2022/23	1,208,886	1,333,709	356,546	35,653	2,934,793
2023/24	1,218,495	1,338,856	354,018	37,065	2,948,434
2024/25	1,225,993	1,353,962	352,523	38,441	2,970,919
2025/26	1,239,448	1,377,115	346,608	39,804	3,002,974
2026/27	1,259,183	1,400,115	355,845	41,145	3,056,288

System Energy Forecast in TWh by Scenario (Financial Years, AEMO, Energy Efficiency and Price) ²⁵			
FY	Neutral	Strong	Weak
2017/18	3.00	2.99	3.00
2018/19	2.95	2.93	2.97
2019/20	2.93	2.90	2.99
2020/21	2.93	2.89	3.01
2021/22	2.94	2.90	3.02
2022/23	2.96	2.91	3.05
2023/24	2.97	2.93	3.08
2024/25	3.00	2.95	3.11
2025/26	3.04	2.97	3.15
2026/27	3.08	2.99	3.18

²⁵ Please note that this is based on the system level forecasts and will therefore be slightly different from the cumulative forecasts of customer tariff classes. This system energy volume forecast includes Gross Metered Solar PV up to FY2020.

Total Solar PV Generation Projections in MWh by Customer Type (Financial Years) ²⁶					
FY	Residential Net Metered Solar PV	Residential Gross Metered Solar PV	Commercial LV Net Metered Solar PV	Commercial LV Gross Metered Solar PV	Total Solar PV
2017/18	14,088	19,255	359	528	34,229
2018/19	17,034	19,255	438	528	37,254
2019/20	19,945	19,255	516	528	40,243
2020/21	42,054	0	1,120	0	43,174
2021/22	44,849	0	1,195	0	46,045
2022/23	47,591	0	1,269	0	48,860
2023/24	50,284	0	1,342	0	51,625
2024/25	52,931	0	1,413	0	54,345
2025/26	55,538	0	1,483	0	57,022
2026/27	58,108	0	1,553	0	59,660

²⁶ Please note the gross PV generation scheme is to be closed from as of financial year 2021, and therefore the customers are going to be switched to the net scheme.