Trends in ACT Electricity Consumption

ActewAGL

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Executive Summary

Jacobs SKM has been engaged by ActewAGL to undertake an analysis to identify the key factors influencing electricity consumption from ActewAGL Distribution's Australian Capital Territory electricity distribution network and to develop a forecast of electricity consumption for the 2014/15-18/19 regulatory period, as well as for 2013/14. The review was undertaken in three stages:

1) Historical period
    a) Analysis of the accuracy of the historical forecast over the 2008-2013 regulatory period
    b) Weather normalisation of the historical energy consumption over 2000-2013
    c) Compilation of historical values of potential explanatory variables
2) Development of models relating weather normalised energy consumption to explanatory variables
3) Application of projections of selected explanatory variables to preparation of energy consumption forecasts for the period 2015-2019.

The key findings from the analysis are:

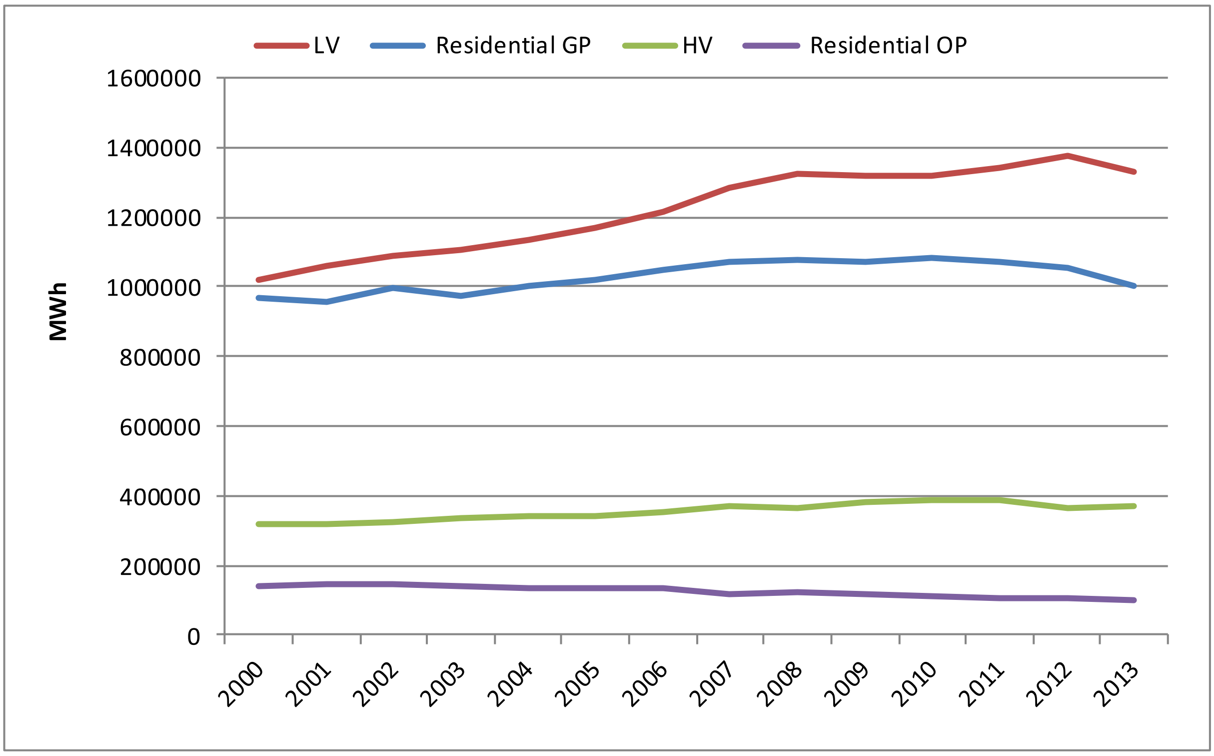
Stage 1a

- The historical forecast fits actual demand if forecast input parameter values are used to derive the expected consumption over the 2008-2013 period;
    - On further analysis of some of the input variables used, using the actual input parameter values experienced causes the forecast model to depart significantly from the actual energy.

Stage 1b

- Analysis of actual data over the 2000-2013 period indicates that:
    - Weather normalisation using heating and cooling degree days (HDDs and CDDs) is important for residential and low voltage non-residential (LV) customers but not for high voltage non-residential (HV) customers;
    - Growth in weather normalised residential GP (general purpose) demand starts to decline in 2008 and residential GP demand starts to fall from 2010 onwards (refer to Exec Figure 1)
    - LV and HV demand have been approximately constant since 2008.
    - Residential OP (off-peak) demand has been in a steady decline since 2002

Exec Figure 1 : Weather normalised annual energy



Stage 1c

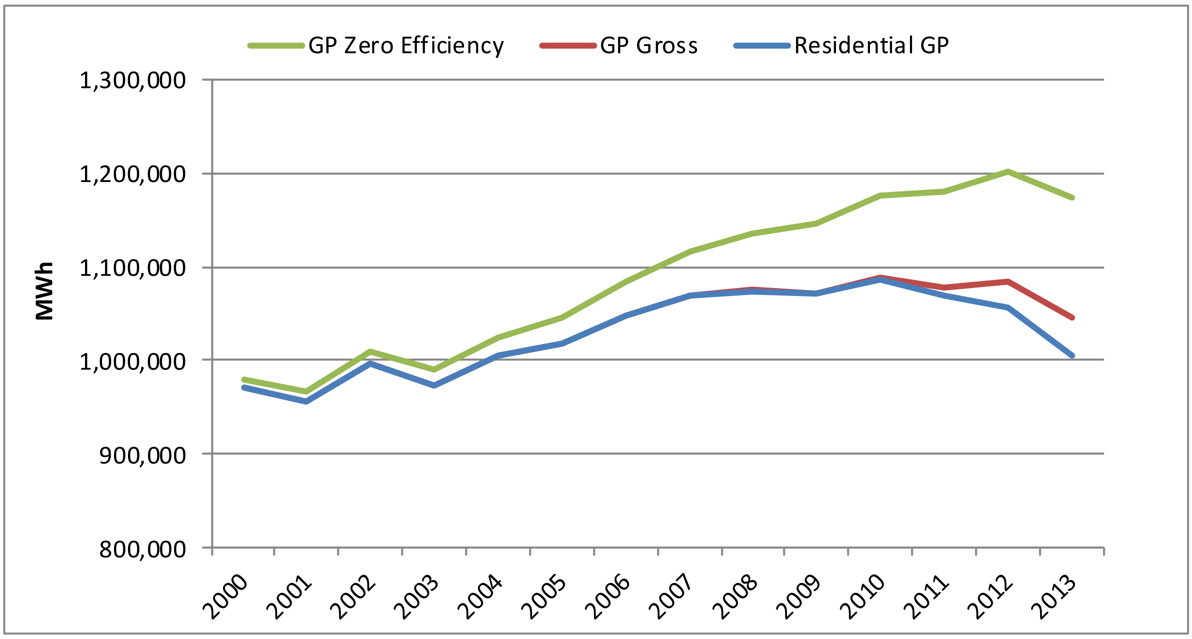
Explanatory variables potentially related to energy consumption include economic growth factors, financial influences, demographics, price factors and energy saving factors. A full list of factors considered in the Stage 2 analysis is tabled below.

Exec Table 1 : Long-term explanatory variables considered and sources of historical information

Key driver	Variable used	Source of information
Economic growth	Gross State Product (GSP)	ABS 5220.0 Table 1
Economic growth	State Final Demand (SFD)	ABS 5220.0 Table 9
Financial influences	CPI	ABS 6401.1
Financial influences	Exchange rate	Reserve Bank of Australia
Financial influences	Interest rate	Reserve Bank of Australia
Demographics	Population	ABS 3101.0 Table 4
Demographics	Households	ABS 3236.0
Demographics	Employment	ABS 6202.0
Energy Price Movement	Electricity retail prices of residential, LV and HV	ActewAGL
Energy savings	Supply side - kWh of PV (photovoltaic) output	ActewAGL
Energy savings	Demand side - energy efficiency - % of energy saved	AEMO estimates

Energy Efficiency and PV appear to be playing central roles in the energy decline post 2008, particularly for the residential sector (Refer to Exec Figure 2, in which: gross = GP + PV; zero efficiency = gross with efficiency gains since 2000 removed).

Exec Figure 2 : Residential annual energy with and without efficiency savings



Stage 2

The modelling has been undertaken using regression analysis to determine the parameters A, B, C, D, etc in multiplicative models of the form:

Energy = a*(Factor 1)^B *(Factor 2)^C *(Factor 3)^D* …

Parameter derivation is undertaken by converting the model to additive form:

Ln(Energy) = A + B*ln(Factor 1) + C*ln(Factor 2) + D*ln(Factor 3) + …

In this equation ln() represents the natural logarithm function. The best models are those which are most accurate, that is, have the lowest error or highest R^2, subject to:

1) The coefficients are statistically significant (T-statistic over 1.5, preferably 2)
2) The signs of the coefficients are logical (eg price coefficients are negative)
3) Coefficients are not unreasonably high i.e. suggesting an implausible sensitivity of energy use to the relevant factor
4) The residuals are random, i.e. don't show clear trends or patterns

We have also applied the Akaike and Bayesian Information Criteria (AIC and BIC) to model selection. These criteria select the model which achieves high R^2 with the fewest variables and generally align with the requirement for good T statistics.

For **residential GP** we constructed six types of residential GP model, using two different measures of residential GP annual energy (weather normalised gross and zero efficiency measures) on three different bases: total energy; average energy per person; and average energy per customer. Our preferences are directed to the Zero Efficiency, per Person and per Customer models, the most suitable of which according to the above criteria are:

- R11 and R16, both based on Employment alone
- R12, based on HHI and interest rates
- R13 and R17, both based on HHI and Price factors and having very similar price elasticities

On both R^2 and AIC criteria, R11 is the best model of the five considered.

Exec Table 2 : Preferred residential GP models R11 and R16

	Coefficients					T-Statistics	
Model	Const.	Employ/ Pers	Employ/ Cust	R^2	AIC	Employ/ Pers	Employ/ Cust
R11	2.88	0.86		0.72	-113.7	5.5	
R16	3.25		0.83	0.48	-112.8		3.4

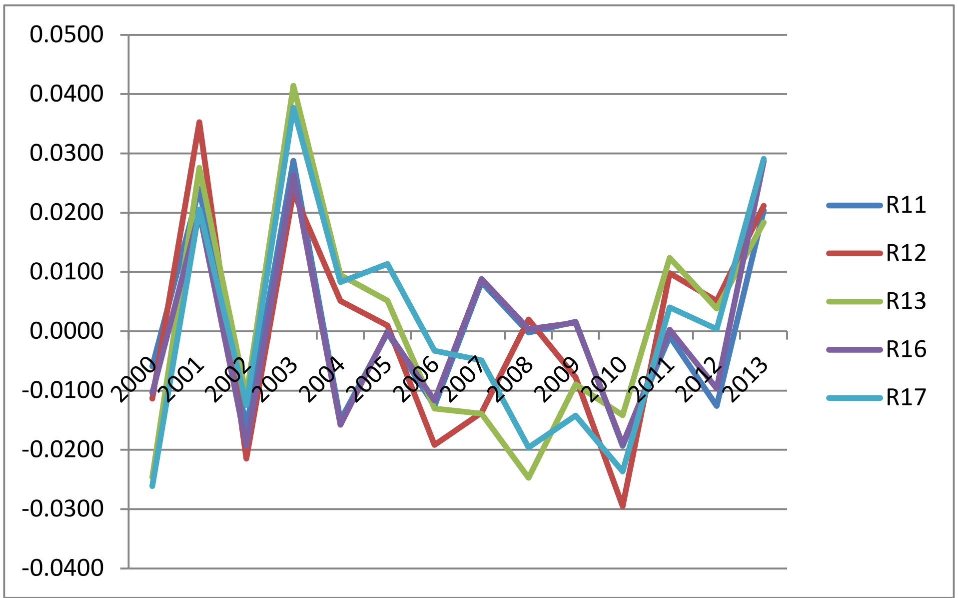
Exec Table 3 : Preferred residential GP model R12

	Coefficients					T-Statistics	
Model	Const.	HHI/ Pers	Int. Rate	R^2	AIC	HHI/ Pers	Int. Rate
R12	7.74	0.14	0.08	0.60	-106.7	4.0	2.5

Exec Table 4 : Preferred residential GP models R13 and R17

	Coefficients						T-Statistics		
Model	Const.	HHI/ Pers	HHI/ Cust	Price	R^2	AIC	HHI/ Pers	HHI/ Cust	Price
R13	7.69	0.23		-0.20	0.54	-104.8	3.2		-2.1
R17	8.83		0.13	-0.18	0.23	-105.8		1.7	-1.8

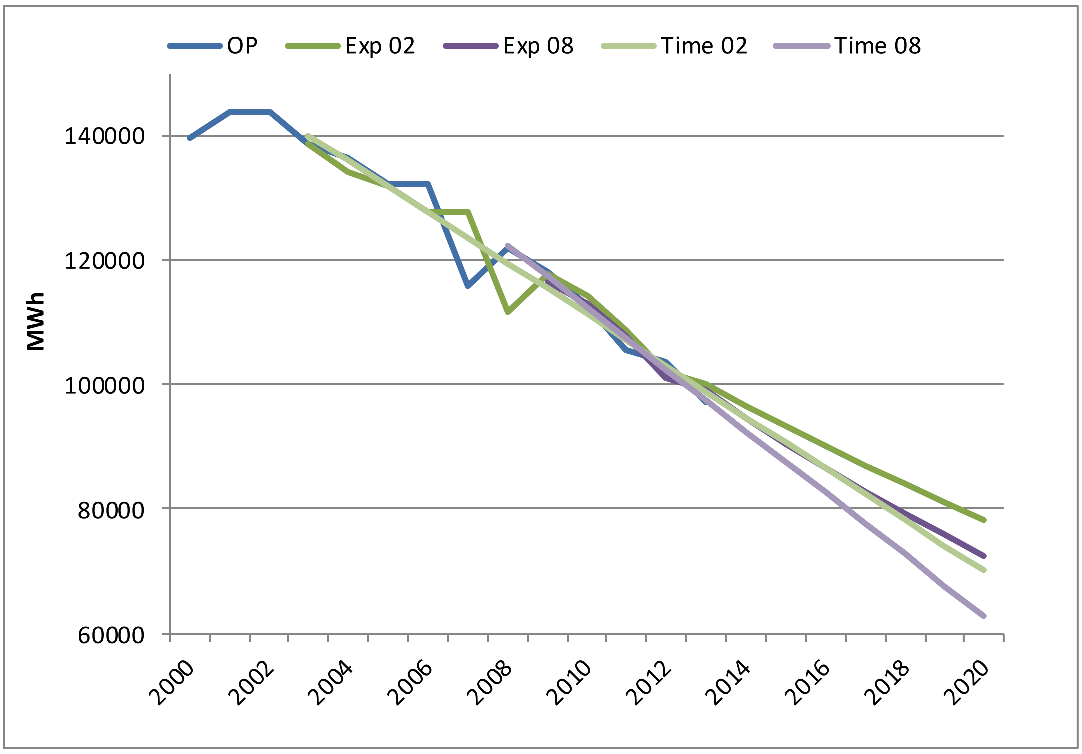
Exec Figure 3 : Preferred residential GP model residuals



It is noted that the residuals are quite high in the final year, 2013, though no higher than in some earlier years. While this may be viewed as making the forecasts less accurate than if the models predicted 2013 accurately, it should be noted that the uncertainty in the forecasts relates to the overall model uncertainty, amplified by the uncertainties in the forecast inputs.

Residential OP demand has been in steady decline since 2002 and can be modelled as an exponential function (fixed percentage each year) or linear function (fixed rate per year). Based on Jacobs SKM's analysis, a fixed rate model using the rate from 2008 to 2013 is preferred because it tracks historical data more accurately than the other models (Time 08 in Exec Figure 4).

Exec Figure 4 : OP model comparison

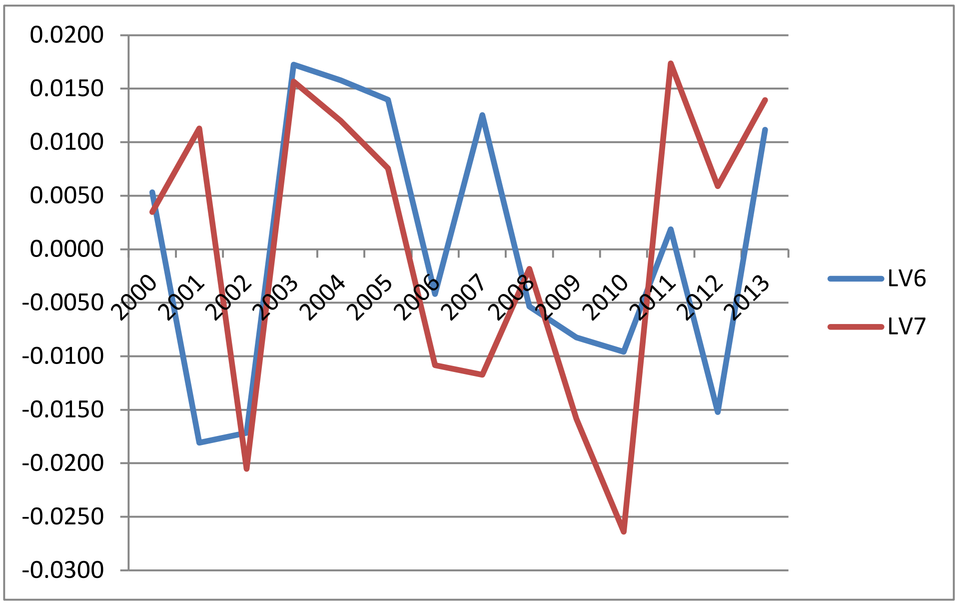


The most suitable **Commercial LV** models are considered to be zero efficiency models based on SFD or GSP plus interest rates, LV6 and LV7 below. On both R^2 and AIC criteria, LV6 is the slightly better model, which uses SFD and Interest Rate as the key drivers

Exec Table 5 : Preferred commercial LV models LV6 and LV7

	Coefficients						T-Statistics		
Model	**Const.**	**GSP**	**SFD**	**Int. Rate**	**R^2**	**AIC**	**GSP**	**SFD**	**Int. Rate**
LV6	0.40		0.65	0.05	0.99	-117.2		29.8	2.5
LV7	-3.03	1.04		0.15	0.99	-113.5	26.1		5.7

Exec Figure 5 : Preferred commercial LV model residuals

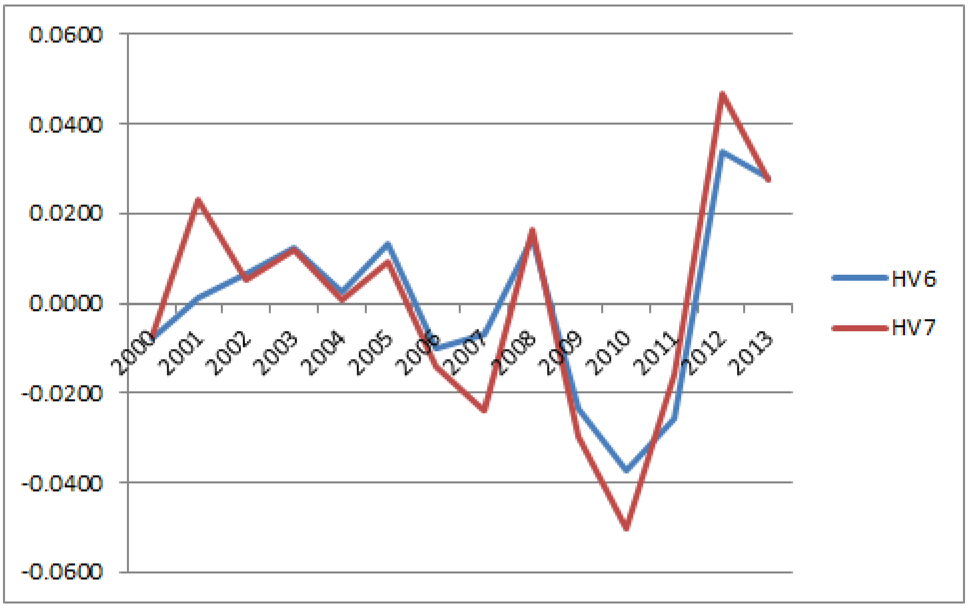


The most suitable **Commercial HV** models are considered to be zero efficiency models based on SFD or GSP plus interest rates, HV6 and HV7 below. On both R^2 and AIC criteria, HV6 is the better model, using SFD alone as the sole driver of demand.

Exec Table 6 : Preferred commercial HV models HV6 and HV7

	Coefficients						T-Statistics		
Model	**Const.**	**GSP**	**SFD**	**Int. Rate**	**R^2**	**AIC**	**GSP**	**SFD**	**Int. Rate**
HV6	1.08		0.46		0.95	-106.3		15.1	
HV7	-1.21	0.72		0.07	0.92	-97.7	10.2		1.5

Exec Figure 6 : Preferred commercial HV model residuals



Stage 3

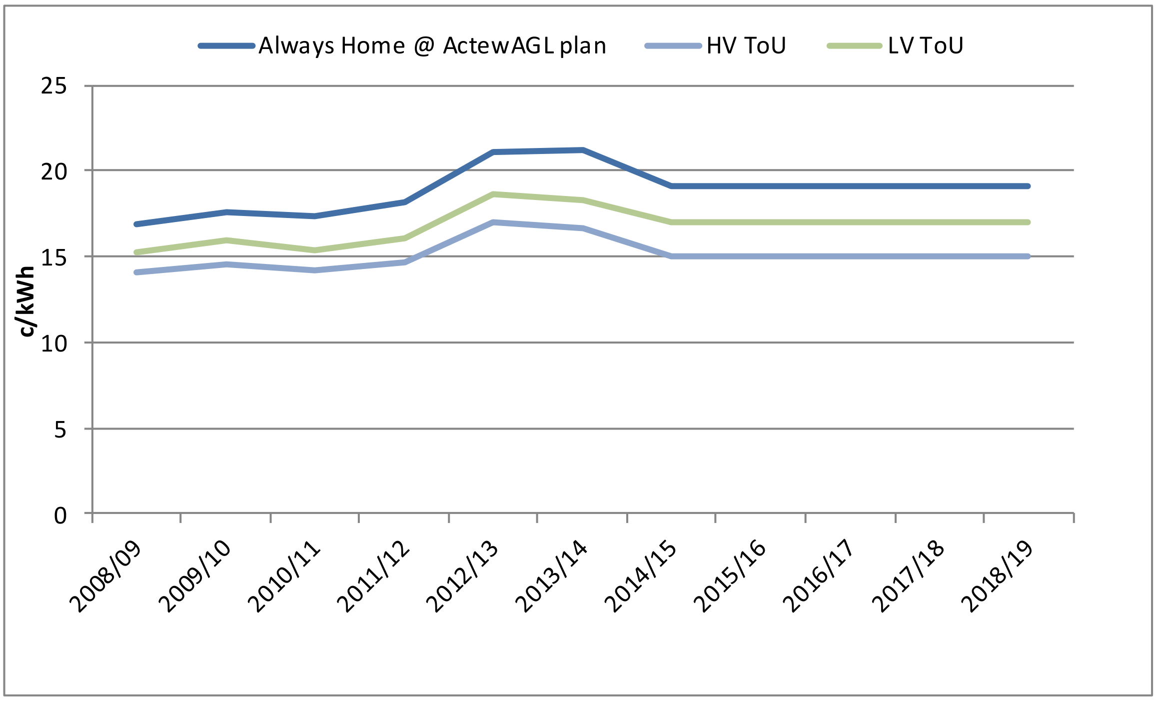
Forecasts of demand drivers

ActewAGL commissioned BIS-Shrapnel to provide forecasts of economic inputs and Jacobs SKM prepared forecasts of other demand drivers. BIS-Shrapnel's economic projections reflect an economy slowing through 2013-14 and 2014-15 and then recovering through the remainder of the period, as illustrated in Exec Figure 7, and this is strongly reflected in the energy forecasts.

Exec Figure 7 : ACT SFD, GSP and HHI projected growth, %

The projected retail tariff paths have been based on the assumptions that: the carbon price will be set to zero from 1 July 2014 and the pass-on will be removed from the tariffs; and network charges will be fixed in real terms from 1 July 2014.

Exec Figure 8 : Projected retail prices of each customer category, c/kWh in $ June 2013

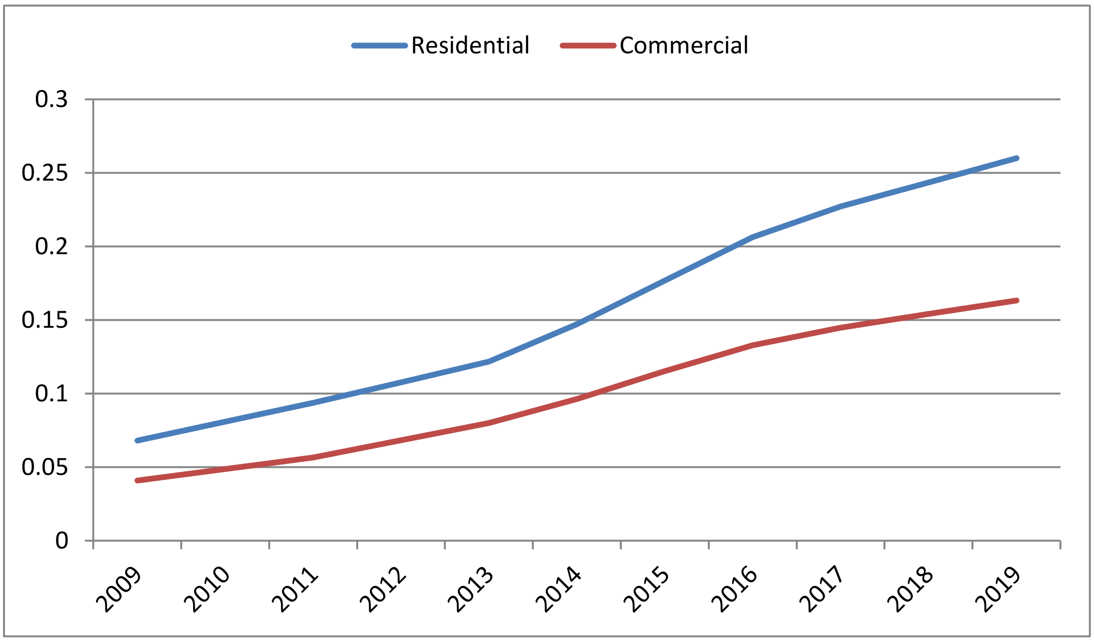


Jacobs SKM's energy savings projections are based on AEMO projections but also allow for the impact of the Energy Efficiency (Cost of Living) Improvement Act 2012 (EEIA) implemented in the ACT. The AEMO savings are based on Commonwealth schemes relating to equipment labelling, Minimum Energy Performance Standards (which place restrictions on the energy performance of appliances, lighting and electrical equipment for sale in Australia) and building-related energy efficiency measures (which focus on regulations for new buildings in the Building Code of Australia)[1]. The AEMO savings are based on normal appliance replacement and building construction patterns. The activities being undertaken under the EEIA by the dominant retailer in the ACT, ActewAGL Retail, have to date focused on door knocking (and arranged house calls) to install standby power controllers, energy efficient light bulbs and door seals in established residences at no direct cost to the customer and on refrigerator buyback[2]. Some of the activities being undertaken under the EEIA are likely to be bringing forward savings that would eventually be made under the national schemes covered by the AEMO savings estimates. However, it is reasonable to assume that most savings that are brought forward are brought forward at least five years; that is, from after 2019, and so are not double counted during the regulatory control period.We have presented efficiency projections in Exec Figure 9 assuming that energy savings targets under the EEIA apply incrementally to the AEMO savings.

1 AEMO 2013, Forecasting methodology information paper, p5-42 and 5-46; and
Pitt and Sherry 2013, Final Report: Quantitative assessment of energy savings from building energy efficiency measures, Prepared for Department of Climate Change and Energy Efficiency, March, p21-35.

2 http://www.actewagl.com.au/Help-and-advice/Assist.aspx accessed on 9 April 2014.

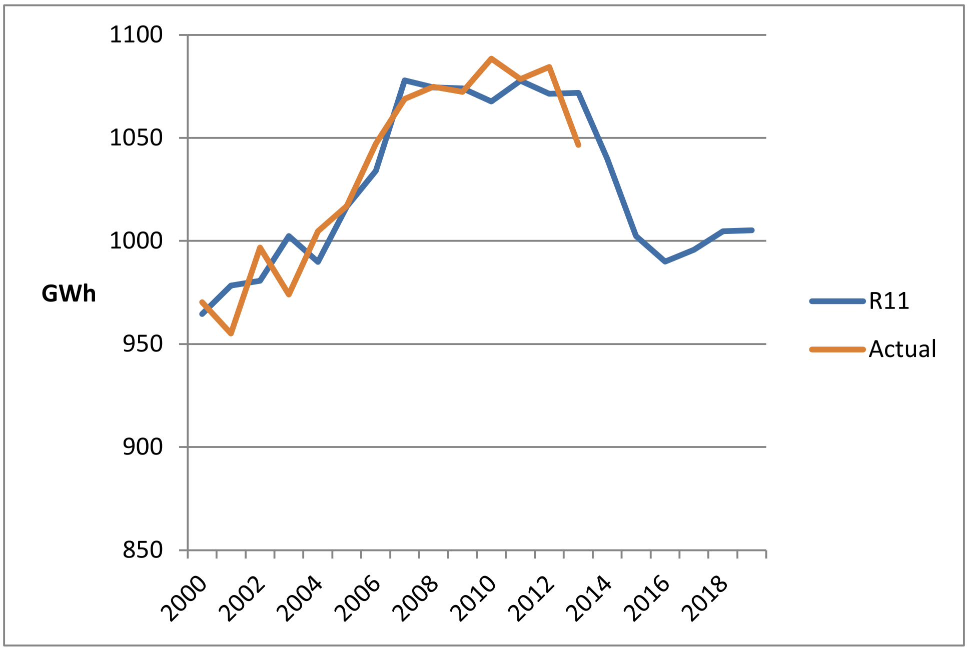
Exec Figure 9 : Projected residential and commercial energy savings (%)



Annual energy forecasts

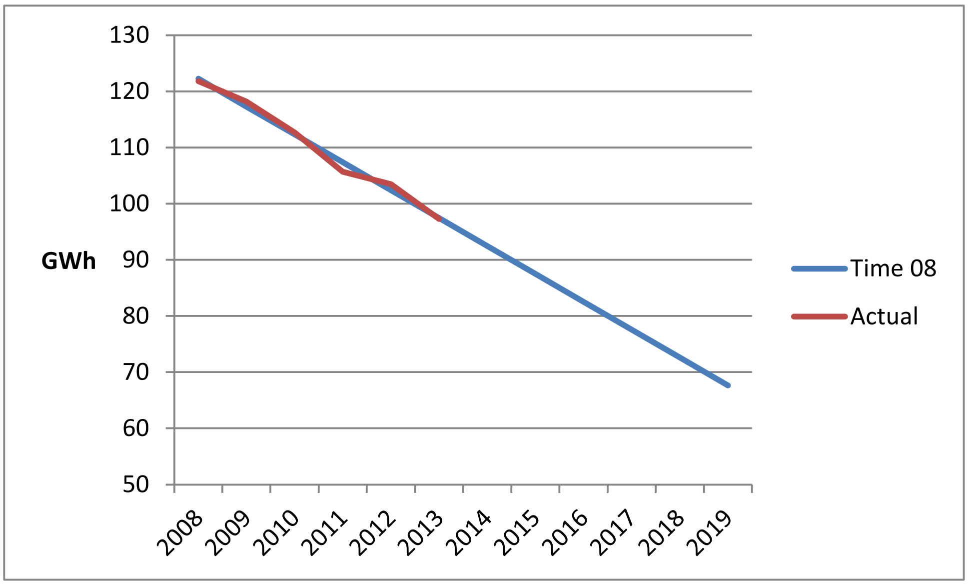
The Residential GP forecast for the preferred model (R11) is presented in Exec Figure 10. This forecast is net of PVs.

Exec Figure 10 : Residential GP annual energy forecast



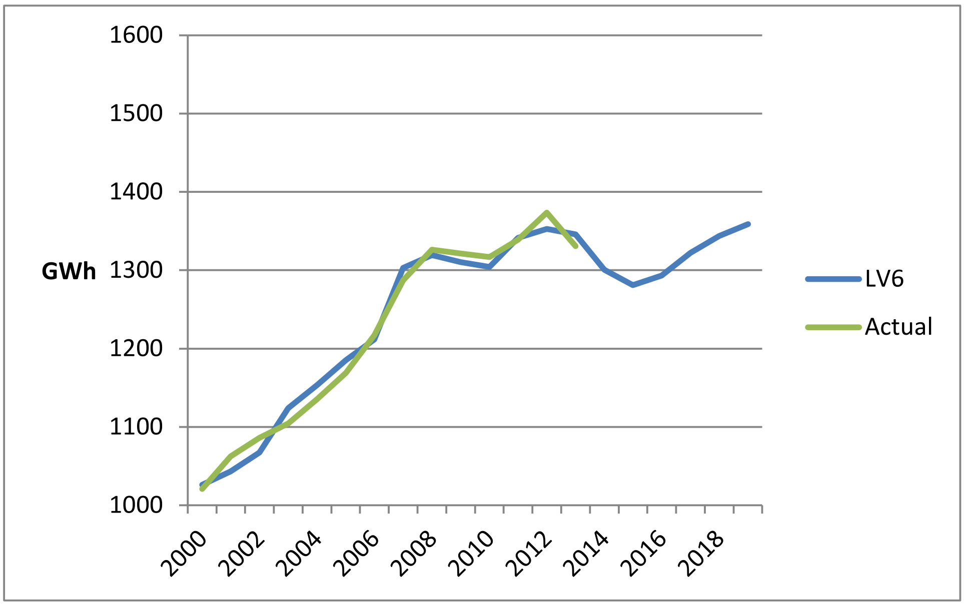
The Residential OP forecast based on the preferred Time 08 model is reproduced in Exec Figure 11.

Exec Figure 11 : Residential OP energy forecast



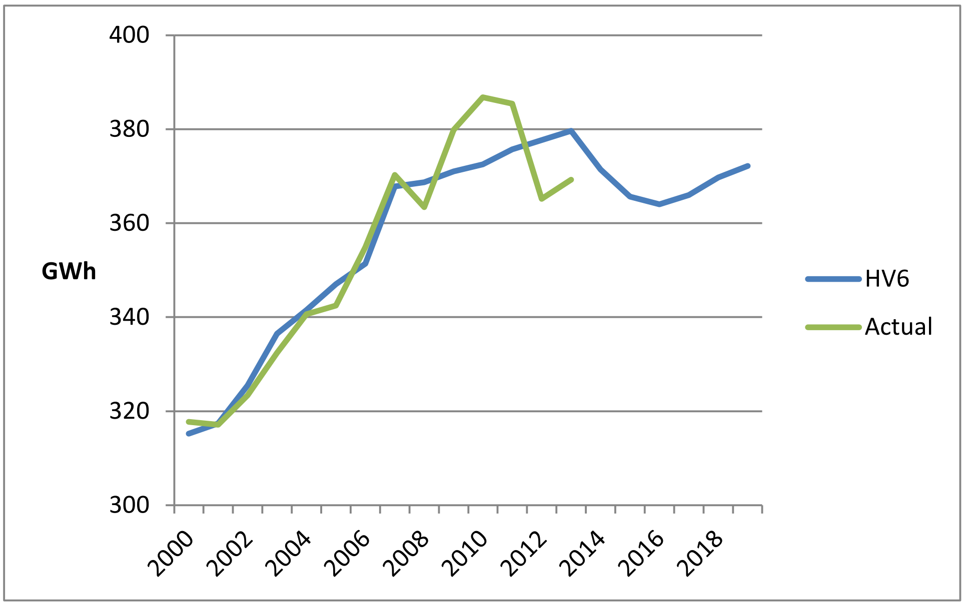
The LV forecast for the preferred model (LV6) is presented in Exec Figure 12.

Exec Figure 12 : LV annual energy forecast



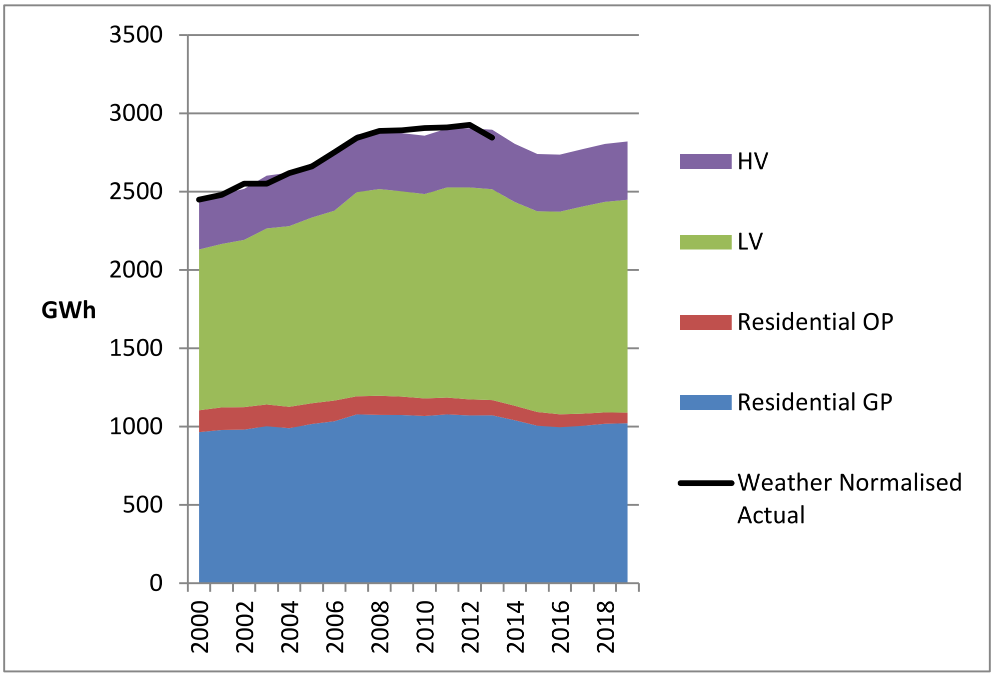
The HV forecast for the preferred model (HV6) is presented in Exec Figure 13.

Exec Figure 13 : HV annual energy forecast



The total energy forecasts for the ActewAGL network at the gross energy level (at the meter, excluding network losses) are illustrated in Exec Figure 14.

Exec Figure 14 : Total energy forecast



Important note about your report

The sole purpose of this report and the associated services performed by Jacobs SKM is to identify the key factors influencing electricity consumption from ActewAGL Distribution's ACT electricity distribution network and to develop a forecast of electricity consumption for the 2014/15-18/19 regulatory period in accordance with the scope of services set out in the contract between Jacobs SKM and the Client. That scope of services, as described in this report, was developed with the Client.

In preparing this report, Jacobs SKM has relied upon, and presumed accurate, any information (or confirmation of the absence thereof) provided by the Client and/or from other sources. Except as otherwise stated in the report, Jacobs SKM has not attempted to verify the accuracy or completeness of any such information. If the information is subsequently determined to be false, inaccurate or incomplete then it is possible that our observations and conclusions as expressed in this report may change.

Jacobs SKM derived the data in this report from information sourced from the Client (if any) and/or available in the public domain at the time or times outlined in this report. The passage of time, manifestation of latent conditions or impacts of future events may require further examination of the project and subsequent data analysis, and re-evaluation of the data, findings, observations and conclusions expressed in this report. Jacobs SKM has prepared this report in accordance with the usual care and thoroughness of the consulting profession, for the sole purpose described above and by reference to applicable standards, guidelines, procedures and practices at the date of issue of this report. For the reasons outlined above, however, no other warranty or guarantee, whether expressed or implied, is made as to the data, observations and findings expressed in this report, to the extent permitted by law.

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1. Introduction

Jacobs SKM were engaged by ActewAGL to undertake an analysis to identify the key factors influencing electricity consumption from ActewAGL Distribution's Australian Capital Territory electricity distribution network and to develop a forecast of electricity consumption for the 2014/15-18/19 regulatory period, as well as for 2013/14. The work was performed in three stages:

- Stage 1: Understanding historical trends in electricity consumption- examine the historical forecast and the trends and influences of demand over the historical period
- Stage 2: Reporting on Trends in Historical drivers for consumption – report on the key drivers of demand and recommendations on the key parameters to include for future forecast
- Stage 3: Developing 2014-2019 electricity consumption forecasts for ActewAGL: using outcomes from stages 1 and 2 derive a new electricity consumption forecast for ActewAGL for the period 2014-19 for the next revenue reset.

This report documents the outcomes of all three stages of the analysis.

Stage 1: Section 2 of the report examines the historical forecast completed in 2008 for the current revenue reset period and analyses the key drivers in that forecast and how it varies from actual consumption over the 2008-2012 period. This section also comments on the relevance of the parameters in the forecast and provides a retrospective "back cast" view if the actual parameter values where used in the forecast.

Stage 2: Section 3 discusses the weather normalisation of the historical data and provides weather normalised data set for the analysis undertaken in Section 5. Section 4 then explores the detailed short and long-term drivers of the ACT consumption from an econometric perspective. Section 5 presents a range of demand models that link weather normalised ACT energy consumption to the long-term drivers, derived by regression analysis. Groups of preferred models which meet a range of "plausibility" criteria are presented as well as the best models which have the best statistical properties.

Stage 3: Section 7 presents forecasts of the economic and other drivers and the application of these forecasts to derive energy forecasts.

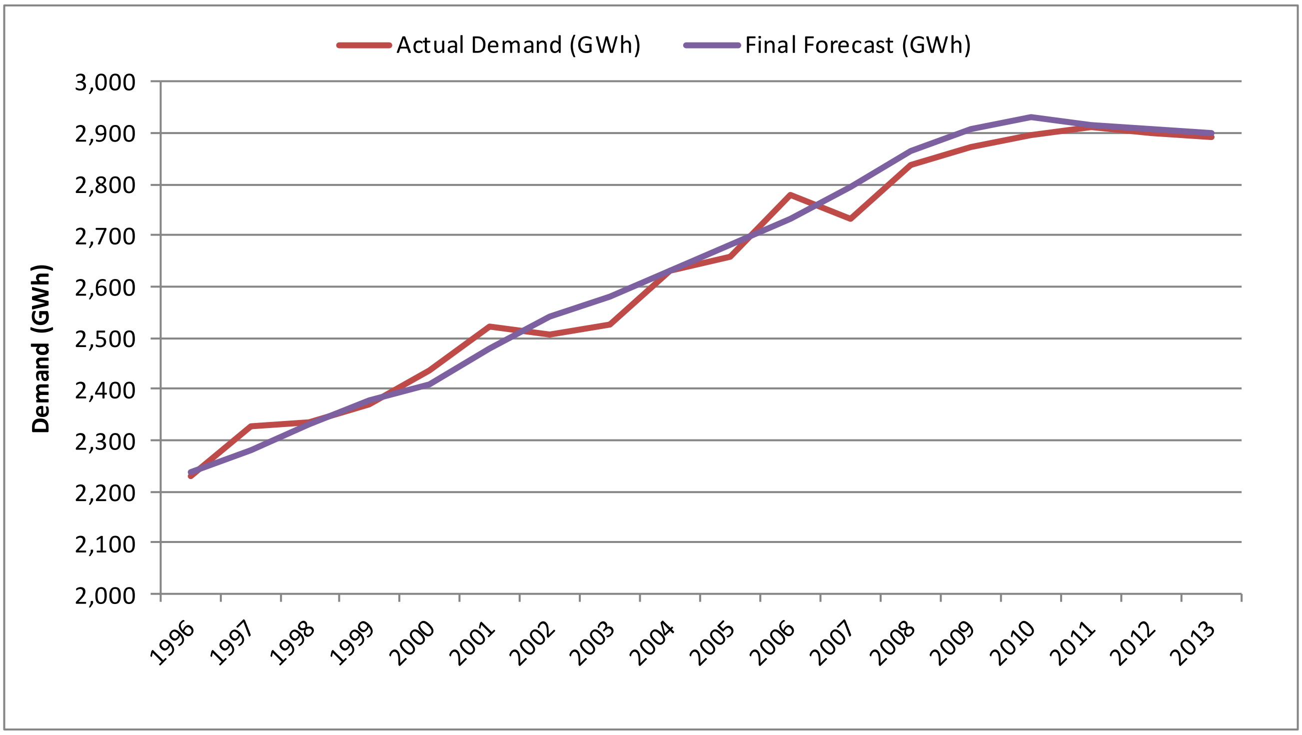
All the charts and analysis was on a financial year basis (i.e. charts show financial year ending) unless otherwise indicated.

2. Review of historical forecast

2.1 Actual versus forecast

Actual demand achieved over the period 2008 to 2013 was very close to previously forecast demand. This is depicted in Figure 2.1 where the maximum error in any of the years from 2008 to 2013 is 1.3%, with the forecast typically being slightly higher (year 2010).

Figure 2.1 : Actual demand and forecast demand until 2012

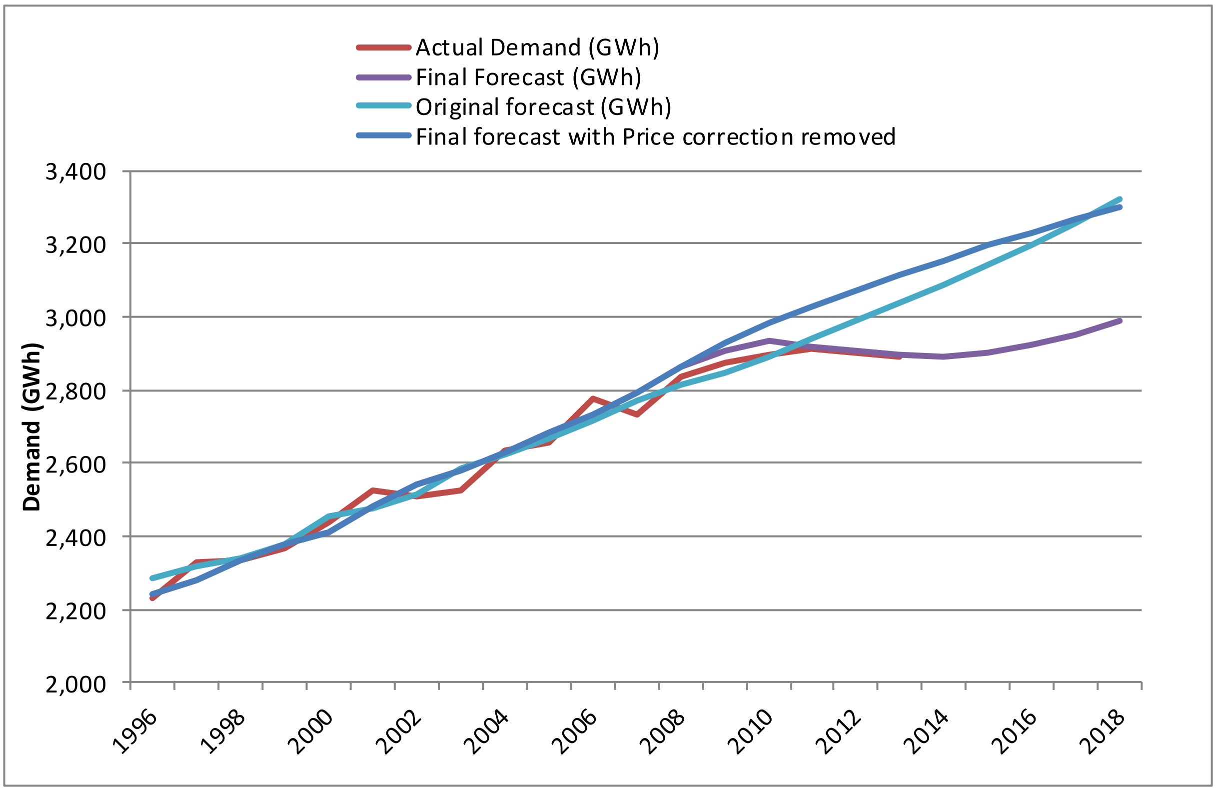


The numbers used to derive the forecast above are those provided by ActewAGL and are the forecast values of the variables used in the regression analysis. To test how robust the forecast was to the changing values of the variables, a back casting approach was undertaken where by the actual values were used. This analysis is discussed further in Section 2.3.

Based on the analysis of forecast versus actuals, the forecast numbers would appear to be very accurate and to provide a realistic view of demand in the ACT system. The following section (Section 2.2) explores this further in terms of the variables used and the relationship to demand in the ACT.

In examining the historical forecast a view of the impacts of the revised pricing assumptions was also considered. In the evolution of the past forecast, there was a revision with new price elasticities being used based on NIEIR estimates for NEMMCO in 2006. As a carbon price was assumed from 2010/11 in the original forecasts, the new price elasticities seem to provide the major impact in terms of the lowering of demand in the forecast and hence the good match to actuals. This is shown in Figure 2.2 where the forecast continue to climb if the original forecast is used or the price elasticities are removed (i.e. original forecast). In reality, the carbon price was not introduced until 2012/13, so the forecasted demand reduction from 2011 proved correct, but for the wrong reasons.

Figure 2.2 : Comparison of demand forecast with changes in price elasticities



2.2 Development of historical forecast

The 2008-2013 demand forecast used by ActewAGL was based on regression analysis for three sectors; domestic demand, domestic off peak demand and commercial demand. For each sector different regression analysis and variables were used to build the forecast. The key regression parameters used for each sector were:

- Domestic: year, State Final Demand (SFD) index, domestic air condition penetration and a constant ;
- Domestic off peak: year, population, household, and a constant; and
- Commercial: year, State Final Demand (SFD) index, population, ActewAGL change to "Dual fuel and a constant.

In addition, each sector has a price elasticity adjustment and also a forecast error adjustment based on the error in the forecast compared to actual demand from the previous three years from 2008 (50% of previous year error + 30% of error two years prior + 20% of error three years prior).

The formulas used for each component of the total forecast were:

Domestic Demand = 49.1×Year - 4.5×SFD + 1.4×Domestic Air conditions - 96,570 + Price Elasticity + Forecast Error;

Domestic Off Peak Demand = 16.5×Year + 0.067×Populaton -10.07×Household - 31,744 + Price Elasticity + Forecast Error;

Commercial Demand = -10.72×Year + 1.78×SFD + 7.70×Population + 8.82× “Dual Fuel”+20,095 + Price Elasticity + Forecast Error;

A number of observations can be made in regard to the above equations/relationships:

- The negative coefficient for SFD in the domestic demand forecast seems to be counter intuitive as it implies that as the State Final Demand increases, the electricity demand decreases.
- The domestic and domestic off peak demand seem to be driven by the year parameter inferring continuous growth.
- The negative coefficient for households for the domestic off peak implies that the more households there are, the lower the off peak demand. This would seem to be counterintuitive as more households and population would likely lead to stronger demand.
- In the domestic off peak equation, the population and household coefficients are opposite and oppose each other. It would be expected that households and population (note the coefficient for population is very small indicating a small impact for this sector of demand) would be positively correlated.
- For commercial demand the negative year coefficient indicates a reducing demand for each year (simple observation of demand shows it growing over the period 1996 to 2008), although this appears to be only a small proportion of the eventual forecast. For commercial demand the population is a major component while the SFD and dual fuel components have a small influence on the end demand calculated.

The domestic and commercial sectors price elasticity applied were based on NIEIR estimates for NEMMCO, 2006 SOO and are shown in Table 2.1.

Table 2.1 : Elasticity

Sector	Price elasticity
Residential	-0.25
Commercial	-0.35
Industrial	-0.38

The price elasticities were applied to the base price year of 2008 using historical and future forecast prices. The prices used were corrected for changes in CPI (i.e. applying real price changes). The price elasticity changes are modelled by applying this to the base year (2008) demand, for the sector being examined, to gain a change in demand (GWh) value related to the relative price change. The full price elasticity impact is also assumed to occur over 7 years based on the proportioning below. This implies that the -0.25 % impact for domestic supply will be fully seen over a 7 year period (i.e. a price change impact in 2008 will eventually fully flow through to demand in 2015).

Table 2.2 : Price elasticity impact over time

Year	0	1	2	3	4	5	6	7
Elasticity Impact	20%	40%	60%	78%	85%	91%	97%	100%

The 2008-2013 forecast was derived from initial work by Jacobs SKM which was subsequently adjusted after a review by AER. The initial forecast used a different regression, with the regression at total consumption level (not split into three sectors) with variables of year, state final demand index and constant, with a price correction applied based on 2007 prices in the domestic, domestic off peak and commercial price changes per annum.

2.2.1 Weather correction

The 2008-2013 demand forecast utilised actual demand data with a weather correction applied. The weather correction used to develop the forecast was a simple annual weather correction using the historical annual heating degree days (HDD) and cooling degree days (CDD). This was based on historical data from July 1994 to June 2011[3], although the average annual statistics used were based on data from 1986 to 2011. The annual average statistics used in the modelling were:

Table 2.3 : Historical statistics for HDD and CDD.

Heating Degree Days (base 18º)													
=INDEX('I	1	2	3	4	5	6	7	8	9	10	11	12	13
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Min	0	-	9	69	188	248	329	265	190	77	15	3	**1,645**
P90	2	1	19	89	215	296	337	288	204	112	38	11	**1,803**
P50	6	8	37	125	251	326	374	329	232	152	71	21	**1,955**
Av	10	11	40	129	249	327	369	328	233	154	72	27	**1,946**
P10	22	20	65	174	277	365	393	363	267	188	117	48	**2,110**
Max	40	43	80	199	313	380	415	374	285	214	139	65	**2,213**
Cooling Degree Days (base 24º)													
=INDEX('I	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Min	-	-	-	-	-	-	-	-	-	-	-	-	**-**
P90	0	-	-	-	-	-	-	-	-	-	-	-	**3**
P50	10	4	-	-	-	-	-	-	-	-	-	1	**21**
Av	12	7	0	-	-	-	-	-	-	-	1	2	**22**
P10	26	18	2	-	-	-	-	-	-	-	5	5	**42**
Max	36	28	3	-	-	-	-	-	-	-	7	13	**63**

Using the P50 (i.e. median) annual value from the historical data, the domestic and commercial demand was adjusted over the historical period 1995 to 2008. Note that no adjustment was made for the domestic off peak demand. The weather correction was based on the actual annual HDD and CDD days for the period 1995-2008 being regressed with the year and actual annual demand by sector, to define a coefficient to adjust the difference between the statistical P50 estimate and the annual actual HDD/CDD values. The weather corrected data was therefore the actual demand measured plus the product of the coefficient for HDD and the difference in HDD from the historical P50 HDD, plus the product of the coefficient for CDD and the difference in CDD day from the historical P50 CDD. The coefficients used for the domestic and commercial weather correction were:

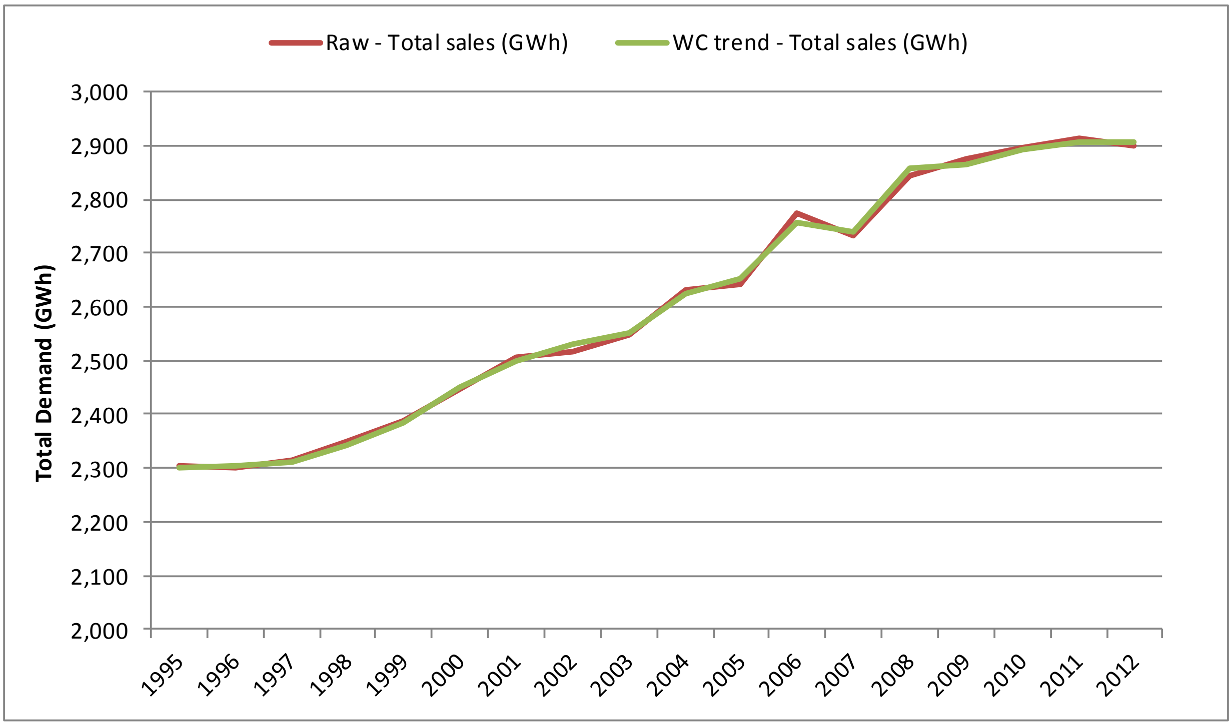
Table 2.4 : Weather correction coefficients.

Demand sector	Domestic	Commercial
HDD coefficient	0.18	-0.12
CDD coefficient	0.68	0.34

The weather correction coefficients are relatively small which also reflects a small impact on demand due to the weather as indicated in Figure 2.3. Interestingly the reverse sign for the HDD coefficient for domestic and commercial negate the correction meaning no matter the weather change, the residential and commercial sectors corrections will be in opposite directions resulting in a small net change. While the CDD coefficient is positive for both sectors the general magnitude of change for CDD is lower than HDD, so the CDD has less impact or correction on demand. It is difficult to understand why the coefficient for demand change between commercial and domestic sectors are opposite for HDD.

[3] Note it would appear that the model has been update in 2012 to include the latest data for weather correction.

Figure 2.3 : Weather corrected historical demand

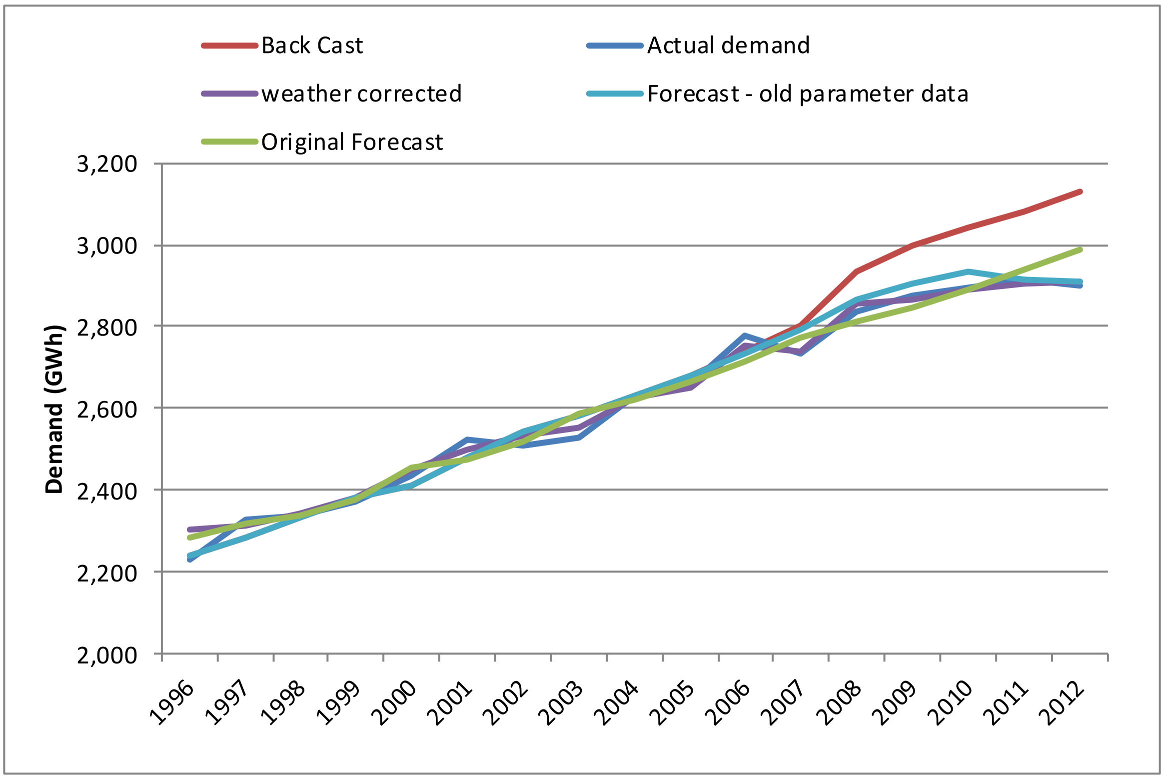


While maximum temperature seems to be tested for correlation to demand in the previous forecast, the HDD and CDD variables were used instead.

2.3 Back casting with actual numbers

The back casting exercise looked at using the variable and regression factors from the forecast and then using actual numbers for the period 2008 to 2012 for the variables in the regression equations. Hence, it used the actual values for SFD, population, air con penetration, price changes and household numbers for 2008 to 2012. Only the dual fuel numbers were kept the same due to no actual information on this parameter for the 2008 to 2012 period. Figure 2.4 highlights the outcomes compared to actuals and the original forecast numbers when applying actual values for the forecast parameters.

Figure 2.4 : Comparison of forecast and back cast with actual demand



The back cast outcomes show an increase in the expected demand for 2008 to 2012 if actual parameter results were used rather than those forecast at the time. This is driven by significant changes in the parameters used in the forecast. Note the price adjustment did not change considerably and in fact was delayed which added to the difference shown (i.e. the assumed full carbon price impact was less as it was not introduced until July 2012 but was assumed to have been introduced in 2011. The major adjustment comes from the changes in the various parameters. The differences between the forecast values and actual values for the key parameters are shown in Table 2.5.

Table 2.5 : Change in forecast values

Parameter	2008	2009	2010	2011	2012
Population – Forecast (000’s)	344.2	346.4	349.7	352.9	356.1
Population – Actual (000’s)	348.4	354.8	361.8	368.0	374.9
Population change (000’s)	4.1	8.4	12.1	15.1	18.9
SFD – Forecast (%)	202.4	203.9	210.1	220.0	230.5
SFD – Actual (%)	202.4	208.7	214.0	221.7	229.7
SFD change (%)	0.0	4.7	4.0	1.6	-0.8
Households – Forecast (000’s)	134.0	135.8	137.6	139.4	141.1
Households – Actual (000’s)	131.7	133.5	135.7	137.9	140.1
Household change (000’s)	-2.3	-2.3	-1.9	-1.5	-1.0
Air con penetration (%) - Forecast	51.5	52.6	53.7	54.2	54.7
Air con penetration (%) - Actual	62.0	64.5	67.0	69.5	72.0
Air con penetration (%) change	10.5	11.9	13.3	15.3	17.3

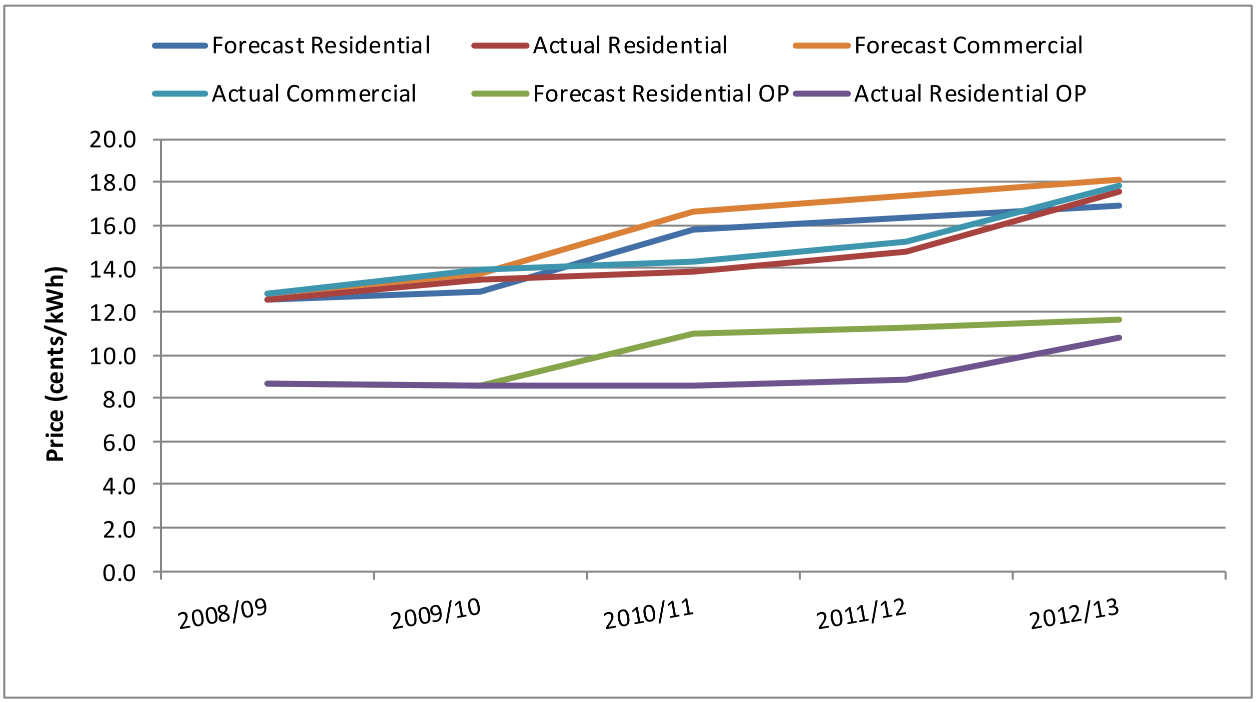
The most significant changes by 2012 arise in the commercial forecast where using actual parameter values gives a demand 170GWh higher than the 2008 forecast. This is driven by a much larger population growth in the ACT than forecast with the actual being 18,900 more people in 2012 than originally forecast back in 2008. Equally the most significant change in the domestic demand forecast occurred due to a significantly higher air conditioner penetration (i.e. 17% more households having air conditioners in 2012 than forecast).

The source of the various parameters used in this analysis was:

- SFD – Australian Bureau of Statistics (ABS) data series 5220.0 Table 9
- Population – ABS data series 3101.0 Table 4
- Households – ABS data series Table 20 (note this data is described as estimated/projected)
- Air condition penetration – ABS data series 4602.0 Table 15 (survey in March 2005, 2008 and 2011, other years growth has been extrapolated).

The difference between electricity price forecasted and actual has also made a slight difference in the forecast and back cast comparison. One of the major changes has been the shift in the carbon price timing and this is depicted in Figure 2.5 where the increase in prices occurs in 2010/11 versus 2012/13 in the actual numbers. Thisresults in a lower reduction in demand in the back cast due to price change, compared to that assumed in the forecast.

Figure 2.5 : Change in average pricing per sector – forecast versus actuals



2.4 Assessment of forecast

The initial impression of the forecast was one that was very good with the difference between actual outcomes by 2012 and the forecast in 2008 of less than 1 %. However, on further inspection and analysis, the demand forecast equations do not seem to capture the underlying drivers of demand as well as first considered. The parameters and variables used in the demand forecast seem in some cases contradictory and also some would seem to be correlated (i.e. households and population) potentially causing issues with the equations. The fact that domestic demand is predominantly driven by the year seems to imply a continued growth in demand and the negative coefficient for SFD implies a declining demand for a growing economy. These assumptions are not particularly insightful in defining drivers for demand.

The initial impression that price elasticities have driven the downward trend would seem to be contradicted by back casting, although the back casting is more showing the influence of the changing forecast parameter numbers than any pricing impacts (note price impact is lower in the back cast than forecast due to a change in timing of carbon pricing and also change in actual prices and CPI). The decomposition of demand and the parameters driving demand is further discussed in Section 4.

3. Weather normalisation

3.1 Introduction

It is proposed to base the forecasts for the 2014-15 to 2019-20 period on new energy models derived from the most recently available data incorporating current consumption trends. Model construction is in two stages:

1) Modelling of the weather impact on energy consumption, i.e. weather normalisation
2) Modelling of the relationship between weather normalised energy and key economic drivers, such as the number of households or gross state product.

From an analytic perspective it is possible to combine these two steps but this has the following quite serious drawback. Weather induced energy variation occurs on a shorter (daily and seasonal) timescale and is greater than economically driven energy variation, which is generally detectable only over periods of several years. The accuracy of a combined model will therefore be determined by how well it predicts the short-term weather variations rather than the long-term variations that we are more interested in projecting. This problem was recently encountered by AEMO in developing quarterly energy models, which they essentially abandoned[4].

The following sections describe the data and analysis used in each stage of modelling.

3.2 Weather normalisation

3.2.1 Data used

The energy and weather data used in modelling is described in Table 3.1.

Table 3.1 : Energy and weather data

	Description	Comments
Network Energy	Daily total electricity energy flow in the network. The composite of energy received from TransGrid and net energy flow from Queanbeyan and Williamsdale. (1992 - 2013)	This is net of distributed generation i.e. solar panels (PVs) and methane engines, and includes transmission losses
Energy Billings	This is the energy read at the meter at the end of the billing period and billed to the customer. ActewAGL has provided monthly billing data of different customer categories, including Residential, Small business (Low Voltage), Industrial (High Voltage). Available from 1994-2013	This is understood to be gross energy to date, i.e. includes PV contributions. Billing periods vary between customer groups: residential – 3 monthly; LV and HV – monthly. Residential and some LV meters record accumulated consumption and these are manually read each working day. HV and larger LV customers have interval meters which allow billing data to be allocated to the month in which it was consumed.
Weather	Daily minimum and maximum temperatures at Canberra Airport over the past 21 years. (1992 - 2013)	
PV	Installations and energy generated by PVs	
Methane	Energy generated from methane from sewage	

[4] 2013 Forecasting Methodology Paper. National Electricity Forecasting. Australian Energy Market Operator, 2013

Weather is one of the key drivers that contribute to energy consumption. In order to capture the impact of weather, Jacobs SKM carried out multiple regression analysis against underlying weather variables. The analysis was based on heating degree days (HDD) and cooling degree days (CDD) defined as:

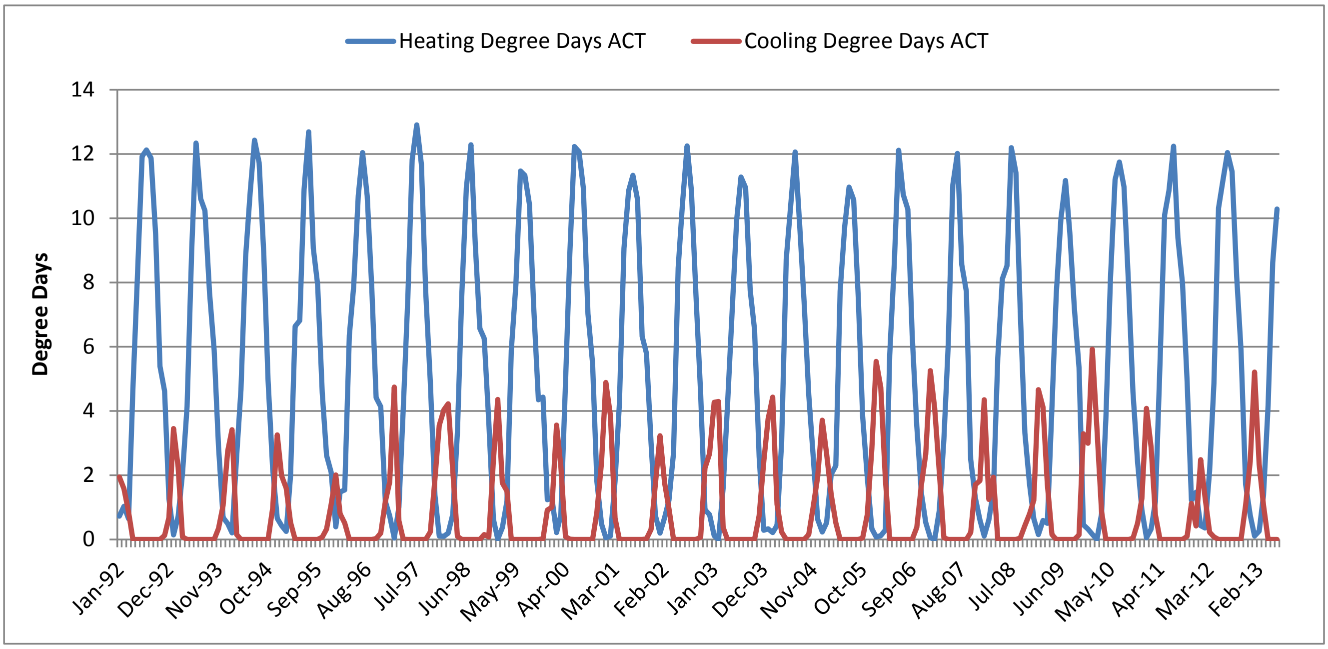
- HDD = Max (0, HDD Threshold – Average daily temperature)
- CDD = Max (0, Average daily temperature - CDD Threshold)

These variables reflect that heating and cooling are not required above and below certain threshold temperatures. 18C is almost universally used as the HDD threshold and has been used here. The CDD threshold is subject to some uncertainty and during the analysis we tested CDD thresholds between 18 and 24 degrees to find the value with the most explanatory power. A threshold of 18C for CDD was considered to be the most reasonable as the regression model with the threshold of 18C best replicated the actual network energy.

Notes:

1) We have not sought to use more refined measures of weather impact, such as temperatures on the day before, because these are necessary only for modelling daily energy or peak demand, whereas our purpose is to model monthly billings data.
2) Because months have varying numbers of days, all energy and CDD/HDD data has been converted to average per day in the relevant month.

Figure 3.1 : ACT monthly CDD and HDD per day with 18C threshold



3.2.2 Weather normalisation methodology

For this study, weather normalisation has been undertaken for network energy and each customer category as follows:

1) Regressing monthly average energy per day against the relevant monthly average HDD and CDD per day on a financial year basis for the financial years 1999-2000 to 2012-2013.

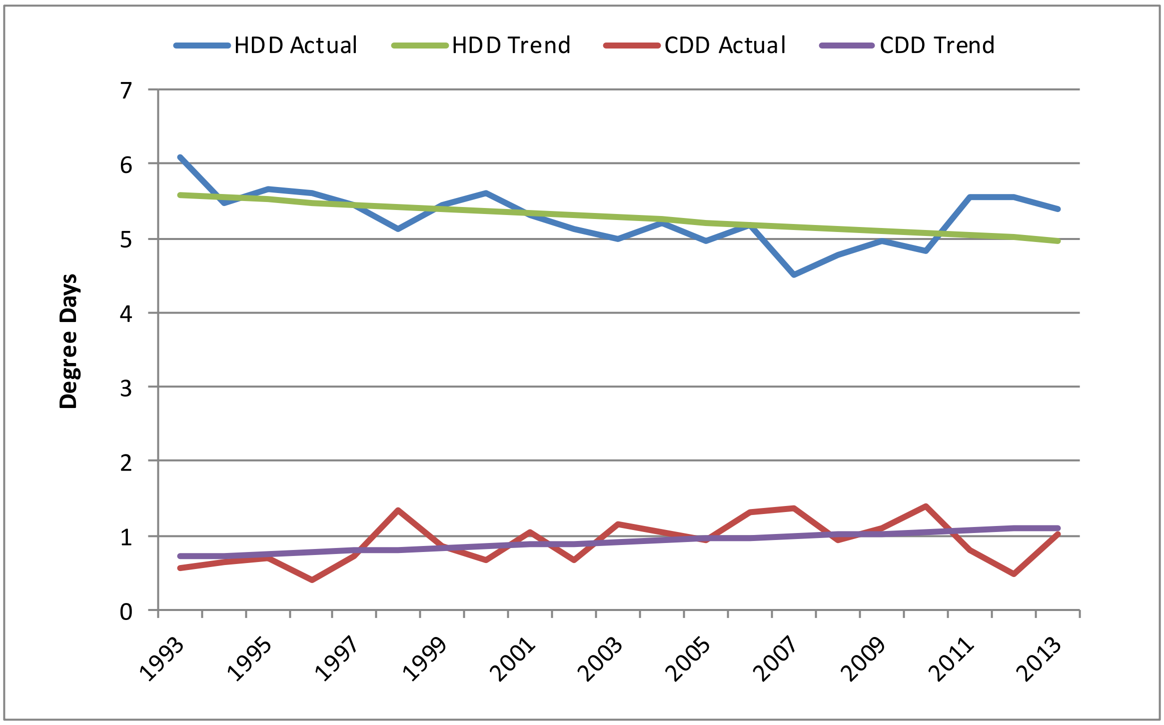
2) Testing the statistical significance of the regression coefficients (t-test) and their stability from year to year, to determine whether HDDs and CDDs significantly impacted each energy type.

3) Calculating the weather normalised average energy per day for each financial year by substituting the average daily HDDs and CDDs for the period 1999-2000 to 2012-2013 into each regression equation, excluding insignificant coefficients.

It is noted that:

- Relevant monthly HDDs and CDDs vary by customer category to match the time profile of energy consumption captured by the billings. For example, residential energy billed in June was consumed over the period March to June and the HDD and CDD measures are weighted averages over the same period
- The average daily HDDs and CDDs for the period 1993-1994 to 2012-2013[5] were:
  - HDDs: 5.28 degree days per day
  - CDDs: 0.92 degree days per day
- Annual average daily HDDs and CDDs show reasonably clear but only marginally statistically significant time trends downwards and upwards respectively (Figure 3.2). These trends have not been utilised in calculating the weather normalised energy values because of the marginality of their significance.

Figure 3.2 : Annual average daily HDDs and CDDs



3.3 Network energy

In this study, the ‘network energy’ comprises the energy received from TransGrid via the connection points at Canberra (Holt), Queanbeyan and Williamsdale less energy losses on the Grid plus embedded generation.

[5] The longest period for which Jacobs SKM was able to secure weather data.

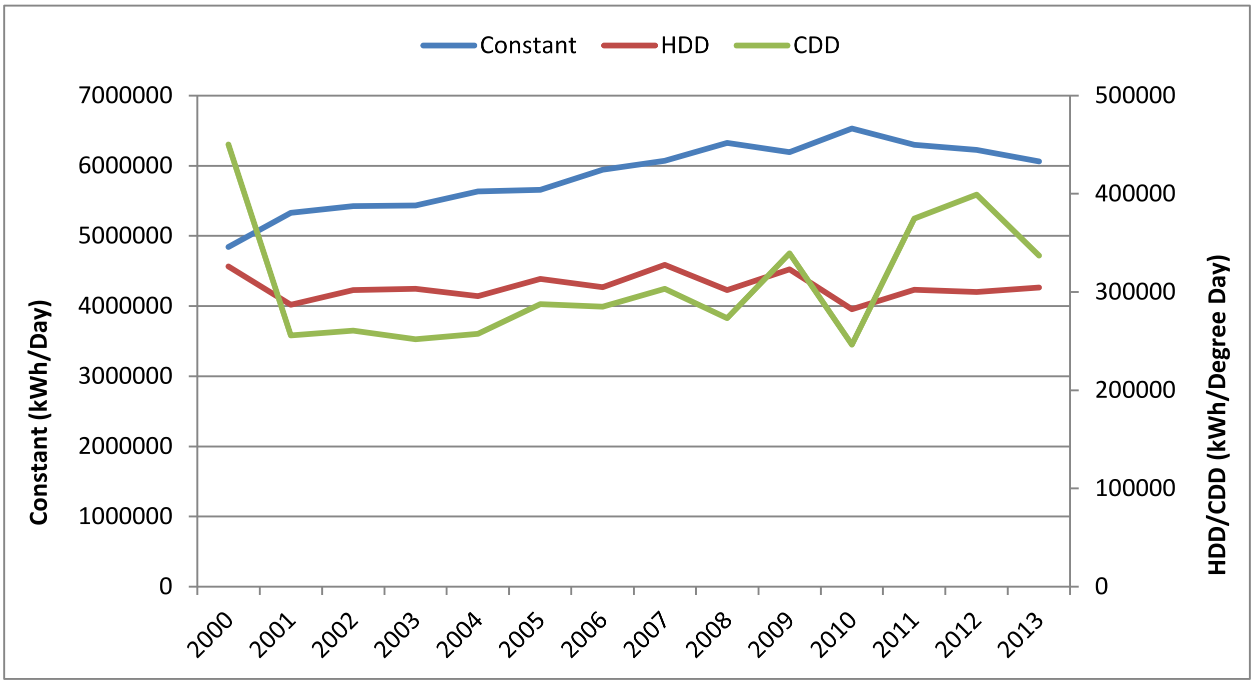
The weather normalisation regression results were as follows:

Table 3.2 : Regression of network energy against CDD and HDD

	2000	2001	2002	2003	2004	2005	2006
Constant	4,841,984	5,329,851	5,424,034	5,435,971	5,633,368	5,656,294	5,941,530
HDD	326,097	287,090	301,982	303,122	295,770	313,451	304,822
CDD	450,364	255,687	260,748	251,829	257,344	287,723	285,209
Standar Error	155,491	254,974	208,879	198,762	282,174	202,671	278,672
R-Sqr	0.984	0.953	0.971	0.972	0.945	0.970	0.946
T-Stat Constant	39.305	26.390	32.115	33.145	23.735	28.801	26.207
T-Stat HDD	21.465	11.633	14.014	14.793	10.249	12.937	11.141
T-Stat CDD	7.853	3.897	2.999	4.766	3.152	3.551	4.491

	2007	2008	2009	2010	2011	2012	2013
Constant	6,072,785	6,324,995	6,194,044	6,528,623	6,297,543	6,224,058	6,061,313
HDD	327,566	302,117	323,119	282,429	302,304	300,011	304,451
CDD	303,333	273,428	339,277	246,274	374,686	399,294	337,163
Standar Error	198,843	259,569	140,355	241,753	302,349	277,550	313,199
R-Sqr	0.971	0.947	0.988	0.949	0.940	0.954	0.934
T-Stat Constant	36.662	28.594	59.650	32.436	26.644	28.423	24.186
T-Stat HDD	15.204	10.437	24.938	11.206	10.635	11.410	10.094
T-Stat CDD	6.023	3.094	9.487	4.377	3.862	2.634	3.937

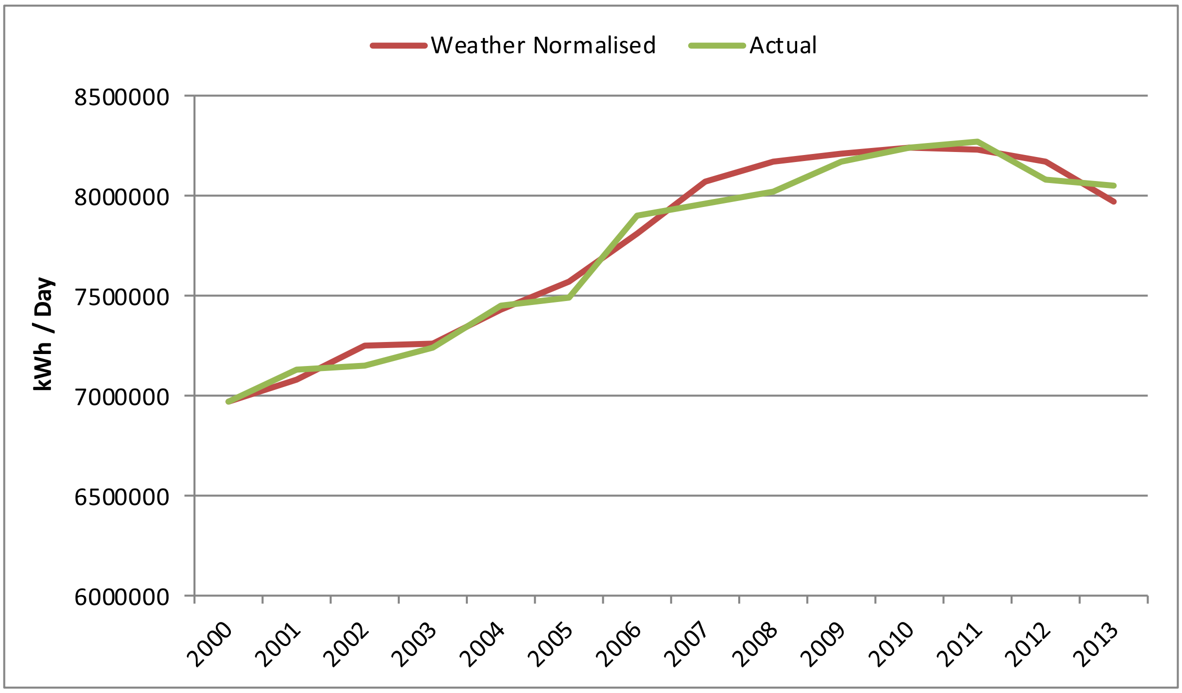
Figure 3.3 : Constant, HDD & CDD coefficients for network energy



As Table 3.2 shows, both HDD and CDD coefficients are statistically robust with positive T-statistics. The regressions imply that ActewAGL's load is 75% base load (constant), 21% heating load (HDD related) and 4% cooling load (CDD related). It is also interesting to note that the constant grew from 2000 to 2010 and then declined while the CDD and HDD coefficients have been staying approximately at the average level over the past fourteen years, with some recent volatility in the CDD coefficients (Figure 3.3). Given that the number of customers with cooling and heating loads has increased over the period, this implies that there have been significant gains in cooling and heating efficiency.

The regressions have been used to calculate weather normalised network energy by multiplying the HDD and CDD coefficients by the average (normal) HDD and CDD values over the period. Annual normalised versus actual network energy is depicted in Figure 3.4. The normalised curve is smoother and shows a clear growth reduction in 2008 followed by a decline in energy use from 2010.

Figure 3.4 : Weather normalised Vs actual network energy (average kWh per day)



It is highly likely that different customers will have different energy consumption responses to the change of the temperature/ weather depending on their size. Small residential customers' electricity consumption can be more sensitive to the weather compared to large industrial customers. In addition, different customer categories have different consumption periods, e.g. residential customers are billed every three months and their consumption is recorded against the month in which they were billed. Consumption of small businesses is also recorded against the month in which they were billed, but they are billed every month. Larger customers have interval meters and their consumption is recorded against the month in which it was consumed. As a result, it is reasonable to apply weather normalisation to different customer categories separately with different definitions of CDD and HDD in order to incorporate the customer size and billing periods.

3.4 HV (High Voltage) billings

Industrial entities get billed at the end of each month which implies there is no need to apply adjustment on CDD and HDD. By regressing industrial billing daily average information against monthly average CDD and HDD per day, the following result is obtained:

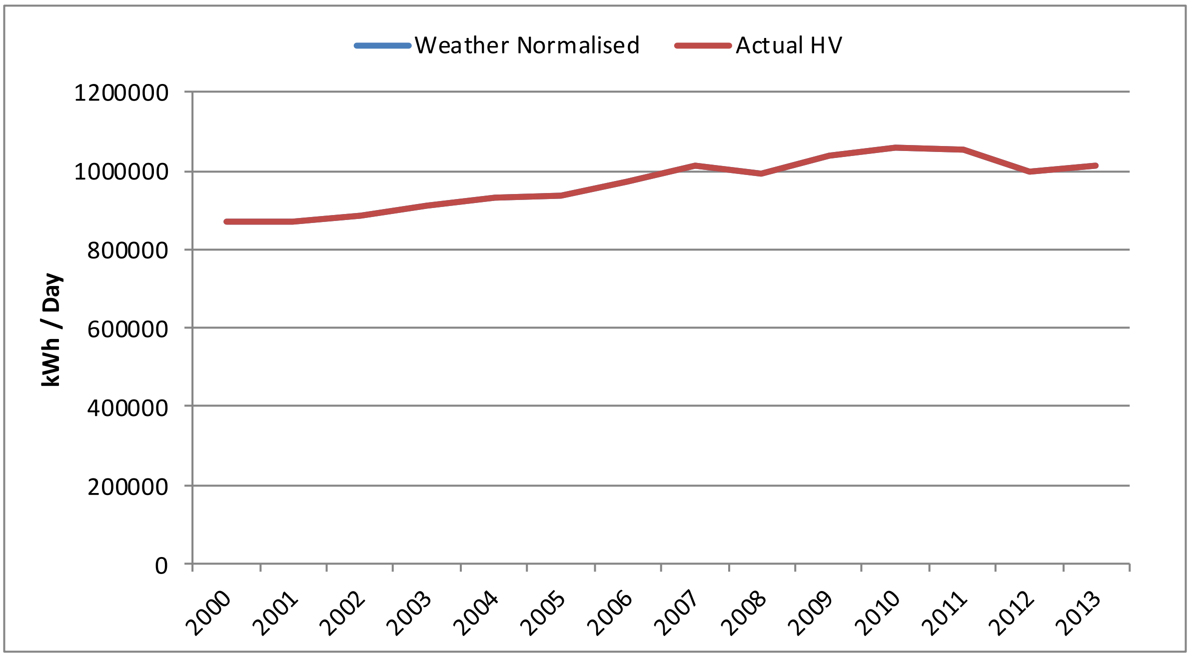
Table 3.3 : Regression of HV billing against HV CDD and HV HDD

	2000	2001	2002	2003	2004	2005	2006
Constant	868,769	836,492	908,775	908,258	937,106	937,439	928,549
HDD HV	1,216	4,190	-1,280	1,335	9	1,492	5,736
CDD HV	-10,691	10,563	-22,349	-3,306	-5,543	-5,850	11,800
Standar Error	55,997	62,855	67,744	61,566	43,513	51,156	66,155
R-Sqr	0.095	0.055	0.096	0.037	0.048	0.071	0.083
T-Stat Constant	19.582	16.801	16.591	17.879	25.603	18.911	17.253
T-Stat HDD HV	0.222	0.689	-0.183	0.210	0.002	0.244	0.883
T-Stat CDD HV	-0.518	0.653	-0.793	-0.202	-0.440	-0.286	0.783

	2007	2008	2009	2010	2011	2012	2013
Constant	974,461	956,775	967,953	1,042,145	1,025,381	969,821	994,371
HDD HV	5,068	5,366	10,439	2,033	3,037	3,907	2,132
CDD HV	12,986	11,156	19,283	5,760	17,814	13,350	5,766
Standar Error	36,642	20,853	30,245	37,287	30,756	31,902	39,911
R-Sqr	0.187	0.374	0.609	0.047	0.273	0.160	0.036
T-Stat Constant	31.925	53.839	43.258	33.570	42.647	38.530	31.137
T-Stat HDD HV	1.276	2.307	3.739	0.523	1.050	1.293	0.555
T-Stat CDD HV	1.399	1.571	2.502	0.664	1.805	0.766	0.528

Note that the low T-Stats for both HDD and CDD demonstrate the insignificance of CDD and HDD for these customers and hence there is no need to weather normalise HV load.

Figure 3.5 : Weather normalised and actual HV billings (average kWh per day)



3.5 LV (Low Voltage) billings

Due to the fact that small businesses are billed through the month, the energy captured in one month's billings used covers both that month and the previous one, with a triangular weighting of the days. Similarly weighted CDD and HDD averages are applied in the weather normalisation, in order to reflect the billing structure of the LV customers.

Table 3.4 : Regression of LV billing against LV CDD and LV HDD

	2000	2001	2002	2003	2004	2005	2006
Constant	2,470,649	2,625,735	2,670,955	2,751,580	2,838,042	2,941,121	3,036,481
HDD	31,295	34,074	34,958	32,874	31,004	32,456	36,264
CDD	168,035	115,201	131,444	111,028	109,310	98,573	115,908
Standar Error	190,139	82,111	61,717	152,183	84,501	76,501	118,832
R-Sqr	0.332	0.736	0.762	0.408	0.629	0.593	0.645
T-Stat Constant	15.551	37.826	50.184	20.316	35.690	39.512	29.248
T-Stat HDD LV	1.634	4.071	5.228	1.974	3.222	3.560	2.805
T-Stat CDD LV	2.109	4.990	4.722	2.490	3.905	3.232	4.016

	2007	2008	2009	2010	2011	2012	2013
Constant	3,283,491	3,465,832	3,307,973	3,430,382	3,302,783	3,420,373	3,401,429
HDD	26,326	19,134	37,647	19,155	38,300	30,517	27,016
CDD	113,647	62,406	124,483	83,837	180,069	187,685	112,481
Standar Error	89,882	114,741	72,441	87,302	198,892	104,354	146,433
R-Sqr	0.749	0.162	0.841	0.646	0.464	0.411	0.386
T-Stat Constant	43.091	28.908	61.265	42.636	20.653	31.664	25.454
T-Stat HDD LV	2.695	1.288	5.505	1.890	1.986	2.474	1.728
T-Stat CDD LV	4.909	1.230	6.823	3.671	2.793	2.252	2.371

Compared to HV, the T-Stats for HDD and CDD coefficients are more significant which is intuitively correct as small businesses are likely to be more responsive to the change of temperature compared to large industrial customers. The time trends of the weather normalisation constant and coefficients are similar to the trends in the Network Energy weather normalisation coefficients

Figure 3.6 : Constant, HDD & CDD coefficients, LV billings

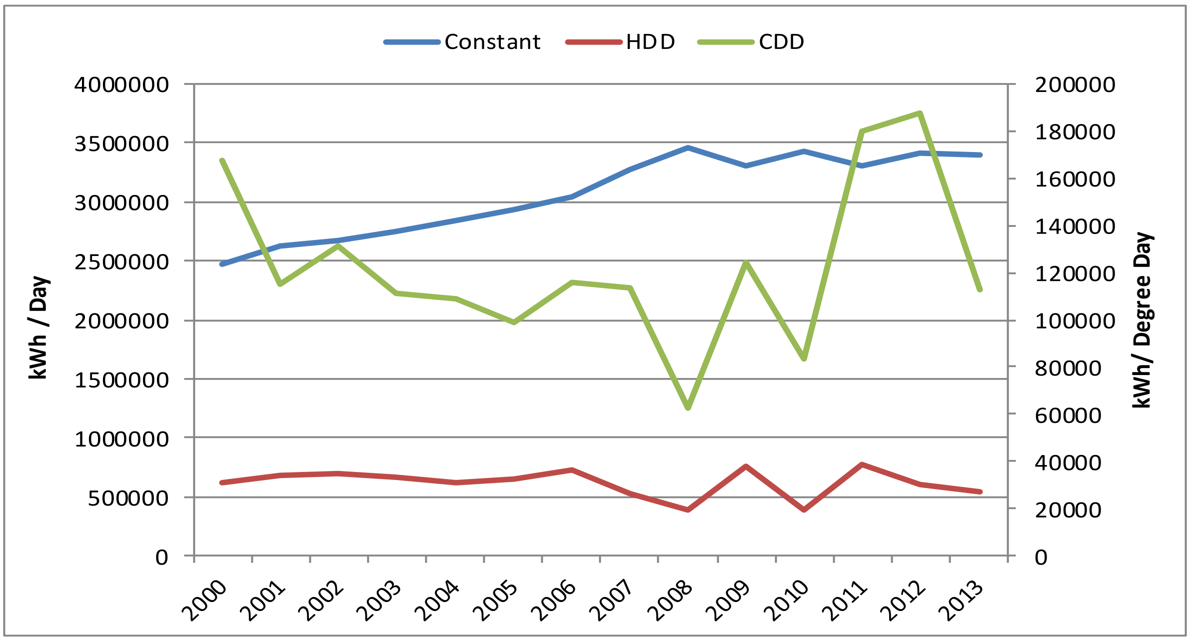
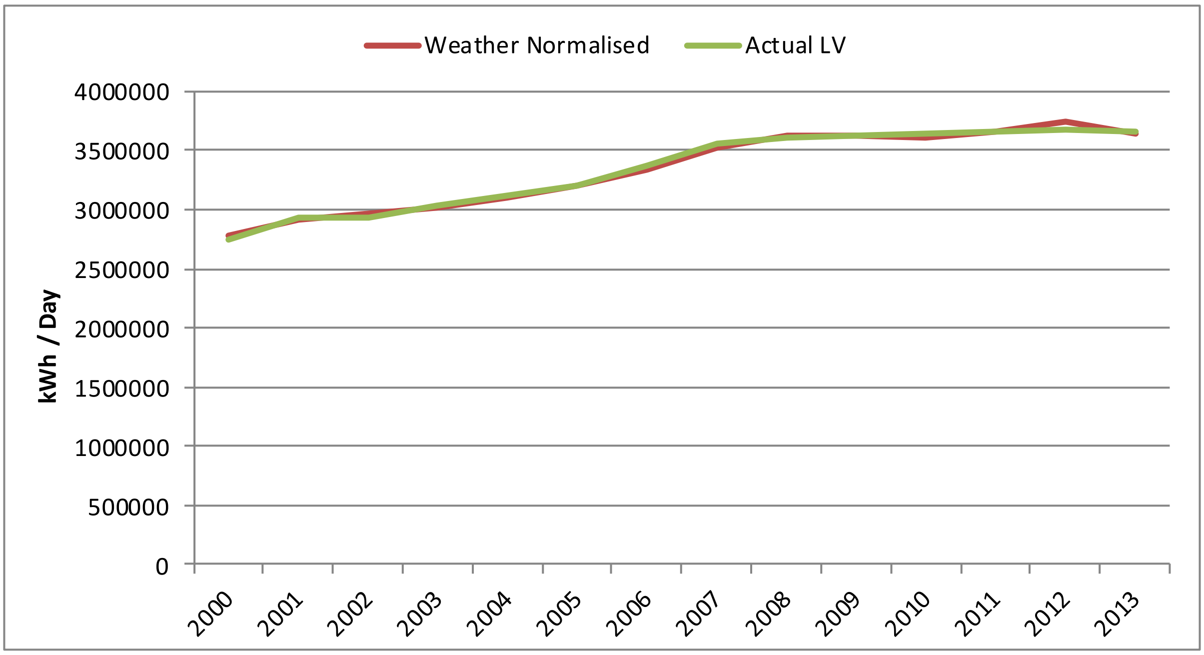


Figure 3.7 : Weather normalised Vs actual LV billings (average kWh per day)



3.6 Residential off-peak billings (OP)

Unlike small businesses (LV), every residential customer gets billed quarterly (every three months) and the energy captured in one month's billings used covers both that month and the previous three, with a weighting of the days that is 1/6 in the first and last months and 1/3 each in the middle two months. Hence similarly weighted CDD and HDD averages are used in the analysis.

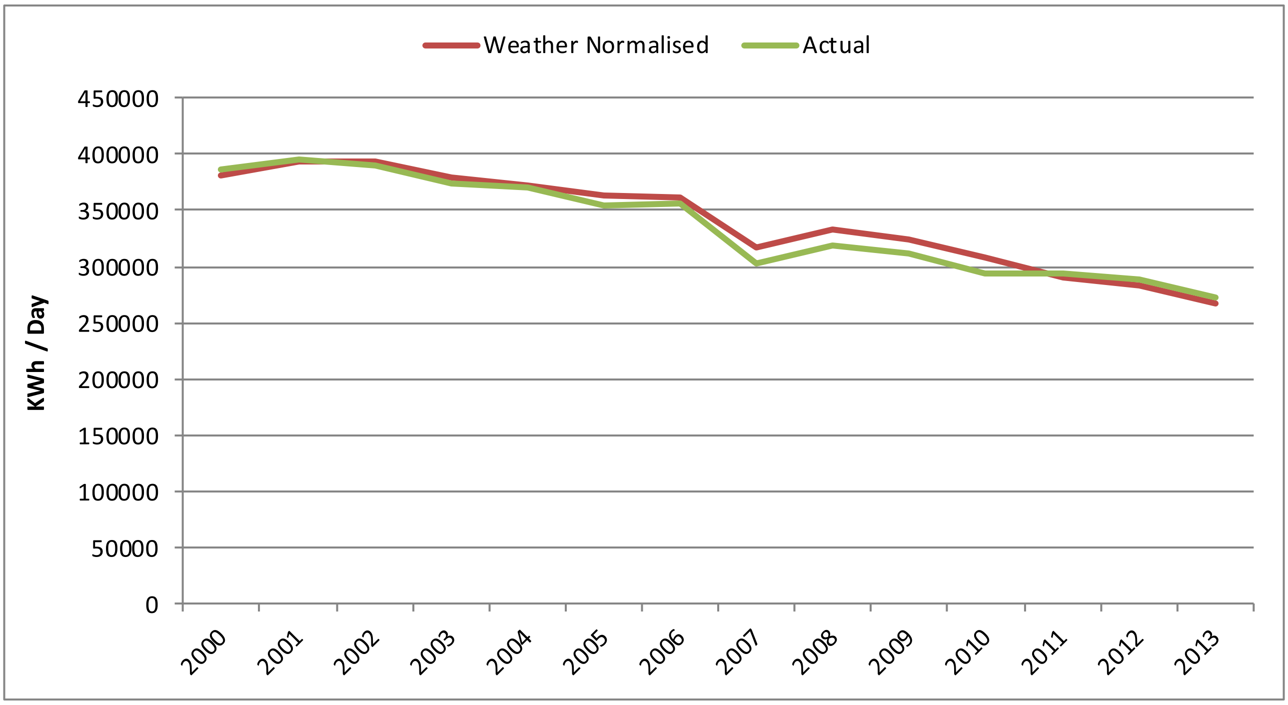
Table 3.5 shows that while residential OP usage is sensitive to HDDs it is not significantly sensitive to CDDs. Weather normalised OP usage is therefore based on normalisation to HDDs only. Both actual and weather normalised OP usage have been in steady decline since about 2003, owing to replacement of off-peak water heaters with solar and gas-fired appliances.

Table 3.5 : Regression of OP billing against residential CDD and residential HDD

	2001	2002	2003	2004	2005	2006
Constant	266,549	296,015	330,629	263,226	286,332	220,719
HDD Residential OP	21,256	17,863	14,003	21,839	17,523	26,090
CDD Residential OP	141,309	65,019	-353,737	-47,765	-388,459	33,150
Standard Error	74,858	75,263	78,251	98,722	79,042	87,696
R-Sqr	0.559	0.501	0.623	0.512	0.620	0.579
T-Stat Constant	4.002	4.581	4.016	2.342	3.463	2.601
T-Stat HDD Resid OP	2.595	2.084	1.377	1.531	1.679	2.287
T-Stat CDD Resid OP	0.577	0.039	-0.934	-0.130	-0.685	0.188

	2007	2008	2009	2010	2011	2012	2013
Constant	160,254	171,524	168,453	151,668	86,858	154,039	110,903
HDD Residential OP	27,818	30,354	29,453	28,965	32,696	24,141	27,278
CDD Residential OP	84,208	8,831	-9,946	24,179	405,460	154,755	117,877
Standard Error	51,333	45,727	40,798	35,117	64,199	33,770	37,654
R-Sqr	0.831	0.881	0.910	0.919	0.747	0.905	0.906
T-Stat Constant	3.384	3.983	5.187	4.191	1.502	5.427	3.034
T-Stat HDD Resid OP	4.538	5.153	6.649	6.000	4.428	6.610	6.304
T-Stat CDD Resid OP	0.557	0.034	-0.133	0.273	1.567	0.074	0.796

Table 3.6 : Weather normalised vs actual OP billings (ave kWh per day)



3.7 Residential General (GP)

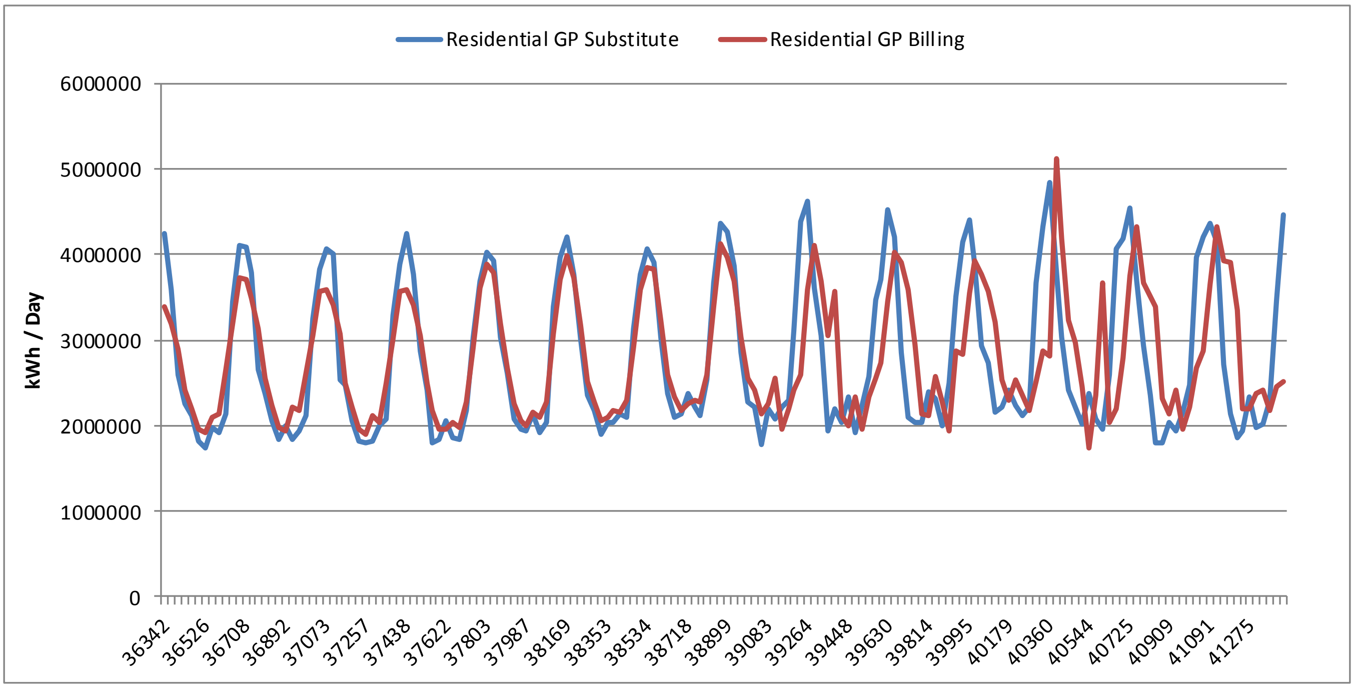
Initial attempts to weather normalise Residential GP billings data revealed a material change in its definition in 2007, which produced discontinuities in both actual and weather normalised estimates. A full description of the preliminary analysis is provided in Appendix A.

Jacobs SKM believed the discontinuity would unduly influence econometric analysis of this data and therefore decided to estimate residential energy consumption based on total network energy, energy used by other customers, network losses and distributed generation, rather than using residential billings in weather normalisation directly. The formula used to calculate the approximate residential billing was:

Residential GP Substitute = (Network Energy + Distributed Generation)*(1- x%) – HV – LV - OP, where x% is the percentage of energy losses in the network.

A solver routine was created to find the optimum number for x% which minimises the difference between actual residential billing and residential substitute over the data period. The estimated number is 4.566% which is close to the 5% figure advised by ActewAGL. The substitute residential profile is shown below in Figure 3.8, where the change in the pattern of billings in 2007 is clear.

Figure 3.8 : Residential GP Substitute Vs Residential GP billing



As the substitute GP data is derived from daily and monthly read meters, it is appropriate to use the same HDD and CDD values as for LV customers. By introducing the GP substitute, the weather normalisation regression was improved substantially (average R2 of 0.96). As Table 3.7 shows, both HDD and CDD coefficients are statistically robust with positive T-statistics. The regressions imply that ActewAGL's residential load is 47% base load (constant), 46% heating load (HDD related) and 7% cooling load (CDD related). It is also interesting to note that the constant appears relatively flat from 2000 to 2010 and then declined while the CDD and HDD coefficients have been staying approximately at the average level over the past fourteen years, with some recent volatility in the CDD coefficients (Figure 3.9). Given that the number of customers with cooling and heating loads has increased over the period, this implies that there have been significant gains in cooling and heating efficiency.

Table 3.7 : Regression of Residential GP against LV CDD and LV HDD

	2000	2001	2002	2003	2004	2005	2006
Constant	1,068,958	1,304,711	1,314,746	1,292,477	1,391,243	1,362,682	1,517,676
HDD Residential GP	253,154	222,287	238,035	234,169	228,500	236,748	227,560
CDD Residential GP	266,518	146,701	169,591	147,458	159,005	184,976	159,110
Standard Error	187,808	146,244	165,869	106,437	163,854	86,499	166,827
R-Sqr	0.966	0.976	0.972	0.988	0.971	0.991	0.969
T-Stat Constant	7.184	11.263	9.803	14.717	10.094	16.257	11.182
T-Stat HDD Resid GP	13.796	15.704	13.911	21.340	13.636	22.895	13.894
T-Stat CDD Resid GP	3.848	3.898	2.456	5.211	3.354	5.350	4.185

	2007	2008	2009	2010	2011	2012	2013
Constant	1,470,822	1,278,511	1,426,268	1,525,602	1,309,854	1,276,852	1,099,611
HDD Residential OP	250,520	267,119	250,212	244,494	259,869	254,211	267,249
CDD Residential OP	142,156	267,687	198,333	167,205	264,366	288,478	260,744
Standard Error	171,830	165,297	192,656	196,551	256,438	196,210	360,368
R-Sqr	0.970	0.971	0.967	0.960	0.946	0.969	0.897
T-Stat Constant	10.276	9.076	10.007	9.323	6.534	8.248	3.813
T-Stat HDD Resid OP	13.456	14.490	14.068	11.932	10.779	13.676	7.701
T-Stat CDD Resid OP	3.267	4.756	4.040	3.655	3.213	2.692	2.646

Figure 3.9 : Constant, HDD & CDD coefficients, Residential GP

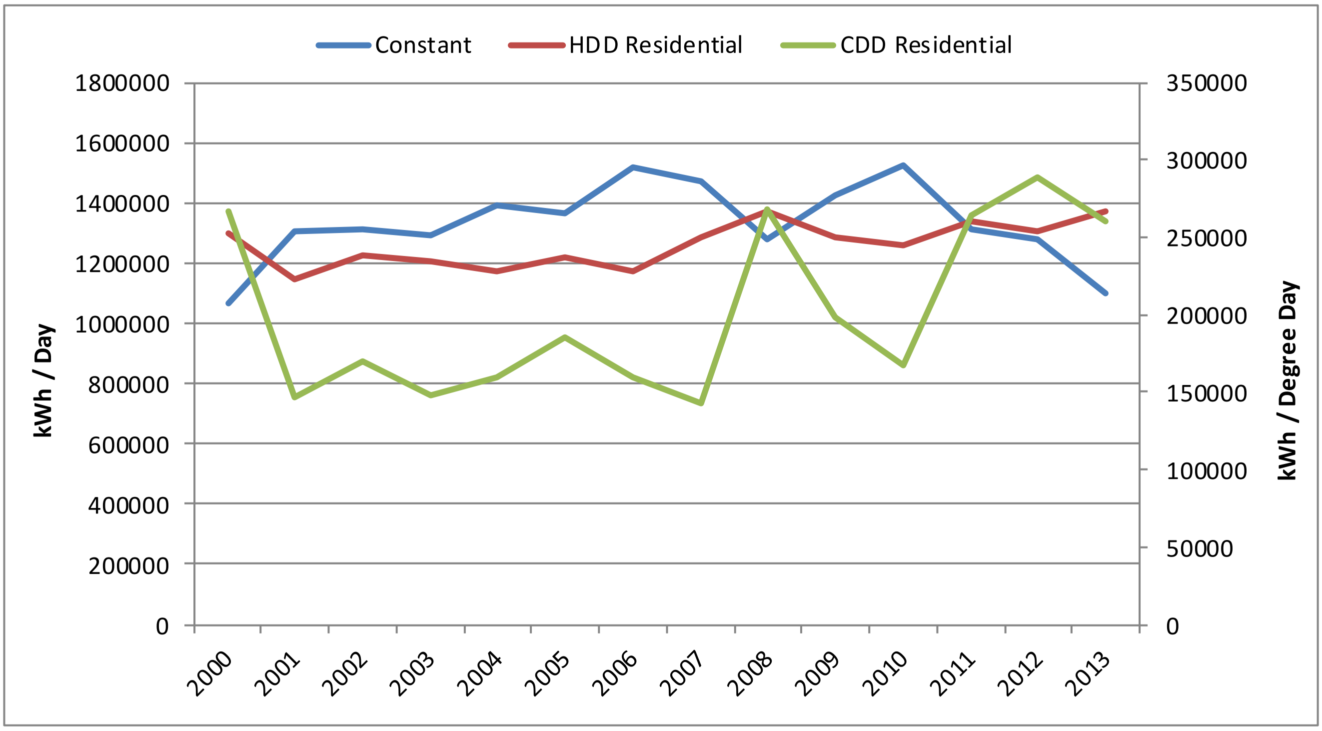
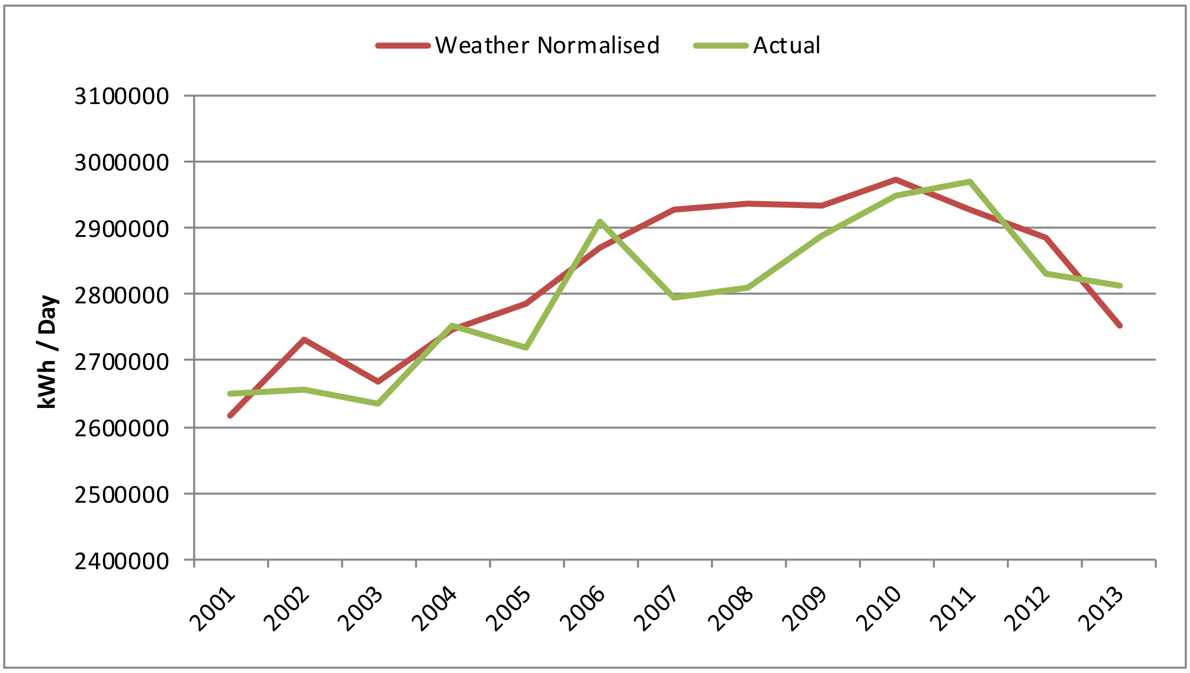


Figure 3.10 : Weather normalisation vs actual for Residential GP (average kWh per day)



3.8 Summary of weather normalisation

Weather normalised average daily and annual energy for each customer group are summarised in Figure 3.11 and Figure 3.12.

Figure 3.11 : Weather normalised average daily energy (average kWh per day)

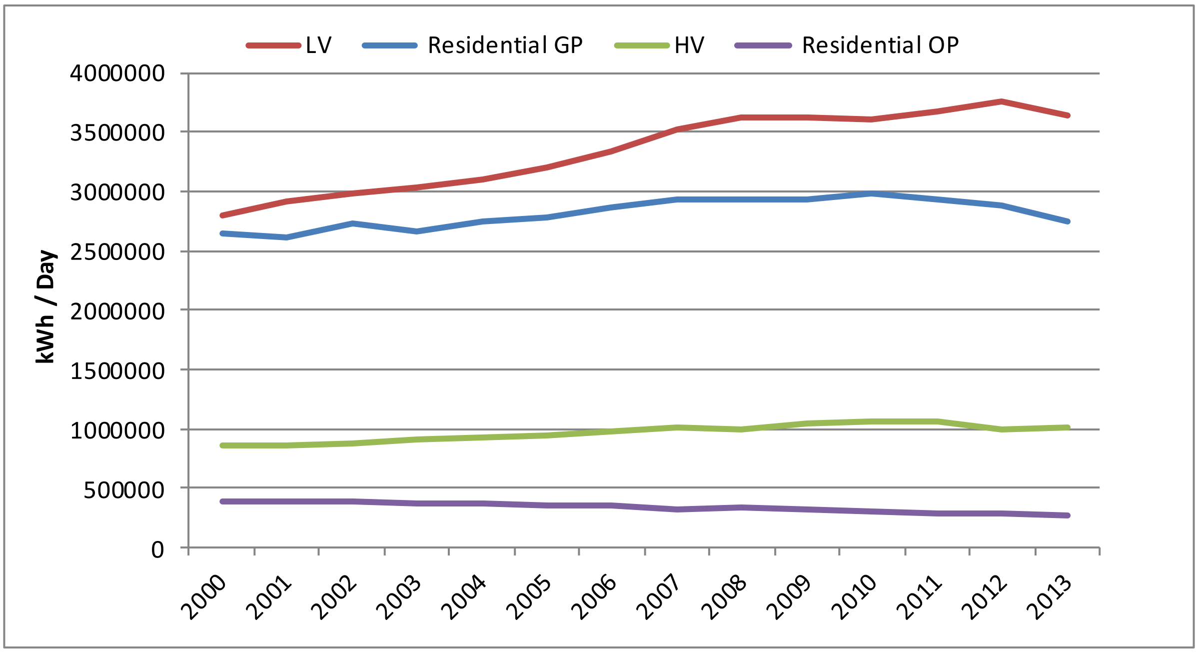
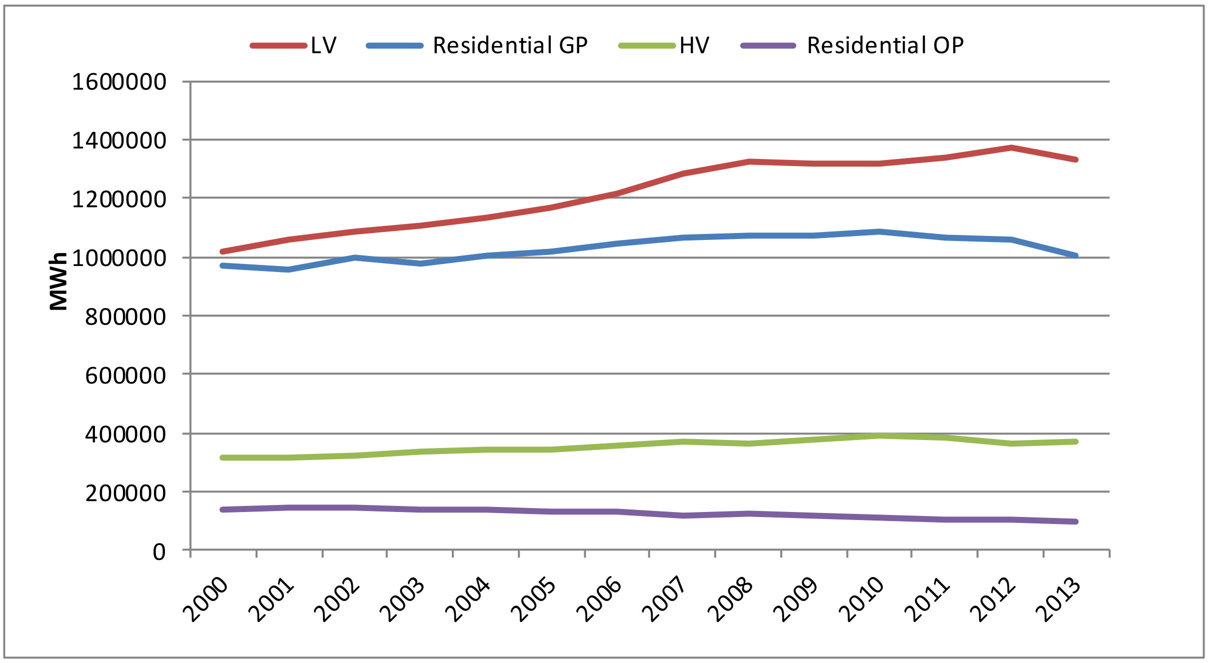


Figure 3.12 : Weather normalised annual energy (MWh)



The change in growth rates evident in the above charts in the middle of the data period, in all categories except OP, are summarised in Table 3.8.

Table 3.8 : Growth rates of weather normalised energy

	Period		
	2000-07	**2007-13**	**2000-13**
Residential GP	1.4%	-1.0%	0.3%
Residential OP	-2.6%	-2.8%	-2.7%
LV	3.4%	0.6%	2.1%
HV	2.3%	0.0%	1.2%
Total	2.2%	-0.2%	1.1%

4. Detailed assessment of historical long-term drivers of demand

4.1 Data and parameters to be considered

It is clear from the weather normalised energy consumption patterns that ACT energy usage grew from 2000 to approximately 2008 and then flattened and in some categories declined from 2010. The likely drivers of the early growth are economic and population growth, both of which continued positively but at a reduced rate beyond 2010 however. The decline is considered more likely to be caused by factors such as increasing energy efficiency and price increases.

The explanatory variables considered and the sources of the historical information are listed in Table 4.1. ABS data was the latest available as at mid-November 2013.

Table 4.1 : Long-term explanatory variables considered and sources of historical information

Key Driver	Variable Used	Source of information
Economic growth	Gross State Product (GSP)	ABS 5220.0 Table 1
Economic growth	State Final Demand (SFD)	ABS 5220.0 Table 9
Economic growth	Household Income (HHI)	ABS 6523.0 Table
Financial influences	CPI	ABS 6401.1
Financial influences	Exchange rate	Reserve Bank of Australia
Financial influences	Interest rate	Reserve Bank of Australia
Demographics	Population	ABS 3101.0 Table 4
Demographics	Households	ABS 3236.0
Demographics	Employment	ABS 6202.0
Energy Price Movement	Electricity retail prices of residential, LV and HV.	ActewAGL
Energy savings	Supply side - kWh of PV (photovoltaic) output	ActewAGL
Energy savings	Demand side - energy efficiency - % of energy saved	AEMO estimates

4.2 Economic growth (GSP, SFD and HHI)

GSP is a measure of the economic output of a state or province (i.e. of a subnational entity). It is the sum of all value added by industries and services within the state.

SFD measures economic activity through the level of spending by the private and public sectors, reported on the basis of consumption of goods and services, and capital investment.

HHI measures the household sector's share of the economy.

Historical ACT GSP, SFD and HHI growth rates from June-2000 to June-2012 are shown in Figure 4.1 below. Whereas GSP and HHI growth (shown in Figure 4.2) over the past thirteen years has been relatively steady SFD is more volatile with growth over 10% in some years. Moreover, SFD growth from 2008 onwards in noticeably lower than in previous years, which demonstrates the impact the global financial crisis has had on consumption of goods and services, and capital investment.

Figure 4.1 : ACT SFD and GSP Growth, %

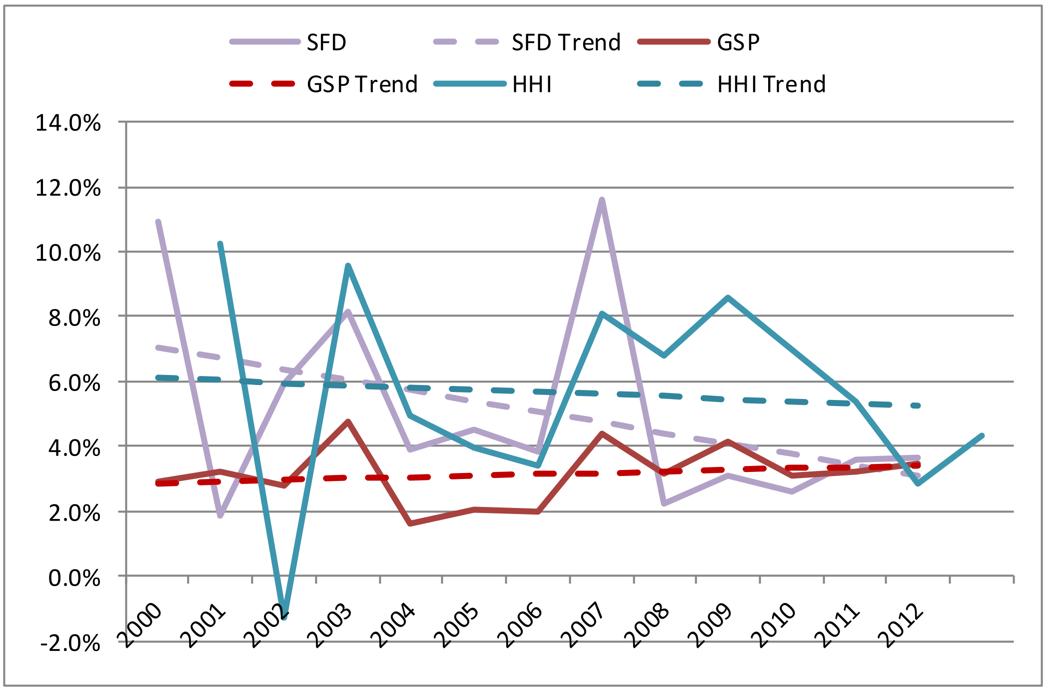
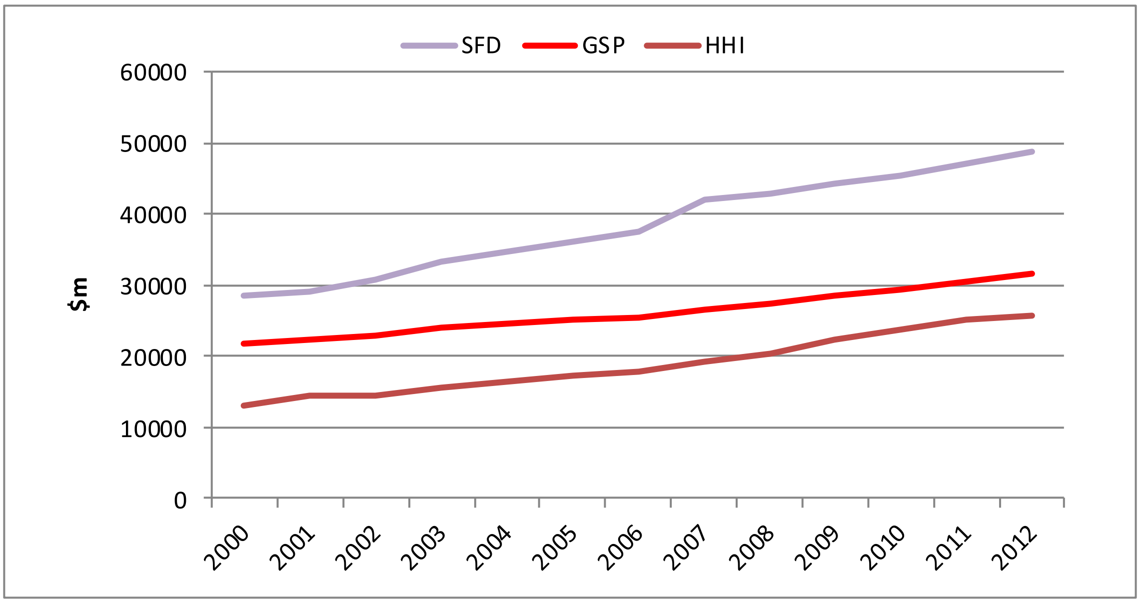


Figure 4.2 : ACT SFD, GSP and HHI ($m)



4.3 Financial indicators

CPI, exchange rates and interest rates over the period 2000 to 2013 are illustrated in Figure 4.3 to Figure 4.5 below. CPI growth and interest rates gradually declined while the exchange rate increased over the period.

Figure 4.3 : CPI % Growth June to June

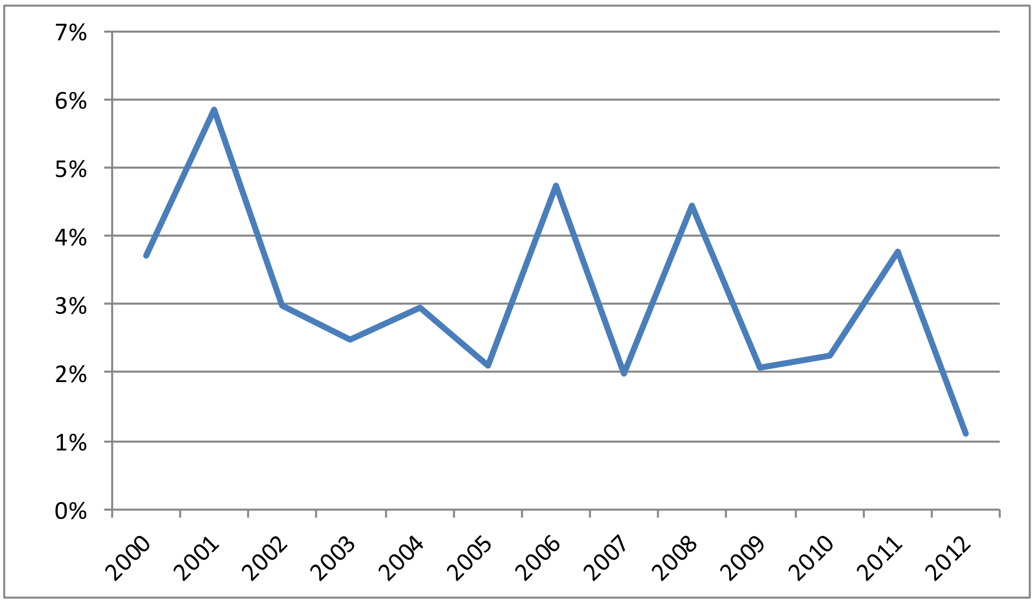


Figure 4.4 : Exchange Rate ($AUD/$USD)

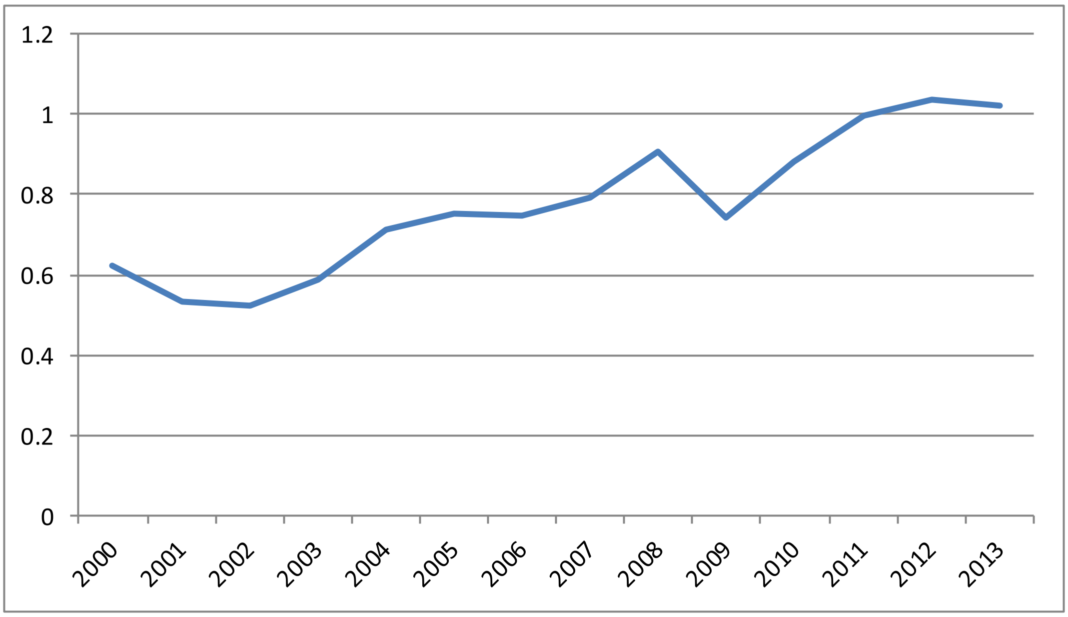
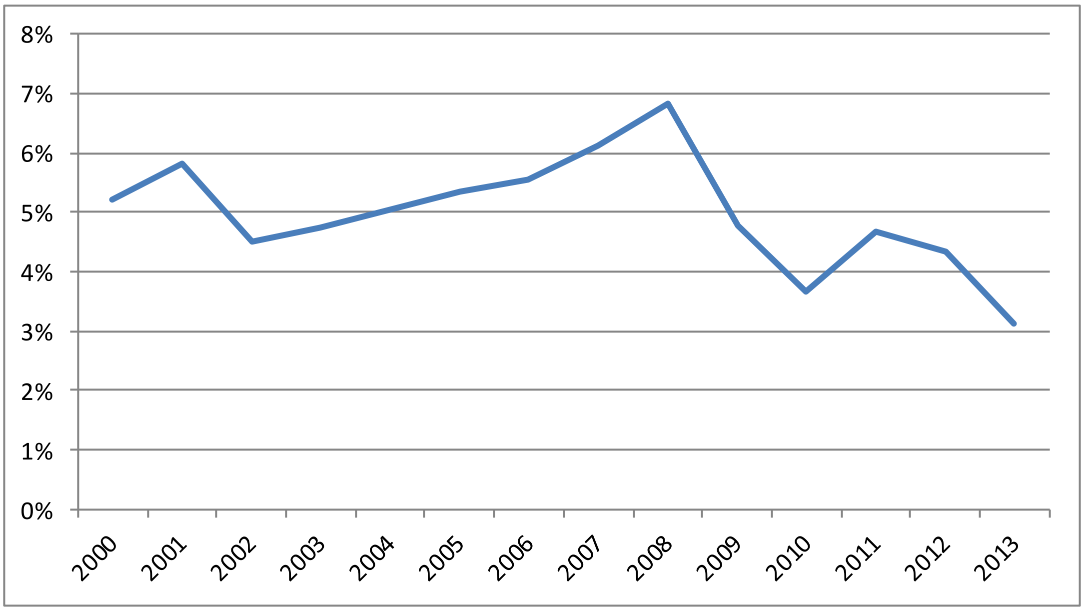


Figure 4.5 : Interest rate (annual average)



4.4 Demographics

Population, number of households and employment figures for the ACT over the period 2000 to 2013 are shown in Figure 4.6 and Figure 4.7. Population and households are highly correlated (R2 = 0.993), consequently only one of them can be used in modelling. Employment is slightly less correlated (R2 = 0.91) and its growth is much more volatile.

Figure 4.6 : Population, number of households and employment

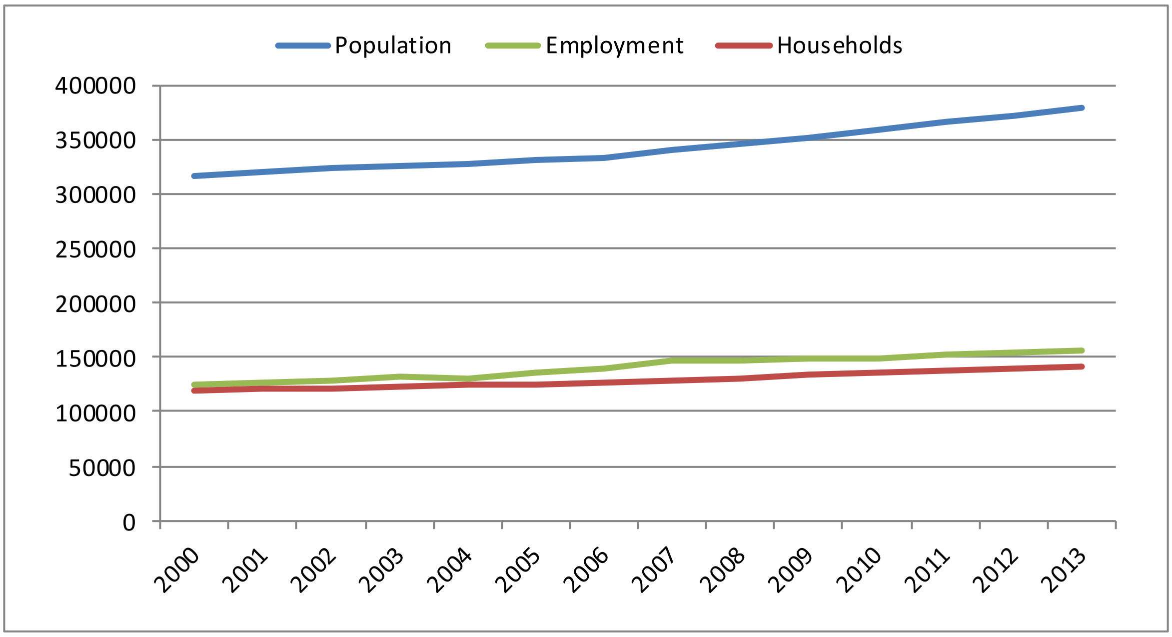


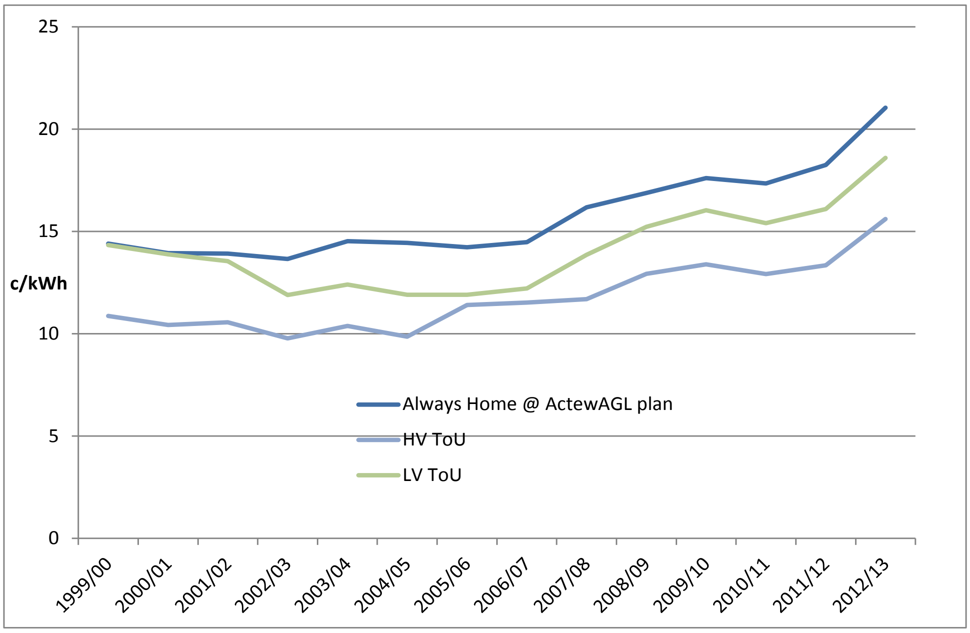
Figure 4.7 : Population, number of households and employment growth rates

4.5 Retail electricity prices

ActewAGL has provided data on the retail electricity tariffs applicable during the period 2000 to 2013. Jacobs SKM has converted the tariffs to prices by applying the tariffs to hypothetical customers using the average energy consumed by that tariff category. In order to calculate the real prices in terms of June $2013 dollars, Jacobs SKM has used actual consumer price index (weighted average of all capital cities) as defined in section 4.3. Representative prices for the residential, LV and HV customers have been based on the “Always Home Plan”, LV ToU (Time of Use) and HV ToU tariffs respectively.

Figure 4.8 illustrates there were significant price increases in all tariffs, mainly due to increases in network tariffs, during the period from 2007 to 2010, followed by a large step increase in 2013 due to the introduction of carbon pricing.

Figure 4.8 : Retail prices of each customer category, c/kWh in $ June 2013



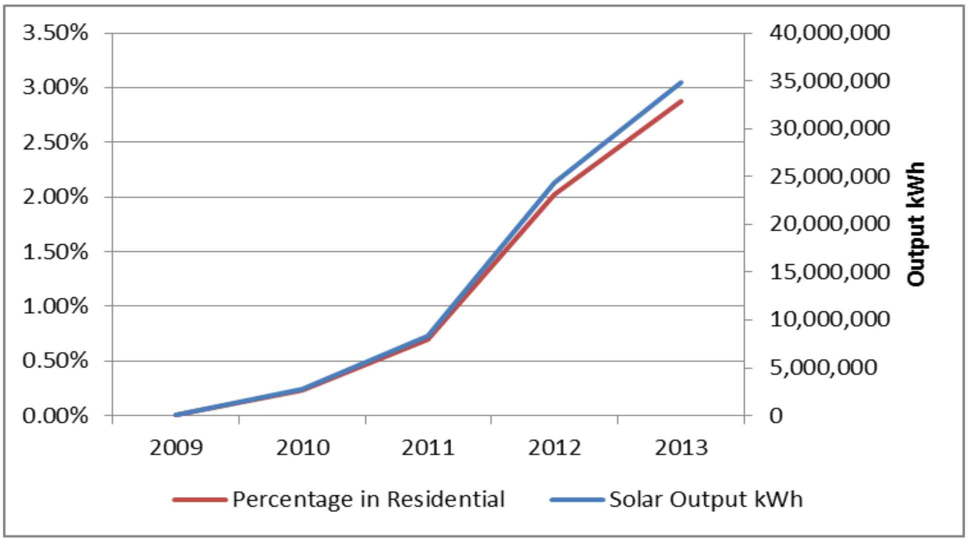
4.5.1 Energy savings

4.5.1.1 PV output

Rapid solar PV uptake in recent years in the residential sector, means PV output is an important component of residential energy consumption. PV is included in Residential Billings but not in Residential Substitute which must be adjusted upwards by adding PV to get the total energy used.

As the historical trend in Figure 4.9 illustrates, solar PV has contributed up to 2.8% of residential energy supply by 2013 and is likely to rise even higher in the future.

Figure 4.9 : Percentage of PV contribution in residential and solar annual output, kWh

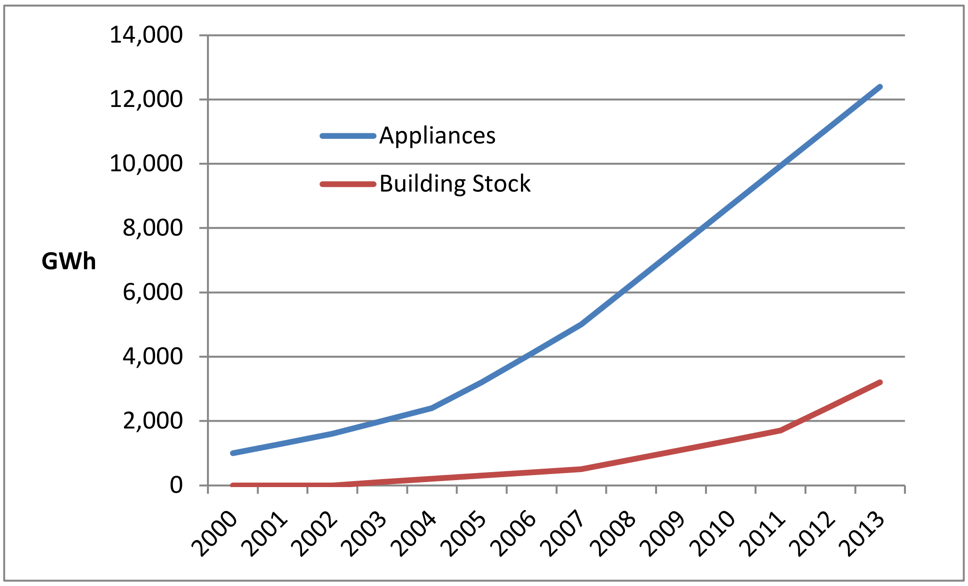


4.5.1.2 Energy efficiency

Jacobs SKM has not found any historical energy efficiency data specific to the ACT. However, we believe that efficiency developments in Australia in general would have affected ACT and have therefore developed energy efficiency indices for the residential and LV categories based on AEMO data applicable to the NEM region[6]. AEMO provides data on energy savings due to efficiency improvements in appliances and building stock, reproduced in Figure 4.10. Separate figures for residential and commercial sectors are provided only for building stock. An earlier version of AEMO's consultant's report[7] suggests that residential savings have been larger than commercial, about 4,000 GWh to 3,000 GWh in 2009, which implies that residential accounts for 60% of the appliance savings. It is noted that the largest savings have been in non-heating and cooling appliances, which is consistent with the residential constant in Figure 4.10. Further analysis is required to determine how to deal with the water heater component of residential savings.

[6] 2013 Forecasting Methodology Paper. National Electricity Forecasting. Australian Energy Market Operator, 2013
[7] Projected Impacts of the Equipment Energy Efficiency Program to 2020. Wilkenfeld and Associates January 2009.

Figure 4.10 : Energy savings due to efficiency improvements in appliances and building stock.



Using this figure we have estimated savings as a percentage of demand for each customer category as in Figure 4.11. Residential energy consumption with and without energy efficiency savings are pictured in Figure 4.12, which shows that without efficiency, consumption would have grown almost linearly to 2010 and then flattened and declined slightly in 2013, most likely in response to price increases.

Figure 4.11 : Estimated residential and commercial energy savings (%)

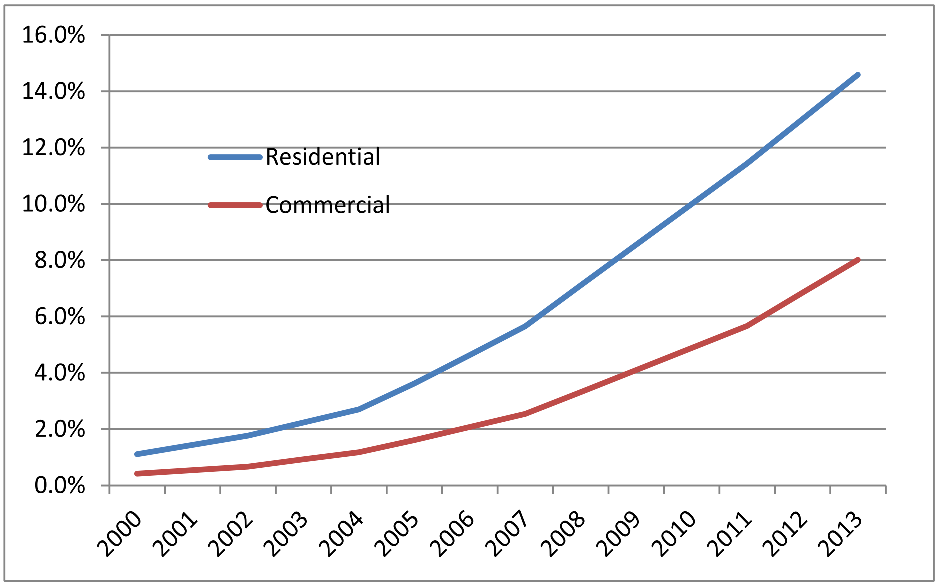
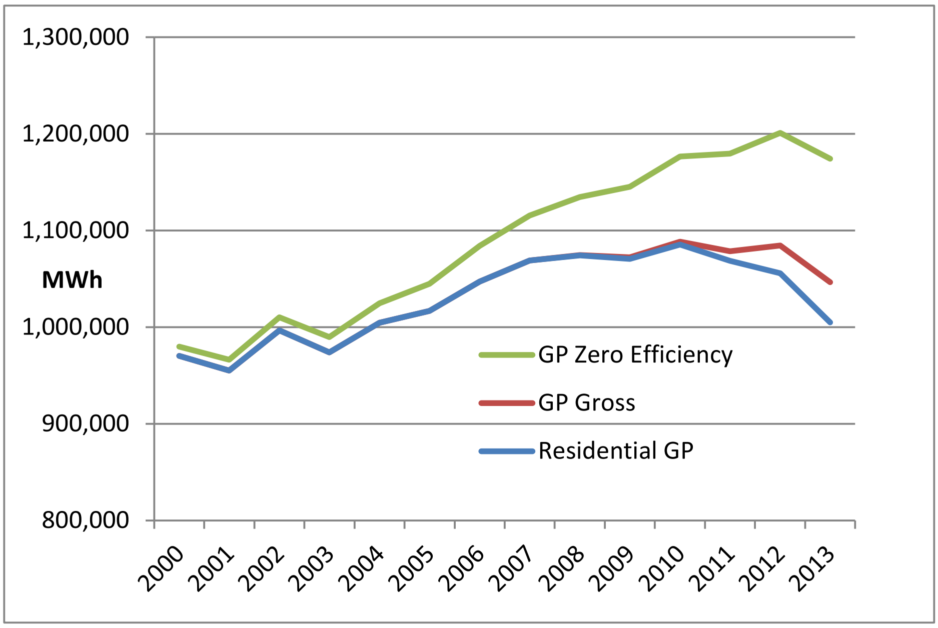
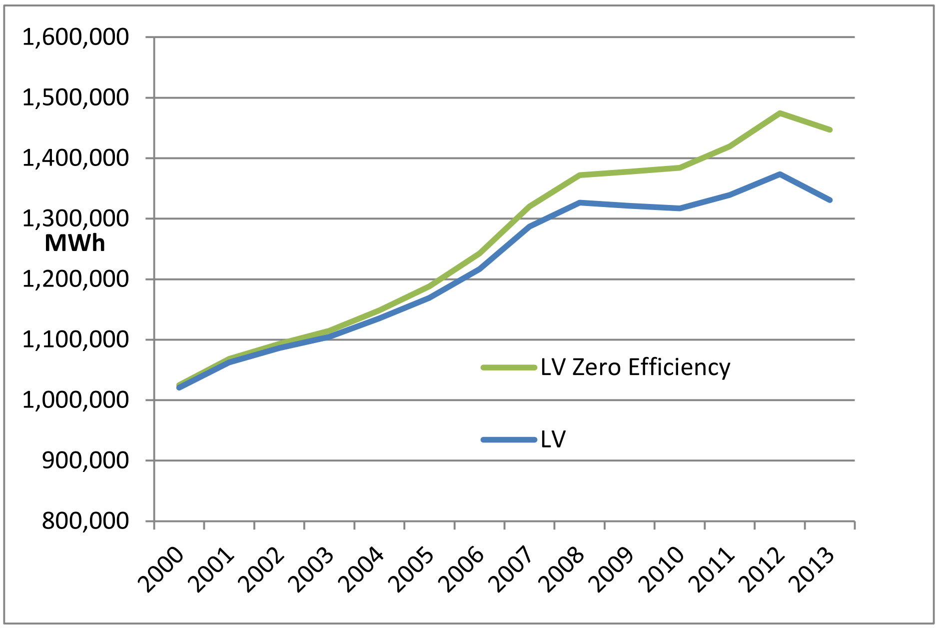


Figure 4.12 : Residential GP annual energy with and without efficiency savings



Commercial LV energy consumption with and without energy efficiency savings are pictured in Figure 4.13, which shows that without efficiency, consumption would have grown almost linearly to 2012 and then declined slightly in 2013, most likely in response to price increases, quite similar to residential energy. However, for LV the efficiency gains have only flattened growth, rather than causing a reduction in usage.

Figure 4.13 : Commercial LV annual energy with and without efficiency savings



The impact of efficiency on energy growth rates is illustrated in Table 4.2 . Over the period 2007-13 efficiency improvements are estimated to have reduced LV growth by 0.9% (from 1.5% to 0.6%) and GP growth by 1.3%, (0.9% to -0.4%) with a further 0.6% GP reduction due to PVs.

Table 4.2 : Impact of efficiency on growth rates of weather normalised energy

	Period		
	2000-07	**2007-13**	**2000-13**
GP	1.4%	-1.0%	0.3%
GP Gross	1.4%	-0.4%	0.6%
GP Zero Efficiency	1.9%	0.9%	1.4%
LV	3.4%	0.6%	2.1%
LV Zero Efficiency	3.7%	1.5%	2.7%

5. Econometric modelling

5.1 Introduction

Econometric modelling is used to establish whether energy usage is correlated with one or more of the economic factors described in the previous section and whether this correlation or model can be used to predict future energy usage. Though it is emphasised that any model is only a correlation, it remains true that the motivation for this approach is the intuition that there is a causal relationship between factors such as population growth and energy usage, moderated by the other factors.

5.1.1 Model structure

The modelling has been undertaken using regression analysis to determine the parameters A, B, C, D, etc in models of the form:

Ln(Energy) = A + B*ln(Factor 1) + C*ln(Factor 2) + D*ln(Factor 3) + …

In this equation ln() represents the natural logarithm function. It is referred to as a multiplicative analysis because it means that:

Energy = a*(Factor 1)^B *(Factor 2)^C *(Factor 3)^D* …

We have also in some cases considered an additive analysis where:

Energy = A + B*Factor 1 +C*Factor 2 + D*Factor 3 +…

In general we consider the multiplicative structure to be more representative of the logical interaction of components, for example price sensitivity would affect demand as a whole rather than a separate component.

5.1.2 Customer categories modelled

In the above, “Energy” represents the weather normalised annual energy used in customer classes HV, LV, OP and GP (gross) as defined in section 3 and summarised graphically in Figure 3.11 and Figure 3.12. Owing to the typically smoothing effects of data aggregation, it is sometimes possible to obtain more accurate models using aggregate categories LV + HV and GP (gross) + OP.

To capture the effects of energy efficiency, rather than using energy efficiency as a factor it has been found better to relate zero efficiency LV and GP, as defined in section 3,to the factors as above. For residential energy it is also useful to consider modelling energy per person or energy per customer.

5.1.3 Selecting the best models

The best models are those which are most accurate, that is, have the lowest error or highest R^2, subject to:

1) The coefficients are statistically significant (T-statistic over 1.5, preferably 2);
2) The signs of the coefficients are logical (eg price coefficients are negative);
3) Coefficients are not unreasonably high i.e. suggesting an implausible sensitivity of energy use to the relevant factor; and
4) The residuals are random, i.e. don’t show clear trends or patterns

We have also applied the Akaike and Bayesian Information Criteria (AIC and BIC) to model selection. These criteria select the model which achieves high R^2 with the fewest variables and generally align with the requirement for good T statistics.

In our analysis we have assessed models based on all relevant factor combinations. Our report on this analysis, in the following sections, focuses on the best models, that is the models meeting criteria 1 to 4 above and having the highest R^2 and lowest AIC or BIC, and also explains why various factors do not enter into these models.

5.2 Residential GP

We have constructed six types of residential GP model, using two different measures of residential GP annual energy (weather normalised gross and zero efficiency measures) on three different bases: total energy; average energy per person; and average energy per customer.

5.2.1 Total Energy

The Total Energy models have incorporated one or more of the following factors: Household Disposable Income; GSP; Interest Rate; Population; Employment; and Price (residential). The zero efficiency versions also automatically incorporate efficiency savings.

For Gross Total Energy the best models are based on either: Employment plus Price (residential); Employment alone; or Household Disposable Income plus Interest rates. Model R3 implies that a fall in interest rates accompanies a fall in residential energy use. While this is true of the recent past it is not clear why it should be true in future.

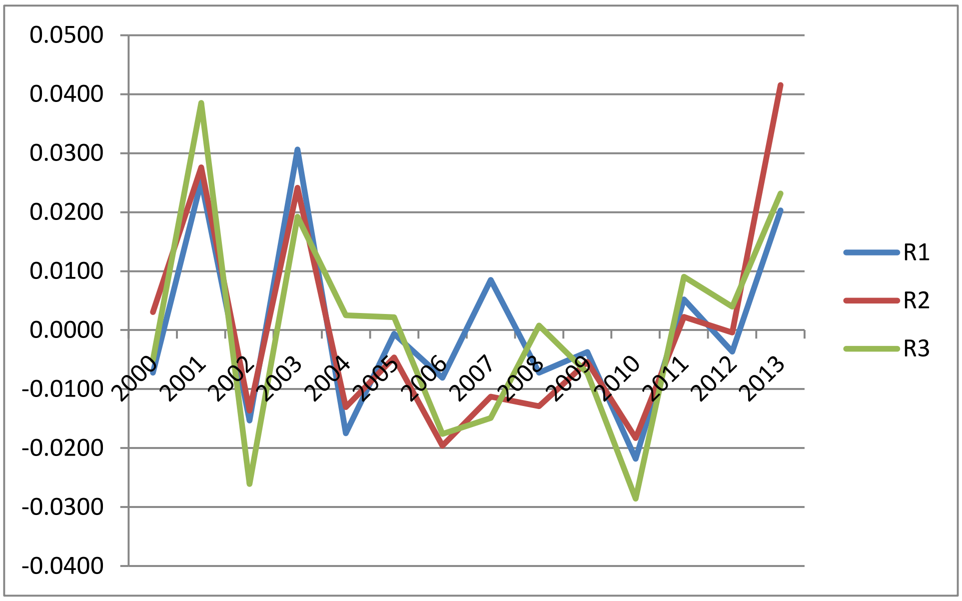
Table 5.1 : Coefficients for the best models of Gross Total Energy

	Coefficients							T-Statistics			
Model	**Const.**	**HHI**	**Employ**	**Int. Rate**	**Price**	**R^2**	**AIC**	**HHI**	**Employ**	**Int. Rate**	**Price**
R1	-1.322		0.730		-0.140	0.877	-110.7		6.2		-2.0
R2	0.648		0.531			0.833	-108.4		7.7		
R3	5.197	0.200		0.076		0.831	-106.3	7.2		2.3	

Our findings in relation to the remaining factors are:

- GSP – correlated with HHI but lower explanatory power and negative coefficient in combination with HHI
- Population - correlated with HHI but lower explanatory power and negative coefficient in combination with HHI

Figure 5.1 : Gross Total Energy model residuals



The model residuals do not show any obvious patterns or trends other than that they are quite similar. However, model R2 has a very high residual in 2013, which is undesirable because it suggests the model does not fit the most recent data very well.

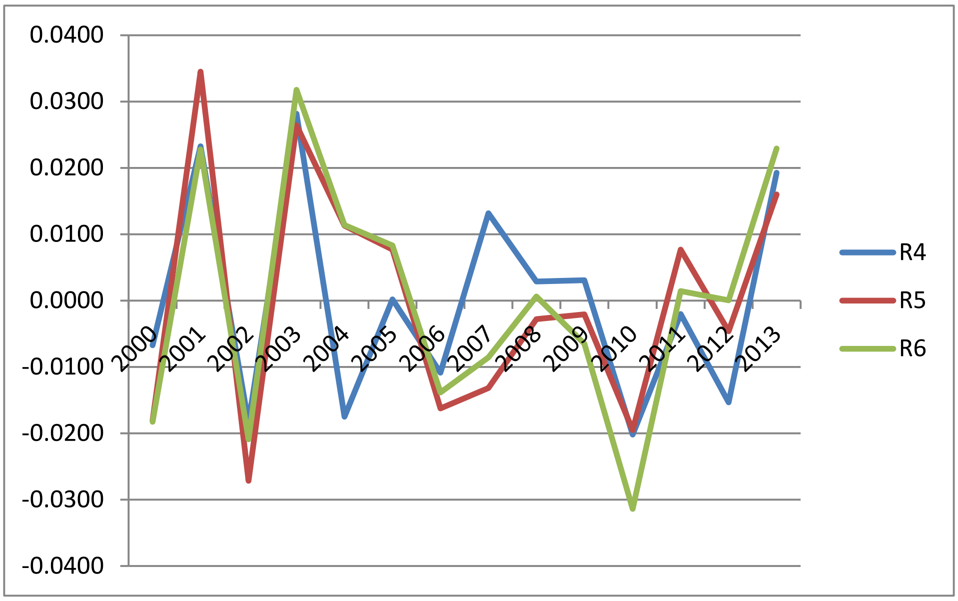
For Zero Efficiency Total Energy the best models are a single factor model based on Employment or two factor models using either HHI or GSP, plus Interest Rates. This is due to the fact that Zero Efficiency Total Energy grows strongly in parallel to these factors, apart from the final year when carbon price is introduced.

Table 5.2 : Coefficients for the best models of Zero Efficiency Total Energy

	Coefficients							T-Statistics			
Model	**Const.**	**HHI**	**GSP**	**Int. Rate**	**Employ**	**R^2**	**AIC**	**HHI**	**GSP**	**Int. Rate**	**Employ**
R4	-4.408				0.962	0.956	-112.6				16.2
R5	3.811	0.338		0.050		0.945	-107.2	12.6		1.6	
R6	0.794		0.628	0.065		0.945	-107.2		12.6	2.0	

The remaining factors generally have low explanatory power (low T-stat). Population and Price combine to yield a model with R^2 and AIC slightly inferior to model R6 but the Population coefficient of 1.8 is considered too high.

Figure 5.2 : Zero Efficiency Total Energy model residuals



The model residuals do not show any obvious patterns or trends.

5.2.2 Average energy per person

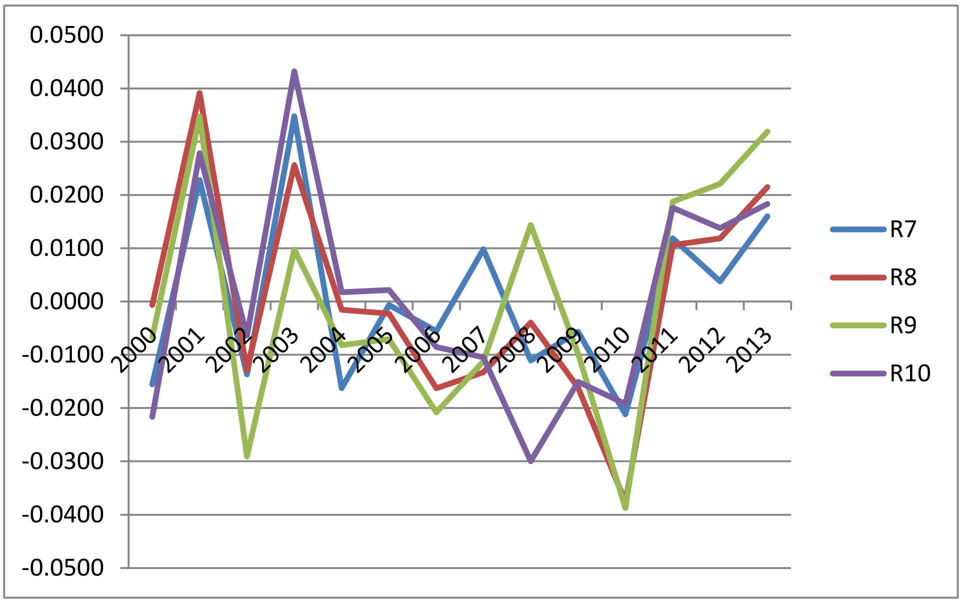
The Average Energy per Person models have incorporated one or more of the following factors: Household Disposable Income per Person; GSP per Person; Interest Rate; Employment per Person; and Price (residential). Population is not considered because Average Energy = Total Energy / Population.

For Gross Average Energy per Person the best models are based on Employment or Interest Rate, or HHI or Interest Rate plus Price (residential).

Table 5.3 : Coefficients for the best models of Gross Average Energy per Person

	Coefficients							T-Statistics			
Model	**Const.**	**HHI/ Pers**	**Employ/ Pers**	**Int. Rate**	**Price**	**R^2**	**AIC**	**HHI/ Pers**	**Employ/ Pers**	**Int. Rate**	**Price**
R7	4.94		0.62		-0.24	0.76	-109.8		3.3		-5.8
R8	8.55			0.08	-0.10	0.65	-104.5			2.0	-1.7
R9	8.40			0.13		0.57	-103.4			4.0	
R10	8.44	0.13			-0.34	0.62	-103.3	1.7			-3.3

Figure 5.3 : Gross Average Energy per Person model residuals



Our finding in relation to the remaining factor is:

- GSP per Person – correlated with HHI per Person but lower explanatory power and negative coefficient in combination with HHI per Person

As with the Total Energy models, the model residuals do not show any obvious patterns or trends other than similarity among themselves.

For Zero Efficiency Average Energy per Person the best models are based on Household Disposable Income or Employment alone or combined with Interest Rate or Price (residential).

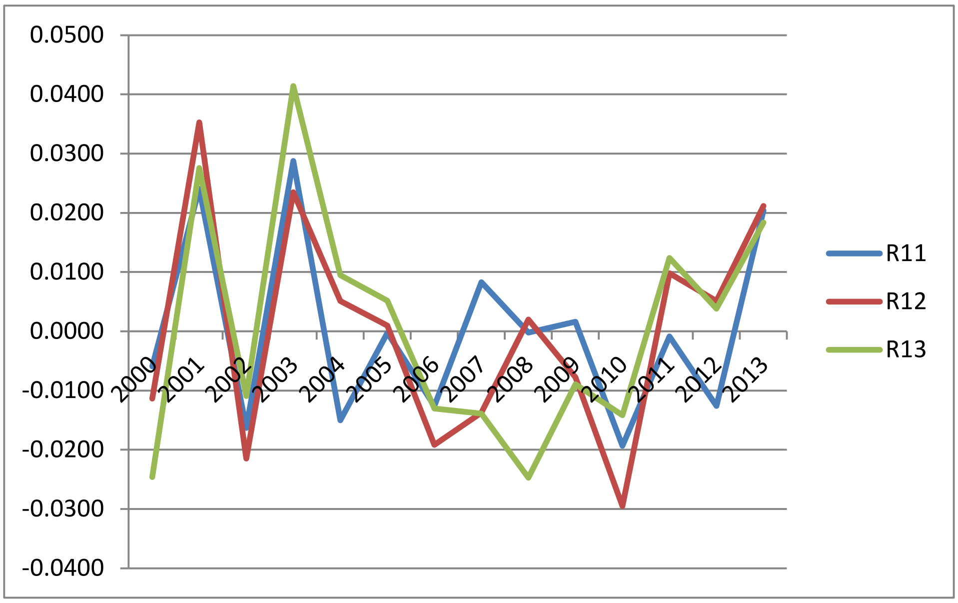
Our finding in relation to the remaining factor is as for Gross Energy.

The model residuals do not show any obvious patterns or trends however it is noted that some residuals are quite high in the final year, 2013, though no higher than in some earlier years. While this may be viewed as making the forecasts less accurate than if the models predicted 2013 accurately, it should be noted that the uncertainty in the forecasts relates to the overall model uncertainty, amplified by the uncertainties in the forecast inputs,

Table 5.4 : Coefficients for the best models of Zero Efficiency Average Energy per Person

	Coefficients							T-Statistics			
Model	**Const.**	**HHI/ Pers**	**Employ/ Pers**	**Int. Rate**	**Price**	**R^2**	**AIC**	**HHI/ Pers**	**Employ/ Pers**	**Int. Rate**	**Price**
R11	2.88		0.86			0.72	-113.7		5.5		
R12	7.74	0.14		0.08		0.60	-106.7	4.0		2.5	
R13	7.69	0.23			-0.20	0.54	-104.8	3.2			-2.1

Figure 5.4 : Zero Efficiency Average Energy per Person model residuals



5.2.3 Average energy per customer

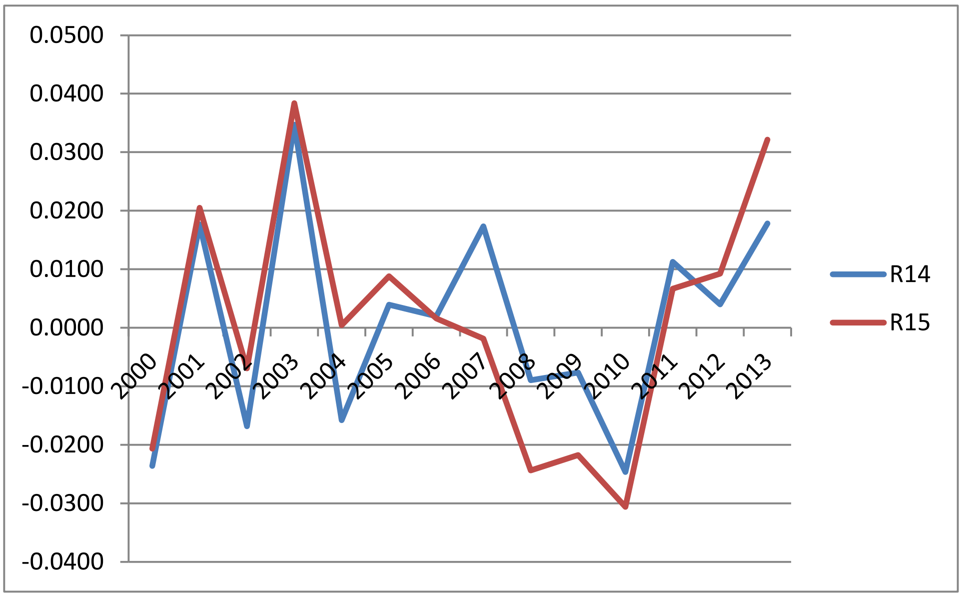
The Average Energy per customer models have incorporated one or more of the following factors: Household Disposable Income per Customer; GSP per Customer; Interest Rate; Employment per Customer; and Price (residential).

There are generally very few satisfactory models for Average Energy per Customer. For Gross Average Energy per Customer the only models meeting our criteria are single and two factor models based on Employment per Customer and Price (residential) or Price alone.

Table 5.5 : Coefficients for the best models of Gross Average Energy per Customer

	Coefficients					T-Statistics	
Model	**Const.**	**Employ/ Cust**	**Price**	**R2**	**AIC**	**Employ/ Cust**	**Price**
R14	5.71	0.58	-0.29	0.84	-107.7	2.0	-6.9
R15	9.77		-0.30	0.78	-105.4		-6.5

Figure 5.5 : Gross Average Energy per Customer model residuals



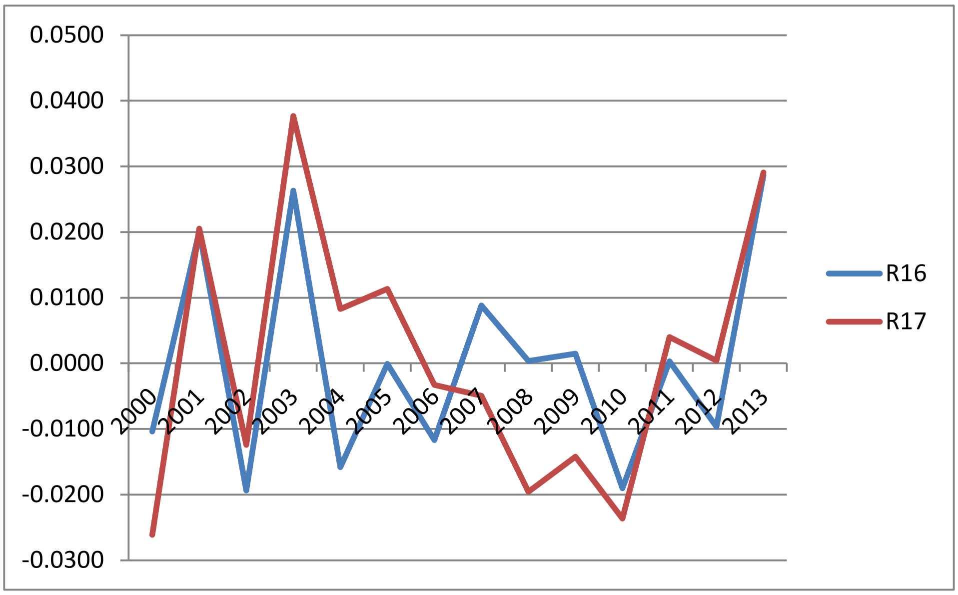
The model residuals do not show any obvious patterns or trend however, model R15 has a very high residual in 2013.

For Zero Efficiency Average Energy per Customer the only models meeting our criteria are based on Household Disposable Income per Customer and Price (Residential) or Employment per Customer combined with Price (residential). The models have low explanatory power.

Table 5.6 : Coefficients for the best models of Zero Efficiency Average Energy per Customer

	Coefficients						T-Statistics		
Model	**Const.**	**HHI/ Cust**	**Employ/ Cust**	**Price**	**R^2**	**AIC**	**HHI/ Cust**	**Employ/ Cust**	**Price**
R16	3.25		0.83		0.48	-112.8		3.4	
R17	8.83	0.13		-0.18	0.23	-105.3	1.7		-1.8

Figure 5.6 : Zero Efficiency Average Energy per Customer model residuals



The model residuals do not show any obvious patterns or trends. It is noted that the residuals are quite high in the final year, 2013, though no higher than in some earlier years. While this may be viewed as making the forecasts less accurate than if the models predicted 2013 accurately, it should be noted that the uncertainty in the forecasts relates to the overall model uncertainty, amplified by the uncertainties in the forecast inputs,

5.2.4 Selecting a residential GP model

The six different types of residential GP model presented above cannot be compared directly on the basis of R^2 or AIC. Given that the Zero Efficiency models automatically take into account changes in energy efficiency (in using them in a forecast, the forecast efficiency gains would be subtracted from the Zero Efficiency projection to derive the Gross projection), it seems reasonable to prefer the Zero Efficiency models to the Gross models, all else being reasonably equal. Similarly, the per Person or per Customer models, may be preferred to Total Energy models because they effectively introduce another factor.

Thus our preferences are directed towards the Zero Efficiency, per Person and per Customer models, the best of which are:

- R11 and R16, both based on Employment alone
- R12, based on HHI and interest rates
- R13 and R17, both based on HHI and Price factors and having very similar price elasticities.

On both R^2 and AIC criteria, R11 is the best model of the five considered.

5.3 Residential OP

Residential OP demand has declined steadily since 2002 (Table 3.6) as a result of the non-replacement of failed off-peak water heaters. This trend cannot be modelled using the generally increasing demand factors used for Residential GP and instead has been modelled as a time trend (linear plus quadratic, Energy = A + B*Year + C*Year^2) and as an exponential or percentage decline (autoregressive model with Energy(Y) = A*Energy (Y-1), where Y=Year and A<1). Models have been constructed over two periods to 2013: from 2002 when the OP decline started and from 2008, after variations in OP demand estimates due to changes in the meaning of billings had passed.

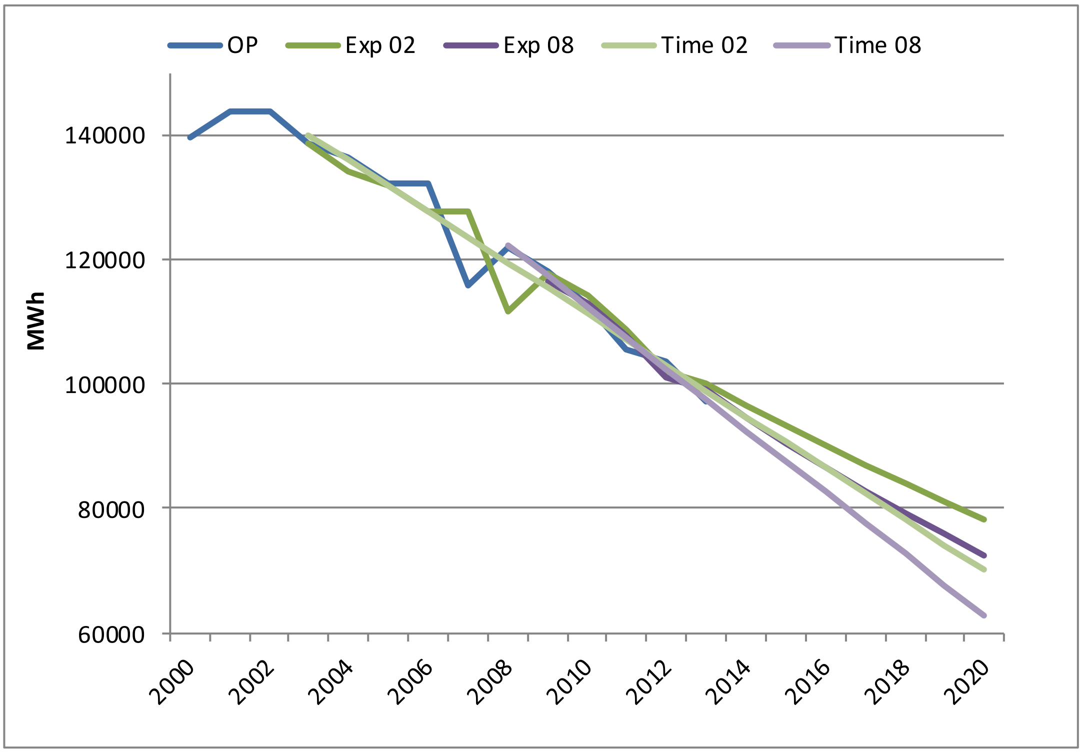
For each period the time trend models yield a lower residual error (R2 is not a relevant comparison because the exponential models do not have constants). Among the time trend models it is only necessary to consider linear models as the quadratic terms are not statistically significant. The shorter period models (08 to 13) have steeper declines than for the longer period.

Projections of each model to 2020 are illustrated in Figure 5.7 and the time trend models are approximately 10,000 MWh lower than the exponential models in 2020 and the shorter period models are approximately 7,000 MWh lower than the longer period models in 2020. On the basis of model accuracy the model Time 08, which also yields the lowest projection, is preferred as it has the lowest residual error.

Table 5.7 : OP model parameters

Model	Annual rate of decline (%)	OP loss per annum (MWh)	Residual error
Exp 02	3.42%		5396
Exp 08	4.35%		1977
Time 02		4213	3244
Time 08		4906	1125

Figure 5.7 OP model projections to 2020



5.4 Commercial LV

We have constructed models of weather normalised gross and zero efficiency measures of commercial LV annual energy (total). The models have incorporated one or more of the following factors: GSP; SFD; Interest Rate; and Price (LV). The zero efficiency versions also automatically incorporate efficiency savings.

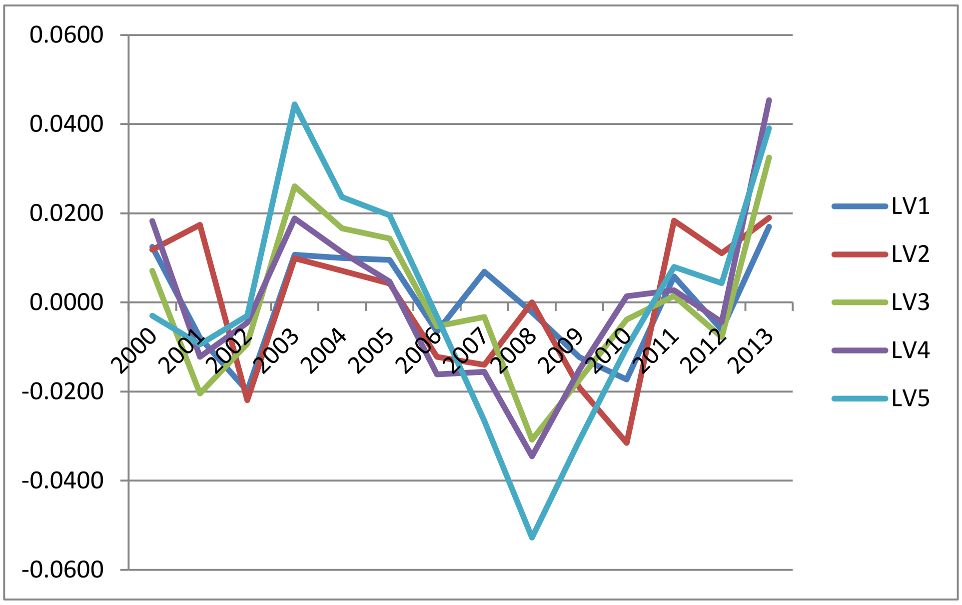
For Gross Energy the best models are based on either GSP or SFD, plus Interest Rate or Price (LV), or on SFD alone.

The model residuals have similar patterns to Residential GP Total Energy. Models LV3, LV4 and LV5 have unattractively high residuals in 2013.

Table 5.8 : Coefficients for the best models of Gross Energy

	Coefficients							T-Statistics			
Model	Const.	GSP	SFD	Int. Rate	Price	R^2	AIC	GSP	SFD	Int. Rate	Price
LV1	1.54		0.55	0.09		0.99	-119.3		27.1	4.4	
LV2	-1.31	0.87		0.16		0.97	-109.7	19.1		5.5	
LV3	1.54		0.54		-0.07	0.97	-107.8		15.9		-1.5
LV4	1.67		0.51			0.96	-107.1		17.5		0.0
LV5	-1.30	0.87			-0.18	0.93	-96.6	10.4			-2.3

Figure 5.8 : Gross Energy model residuals



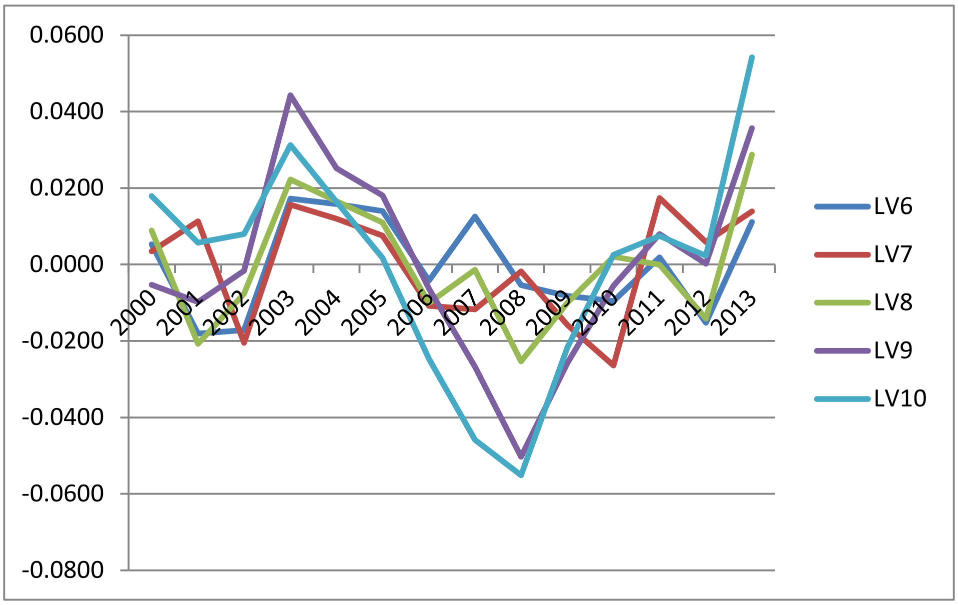
For Zero Efficiency Energy the best models are based on either GSP or SFD, with or without Interest Rate or Price (LV). The model including Price has significantly lower R^2 and higher AIC than the models including Interest Rates.

The model residuals have similar patterns to Residential GP Total Energy. Models LV8, LV9 and LV10 have unattractively high residuals in 2013.

Table 5.9 : Coefficients for the best models of Zero Efficiency Energy

	Coefficients							T-Statistics			
Model	Const.	GSP	SFD	Int. Rate	Price	R^2	AIC	GSP	SFD	Int. Rate	Price
LV6	0.40		0.65	0.05		0.99	-117.2		29.8	2.5	
LV7	-3.03	1.04		0.15		0.99	-113.5	26.1		5.7	
LV8	0.48		0.63			0.98	-112.8	0.0	26.3		
LV9	-2.89	1.02			-0.14	0.96	-97.9	12.7			-1.8
LV10	-2.24	0.92				0.94	-96.2	14.3			

Figure 5.9 : Zero Efficiency Energy model residuals



5.4.1 Selecting a commercial LV model

As with the Residential GP models, we believe that the zero efficiency models should be preferred because they implicitly incorporate the impact of efficiency. Consequently the preferred models are LV6 and LV7. On both R^2 and AIC criteria, LV6 is the slightly better model, which uses SFD and Interest Rate as the key drivers.

5.5 Commercial HV

We have constructed models of weather normalised gross and zero efficiency measures of commercial HV annual energy (total). It is noted that in this case weather normalised is the same as actual energy. The models have incorporated one or more of the following factors: GSP; SFD; Interest Rate; and Price (HV). The zero efficiency versions also automatically incorporate efficiency savings.

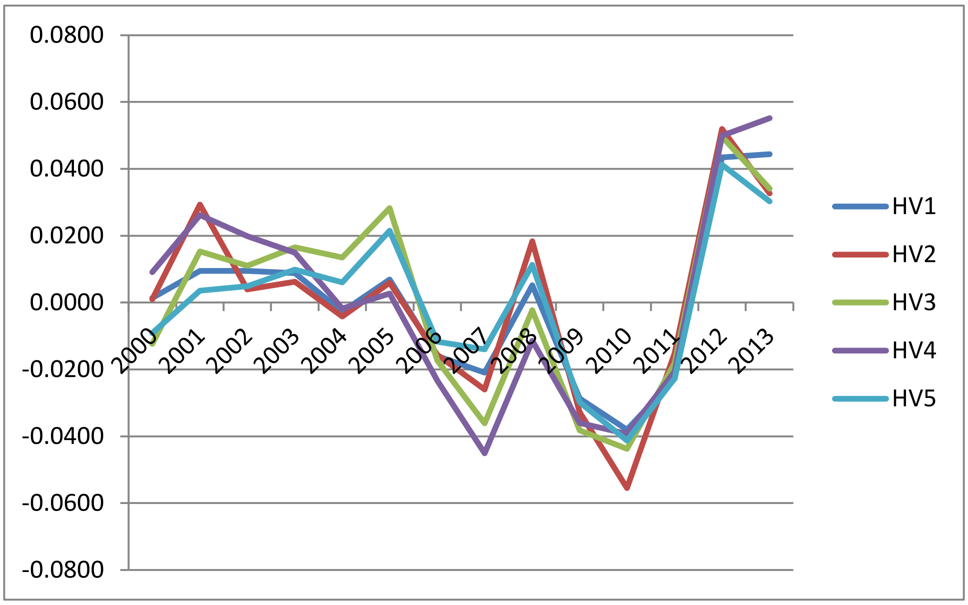
For Gross Energy the best models are based on either GSP or SFD alone, or plus Interest Rate or Price (HV), much as for Commercial LV but with lower R^2 and higher AIC. A model using SFD and price is included in the table, even though its price T-Statistic is below our selection threshold, for comparison with the LV model. Comparison between the HV and LV models that include price (HV3 with LV5 and HV5 with LV3) shows that their price elasticities are very similar bur the HV GSP and SFD growth coefficients are about 33% less than the LV coefficients.

The model residuals are very similar and unfortunately peak in 2012 and 2013.

Table 5.10 : Coefficients for the best models of Gross Energy

	Coefficients							T-Statistics			
Model	**Const.**	**GSP**	**SFD**	**Int. Rate**	**Price**	**R^2**	**AIC**	**GSP**	**SFD**	**Int. Rate**	**Price**
HV1	2.27		0.34			0.88	-101.1		9.4		
HV2	0.51	0.55		0.08		0.84	-94.9	7.1		1.6	
HV3	0.40	0.58			-0.17	0.83	-94.5	6.2			-1.5
HV4	0.95	0.48				0.80	-93.8	6.9			
HV5	2.18		0.37		-0.09	0.89	-100.6		8.2		-1.1

Figure 5.10 : Gross Energy model residuals



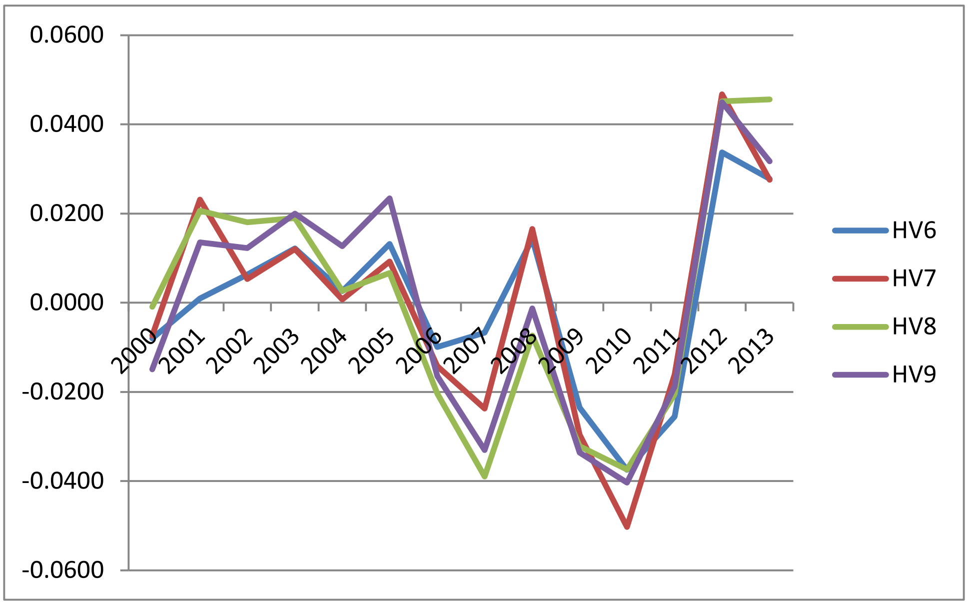
For Zero Efficiency Energy the best models are based on either GSP or SFD alone, or GSP plus Interest Rate or Price (LV), again much as for Commercial LV but with lower R^2 and higher AIC. A model using GSP and price is included in the table, even though its price T-Statistic is below our selection threshold, for comparison with the LV model. Comparison between the HV and LV models that include price (HV9 with LV9) shows that the HV price elasticity is slightly lower numerically and the HV GSP growth coefficient is about 30% less than the LV coefficient.

The model residuals are very similar and also peak in 2012 and 2013.

Table 5.11 : Coefficients for the best models of Zero Efficiency Energy

	Coefficients							T-Statistics			
Model	**Const.**	**GSP**	**SFD**	**Int. Rate**	**Price**	**R^2**	**AIC**	**GSP**	**SFD**	**Int. Rate**	**Price**
HV6	1.08		0.46			0.95	-106.3		15.1		
HV7	-1.21	0.72		0.07		0.92	-97.7	10.2		1.5	
HV8	-0.85	0.66				0.90	-97.3	10.7			
HV9	-1.22	0.73			-0.11	0.91	-96.6	8.5			-1.1

Figure 5.11 : Zero Efficiency Energy model residuals



5.5.1 Selecting a Commercial HV model

As with the Residential GP models, we believe that the zero efficiency models should be preferred because they implicitly incorporate the impact of efficiency. Consequently the preferred models are HV6 and HV7. On both R^2 and AIC criteria, HV6 is the better model, using SFD alone as the sole driver of demand.

5.6 Alternative models considered

A number of other model configurations have been considered for the HV sector to address the high residuals in 2013. While some of the models do reduce the residuals in 2013 this is at the cost of increasing residuals elsewhere with the consequence that overall model accuracy applicable to forecasts is not improved. WE have therefore not produced forecasts with any of these models.

5.6.1 Models with lagged coefficients

Models with lagged price variables and lagged dependent variables have been tested but found not to offer any better predictive power.

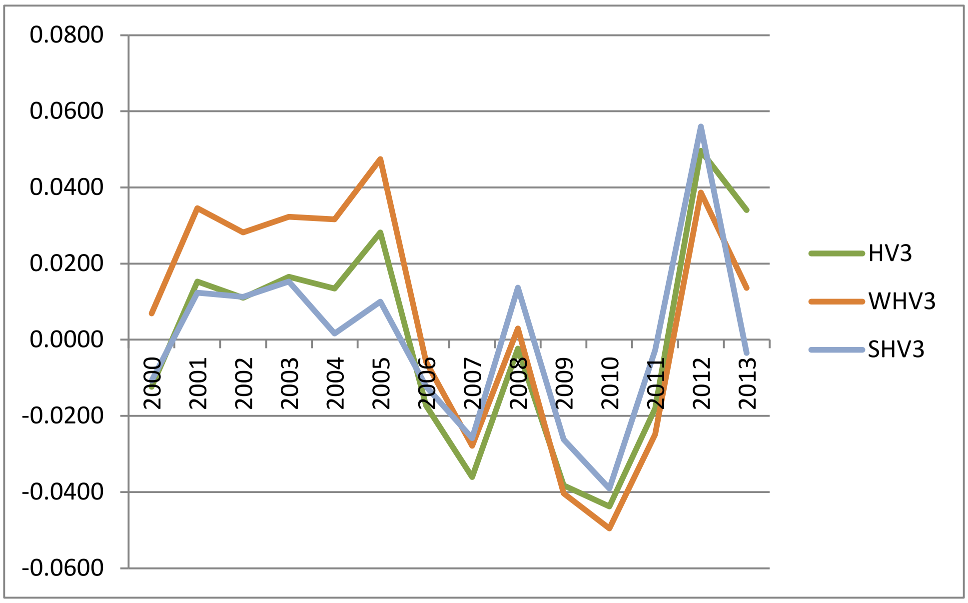
5.6.2 Weighted Least Squares Estimation

The model fit in the last few years of the data period can be improved (at the expense of the fit in the early years) by using a weighted least squares estimate of the coefficients. A preliminary version, WHV3 which is an alternative to HV3, shows in Figure 5.12 how residuals in the last few years can be reduced using this approach.

5.6.3 Sticky Prices

The price series suggest that HV and LV prices declined between 2000 and 2007 and then rose. However, energy use does not seem to have increased in response to this, while it did respond negatively to the large increase in price in 2013. We have re-estimated parameters for HV3 using a price series that remains at the initial level until it is exceeded in 2009. It yields a much higher price elasticity than in HV3 and almost zero residual in 2013, but at the expense of a high residual in 2012 (SHV3 in Figure 5.12). In general this seems a better fit than HV3 but raises the difficult question of how do customers respond if the price falls back to an earlier level.

Figure 5.12 : Residuals for alternative versions of HV3



6. Forecasts

6.1 Forecasts of demand drivers

Forecasts of economic demand drivers including GSP, SFD, HHI, Employment, Population and Interest Rates have been prepared for ActewAGL by BIS-Shrapnel. Jacobs SKM has prepared forecasts of other demand drivers including Electricity Prices, Number of Customers and Energy Efficiency and ActewAGL has provided estimates of PV generation. Drivers listed in section 4 which are not used in any of the preferred models, such as CPI, Exchange Rates, and Number of Households, have not been forecast.

BIS Shrapnel's economic projections reflect an economy slowing through 2013-14 and 2014-15 and then recovering through the remainder of the period and this is strongly reflected in the energy forecasts.

6.1.1 Economic growth (GSP, SFD and HHI)

Projections of ACT GSP, SFD and HHI real growth rates to June-2019 are shown in Figure 6.1 below. Each indicator is projected to have lower growth through 2013-14 and 2014-15, after which growth recovers to recent levels. It is noted that the projections display more correlation than the historical values.

Figure 6.1 : ACT SFD, GSP and HHI projected growth, %

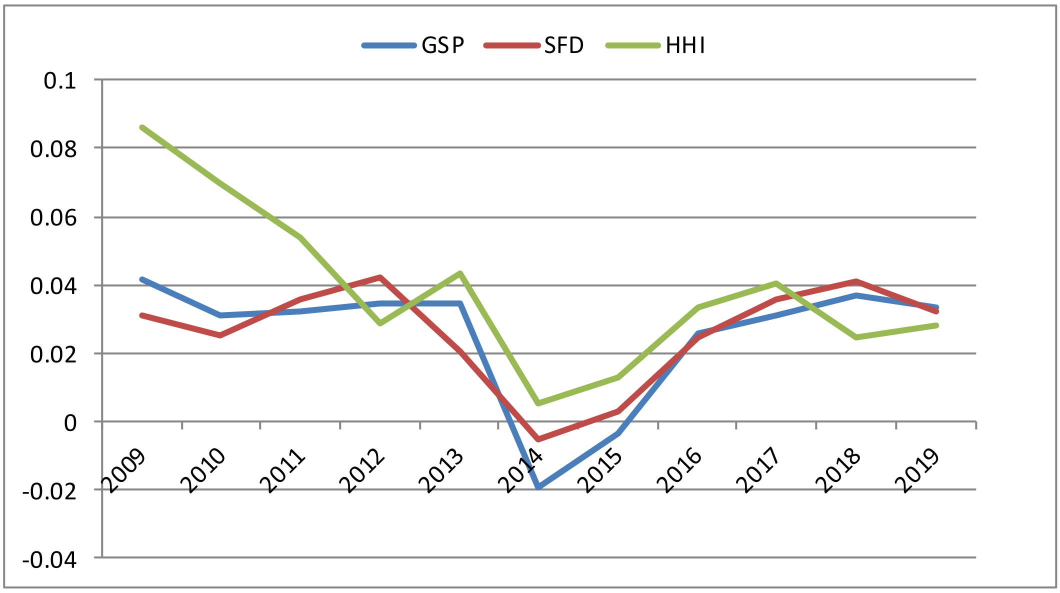
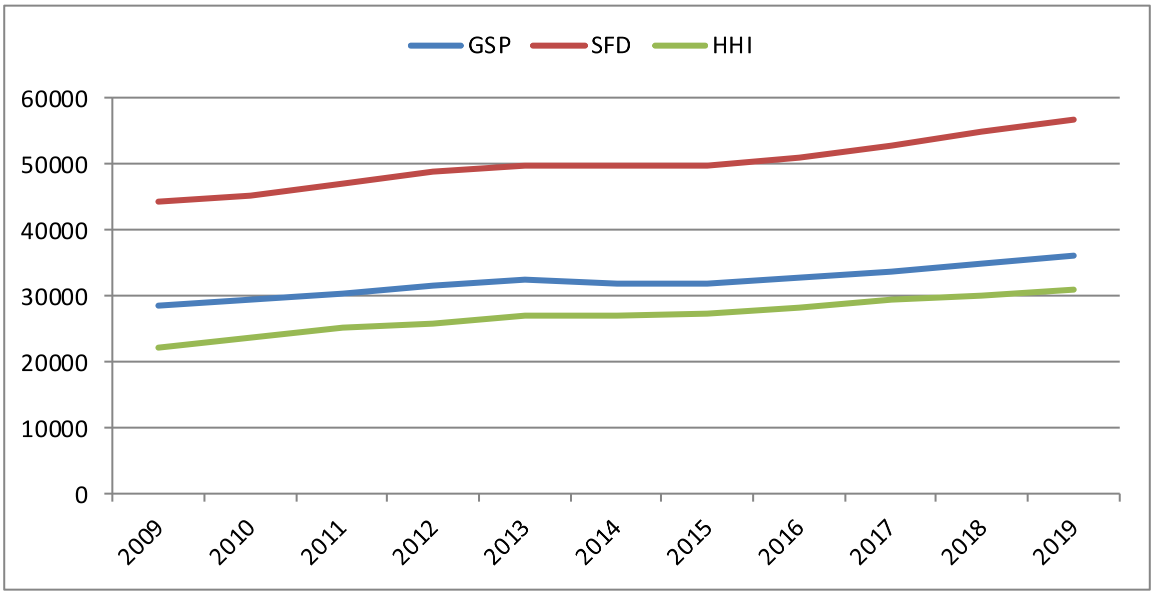


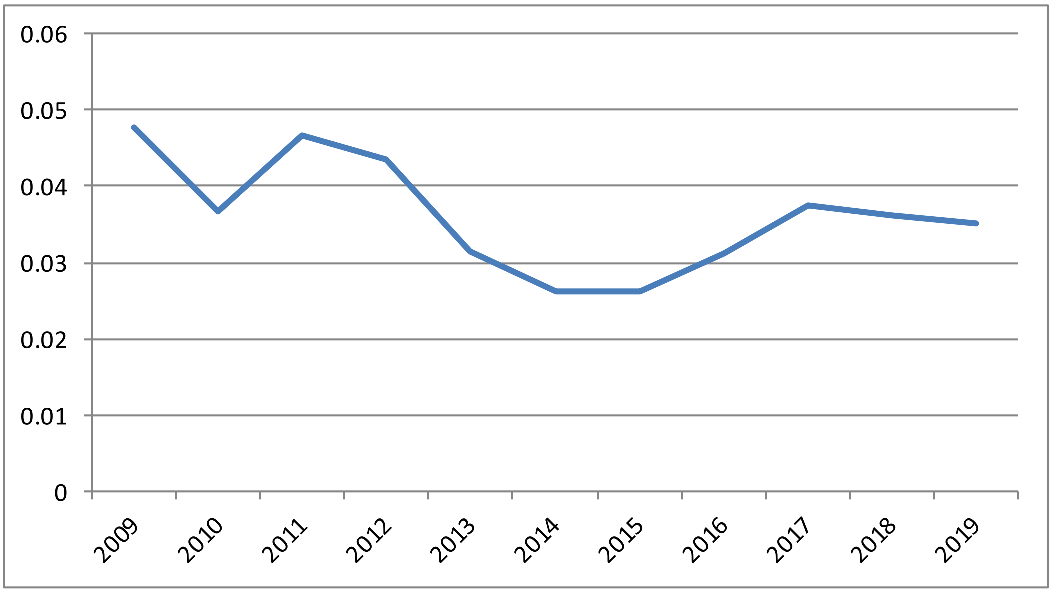
Figure 6.2 : ACT SFD, GSP and HHI projections ($m real)



6.1.2 Financial indicators

Projections of interest rates to June-2019 are shown in Figure 6.3 below. Rates are projected to remain below 3% through 2013-14 and 2014-15, after which they increase to the 3% to 4% range.

Figure 6.3 : Interest rate projection (annual average)



6.1.3 Demographics

Population and employment projections for the ACT to 2019 are shown in Figure 6.4 and Figure 6.5. Population growth is projected to slow from 2013-14 and remain at low levels. Employment is projected to fall in 2013-14 and again in 2014-15 before rebounding strongly for the remainder of the period.

Figure 6.4 : Population and employment

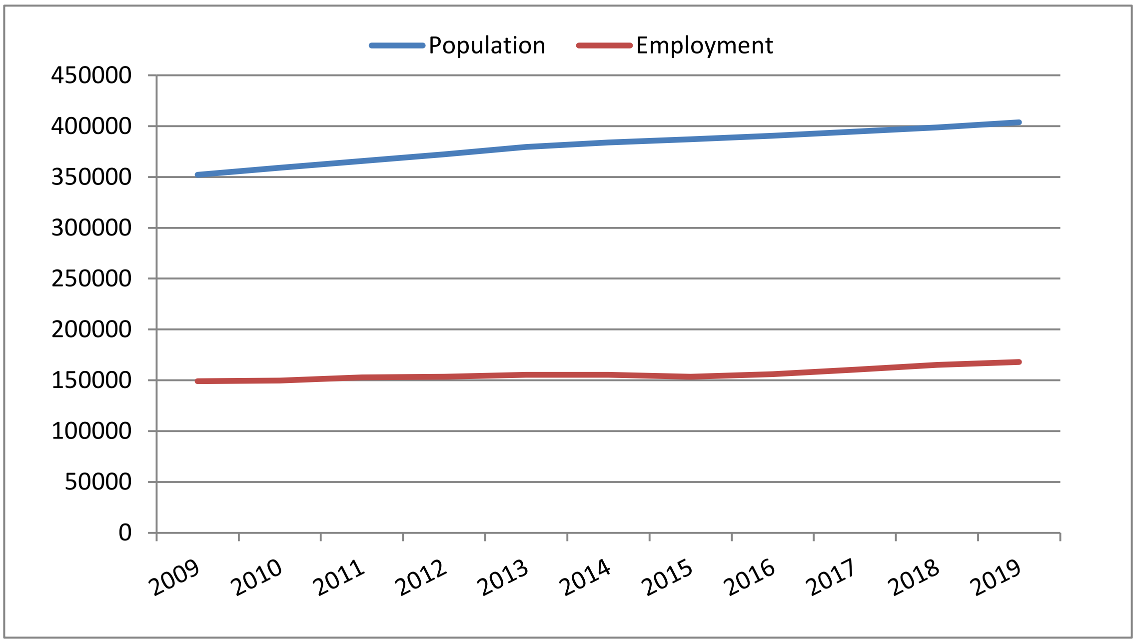
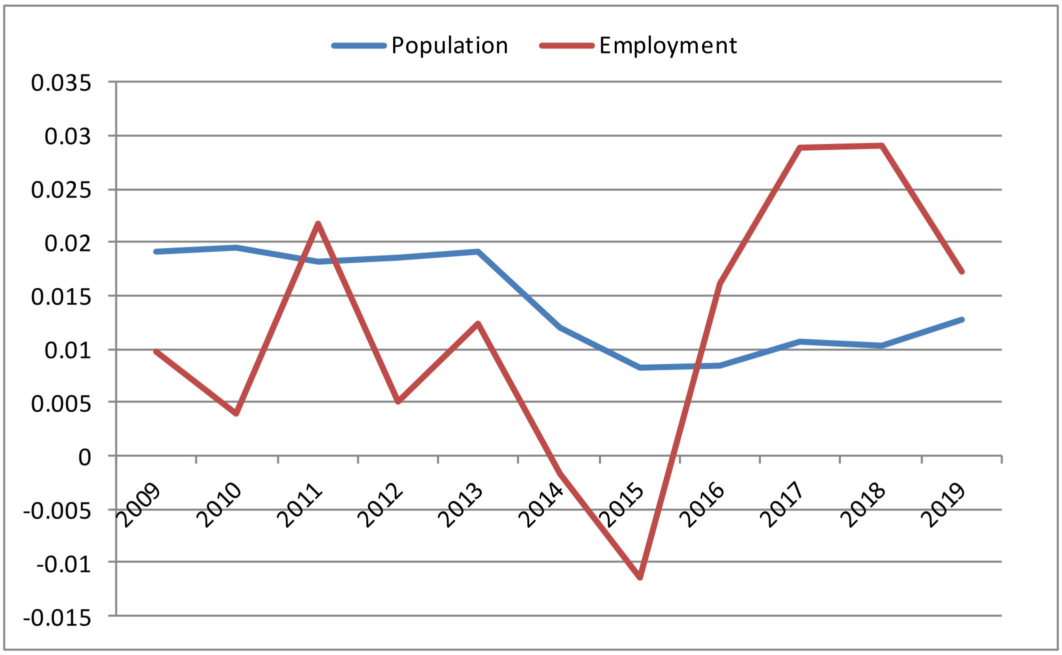


Figure 6.5 : Population and employment growth rates



6.1.4 Retail electricity prices

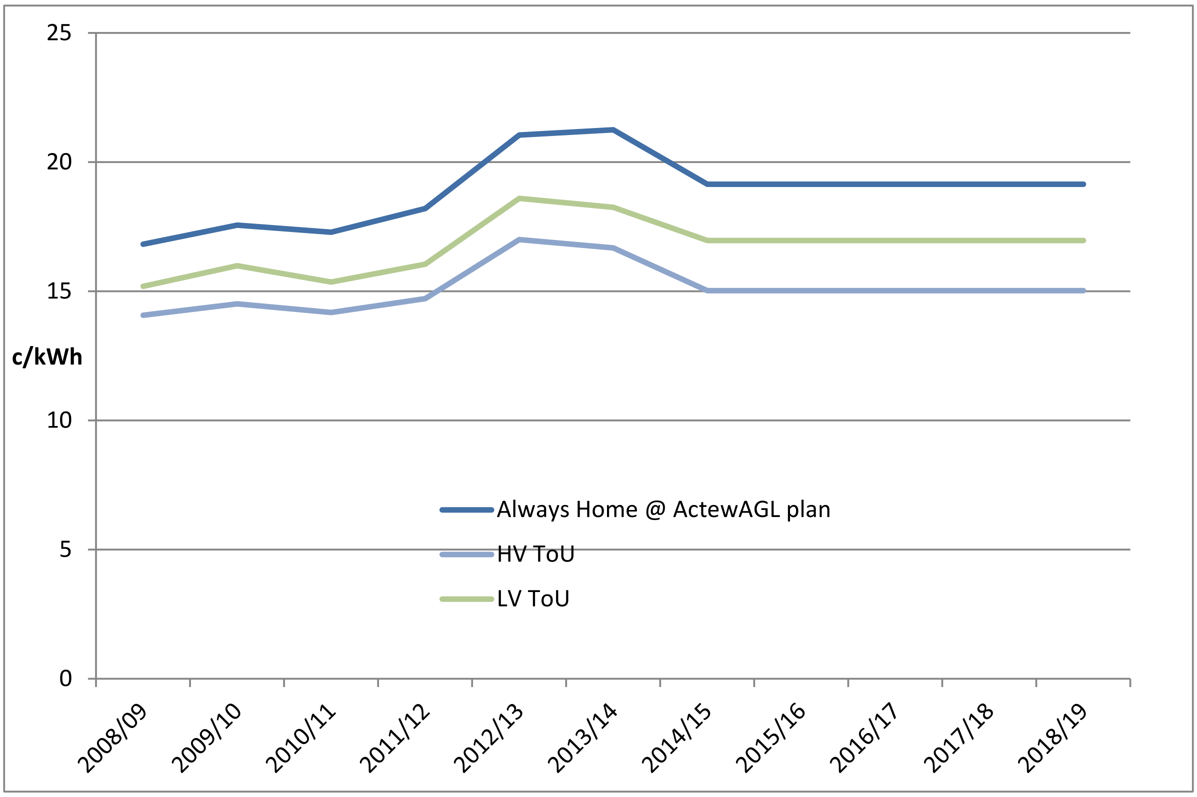
Jacobs SKM has projected the retail tariffs used in the analysis over the period 2014-15 to 2018-19 on the following basis:

- It is assumed that the carbon price is set to zero from 1 July 2014 and the pass-on is removed from the tariffs.
- It is assumed that network charges are fixed in real terms from 1 July 2014.
- The carbon price pass-on in each tariff on 1 July 2012 is estimated from the tariff increase, taking into account the network tariff change at that time.

- The net reductions in each retail tariff on 1 July 2014 are: residential, 9.9%; LV, 7.1%; and HV, 9.9%.

The projected tariff paths are shown in Figure 6.6.

Figure 6.6 : Projected retail prices of each customer category, c/kWh in $ June 2013

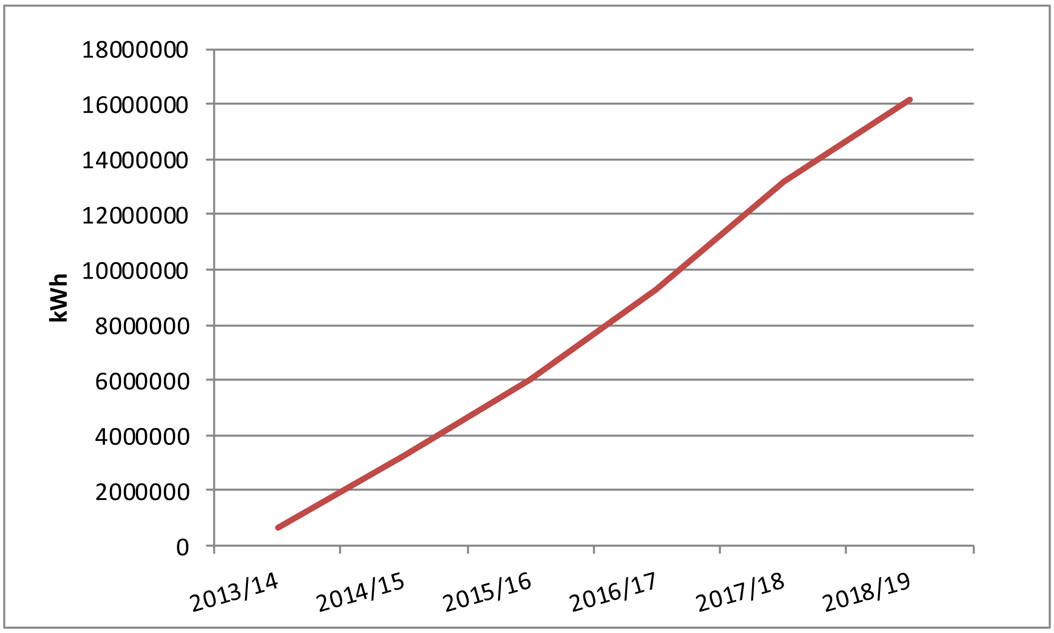


6.1.5 Energy savings

6.1.5.1 PV output

PV uptake and energy generation has been projected by ActewAGL using growth rates derived by AEMO for NSW for the National Electricity Forecast Report (NEFR). From the beginning of July 2013 all new PV applicants have been metered on a net output basis, with the difference between total generation and metered generation being used within the customers' premises and resulting in metered usage falling by that amount, which is labelled "unmetered generation". ActewAGL's projections of unmetered generation for the residential sector are presented in Figure 6.7 below.

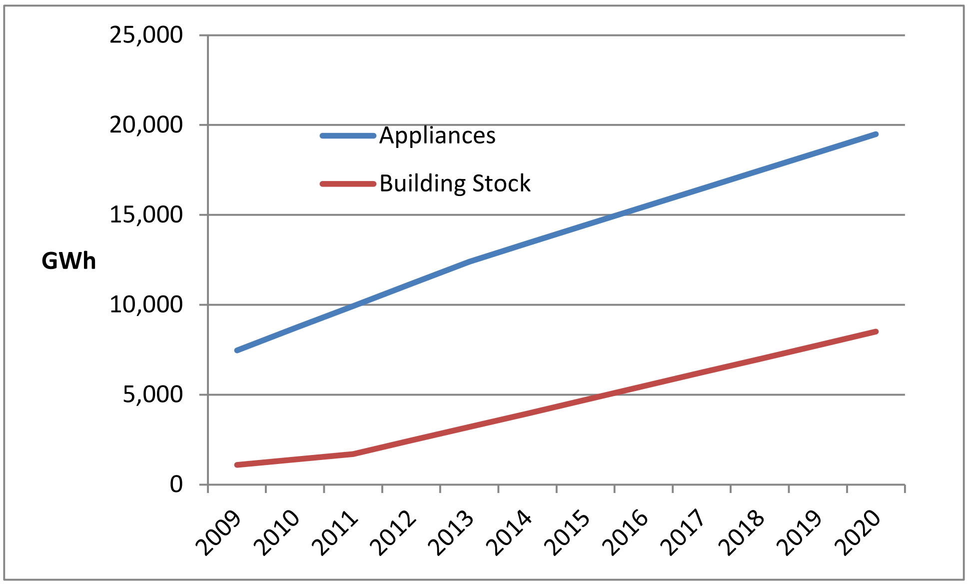
Figure 6.7 : Residential PV unmetered generation (kWh)



6.1.5.2 Energy efficiency

Projections of energy efficiency have been derived from the same AEMO data used to estimate historical energy savings, using the same assumptions regarding the split between the residential and commercial sectors (Figure 6.8). It is noted that the savings due to building stock grow faster in the forecast period than in the historical period, whereas appliance savings growth is steady.

Figure 6.8 : Energy savings projections based on AEMO data.

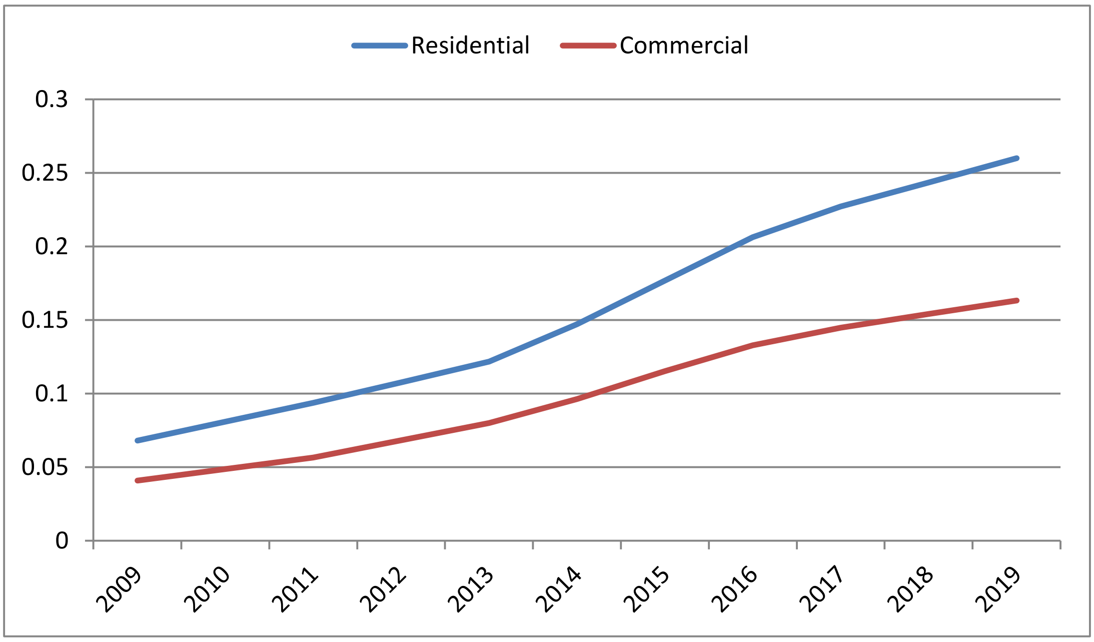


In addition to the energy savings likely to result from the national schemes represented in the AEMO data, the ACT Government has implemented the Energy Efficiency (Cost of Living) Improvement Act 2012 (EEIA), which requires electricity retailers to meet “Energy Savings Obligations” (ESOs) by undertaking “eligible activities”. The ESO’s are set by reference to an “energy savings target”, set as a percentage of total ACT electricity usage to be saved but calculated by reference to greenhouse emissions saved by eligible activities.

The energy savings targets are set by the minister. For the relevant periods under the EEIA, calendar 2013, 2014 and 2015, the minister has set targets of 7%, 13% and 14% respectively. As the greenhouse emissions saved are calculated over 10 year periods, this means annual savings of 0.7%, 1.3% and 1.4% in each year respectively. Given that the savings are accumulated over each year, the actual incremental energy savings in each year would be approximately half the target figure. Converting to the financial years used in the forecast, the cumulative savings would be 0.18%, 0.85%, 2.025%, 3.05% and 3.4% from 2012-13 to 2016-17 respectively. To reflect the greater capacity for savings in the residential sector compared to the commercial sector, we have assumed that this results in cumulative savings of 4.3% in the residential sector and 2.8% in the commercial sector.

The question arises as to how much of the savings reported under the EEIA would have been achieved anyway and are effectively included in the AEMO projections. The AEMO savings are based on Commonwealth schemes relating to equipment labelling, Minimum Energy Performance Standards (which place restrictions on the energy performance of appliances, lighting and electrical equipment for sale in Australia) and building-related energy efficiency measures (which focus on regulations for new buildings in the Building Code of Australia).[8] The activities being undertaken under the EEIA by the dominant retailer in the ACT, ActewAGL Retail, have to date focused on door knocking (and arranged house calls) to install standby power controllers, energy efficient light bulbs and door seals in established residences at no direct cost to the customer and on refrigerator buyback.[9] Some of the activities being undertaken under the EEIA are likely to be bringing forward savings that would eventually be made under the national schemes covered by the AEMO savings estimates. However, it is reasonable to assume that most savings that are brought forward are brought forward at least five years; that is, from after 2019. Applying 100% of the EEIA energy savings targets incrementally to the AEMO projections would therefore not represent double counting during the regulatory control period. Jacobs SKM's energy savings projections are presented in Figure 6.9.

Figure 6.9 : Projected residential and commercial energy savings (%)



8 AEMO 2013, Forecasting methodology information paper, p5-42 and 5-46; and
Pitt and Sherry 2013, Final Report: Quantitative assessment of energy savings from building energy efficiency measures, Prepared for Department of Climate Change and Energy Efficiency, March, p21-35.

9 http://www.actewagl.com.au/Help-and-advice/Assist.aspx accessed on 9 April 2014.

6.2 Annual energy forecasts

In this section we present the translation of the above demand driver projections into annual energy forecasts using the preferred models presented in section 5. The residential GP forecasts are net forecasts, based on the zero efficiency models with efficiency savings and net PV projections subtracted, and the other forecasts are effectively gross forecasts, based on the zero efficiency models with efficiency savings subtracted as there are no PV projections for the other user categories.

Following the general trends in the economic drivers, all the econometric models that exclude electricity price as a factor (all models except GP models R13 and R17 and both OP models) produce forecasts that decline initially and then increase or stay flat. Models R13 and R17 forecast energy increases in 2014-15 because of the price reduction following the assumed removal of the carbon price.

6.2.1 Residential GP forecasts

The drivers included in the preferred residential GP models are listed in Table 6.1.

Table 6.1 : Residential model drivers

Model	Drivers			
R11*	Efficiency	Population	Employment	
R12	Efficiency	Population	HHI	Interest rate
R13	Efficiency	Population	HHI	Price
R16	Efficiency	Customers	Employment	
R17	Efficiency	Customers	HHI	Price
* Best model fit				

Residential GP forecasts for the preferred models are presented in Figure 6.10. It is clear that the models R13 and R17 incorporating electricity prices yield the highest forecasts owing to the projected price reduction in 2014-15. The model with the best fit, R11, yields the lowest forecasts. The wide divergence between the models in the forecast period compared to their similar fit of the actuals is due to the different correlations between the drivers in the forecast period compared to their actual correlations.

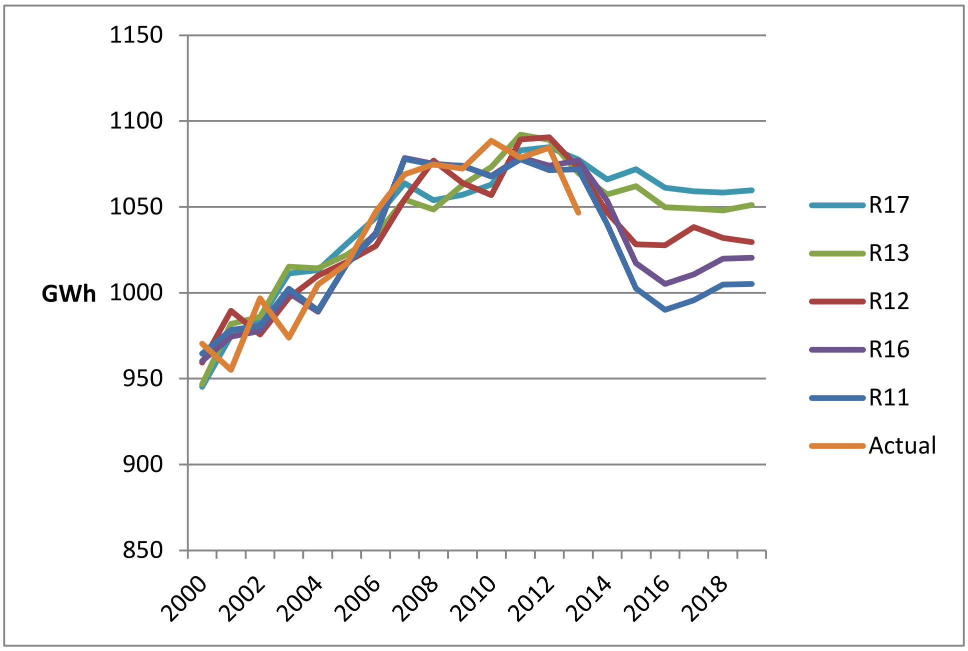
Analysis of the contribution of each driver to the growth between 2013 and 2019 yields the table below. The major contributors are HHI, Employment, population and Customers, with Interest Rate and Electricity Price less influential. Efficiency and PV are effectively the same for each model.

Table 6.2 : Residential GP driver contributions to growth (GWh)

	Driver Contribution							
Model	HH.Disp. Inc.	Employment	Interest Rate	Electricity Price	Population	Customers	Efficiency	PV
R11*	0.0	65.4	0.0	0.0	32.2	0.0	-148.1	-16.2
R12	31.1	0.0	9.5	0.0	80.6	0.0	-148.2	-16.2
R13	51.3	0.0	0.0	20.8	73.2	0.0	-147.8	-16.2
R16	0.0	70.9	0.0	0.0	0.0	37.4	-148.8	-16.2
R17	29.7	0.0	0.0	18.8	0.0	98.8	-148.8	-16.2

*Best model fit

Figure 6.10 : Residential GP Annual Energy Forecast



Average GP usage per customer and per person continues to decline over the forecast period in all model projections (Figure 6.11 and Figure 6.12).

Figure 6.11 : Residential GP energy per customer forecast

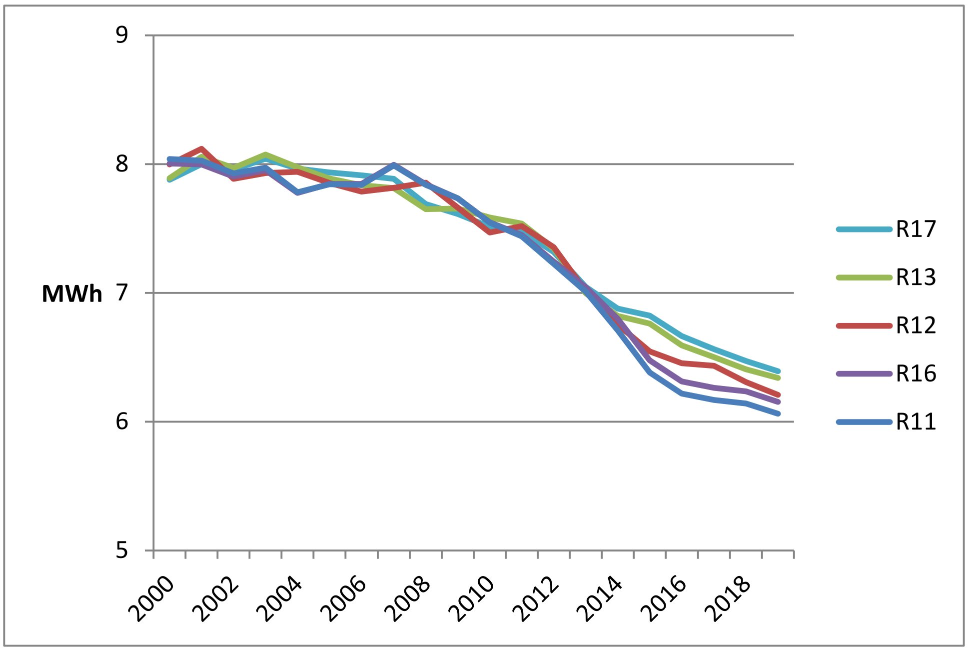
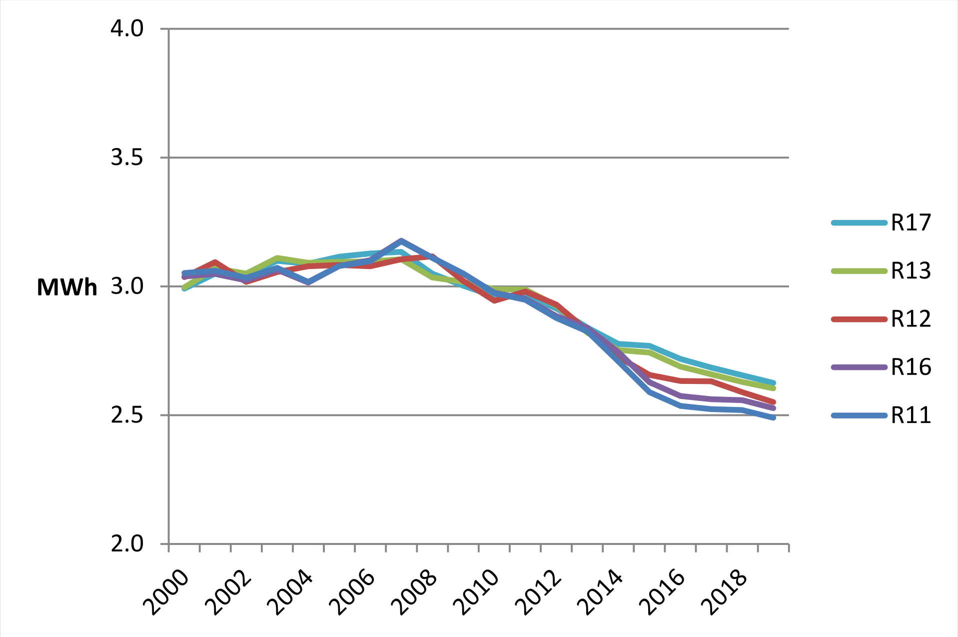
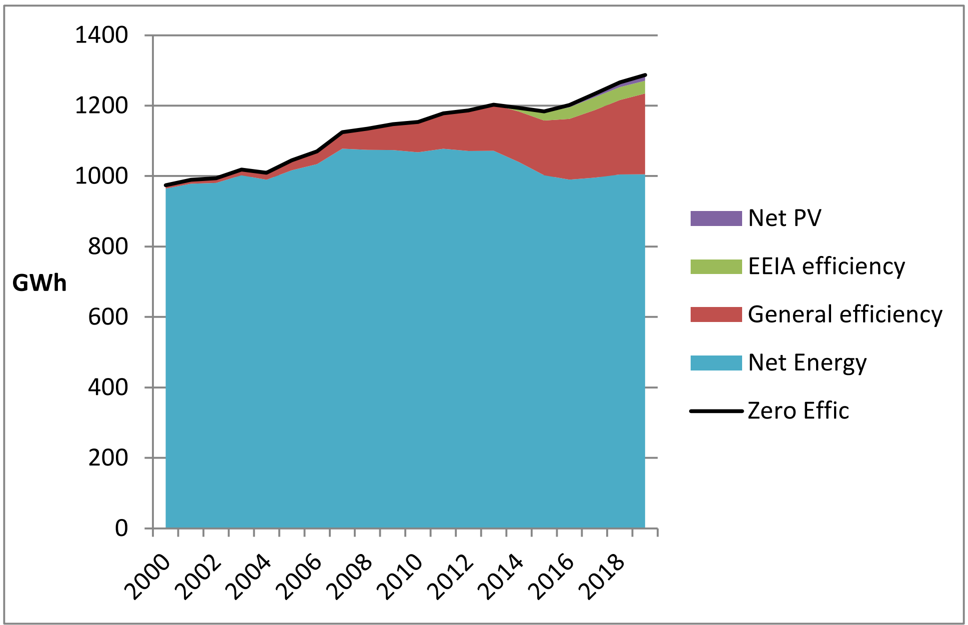


Figure 6.12 : Residential GP energy per person forecast



The recommended model based on fit is the zero efficiency R11 model. Figure 6.13 illustrates how the net energy is calculated from the zero efficiency R11 model by subtracting general efficiency growth, efficiency due to the EEIA and net PVs.

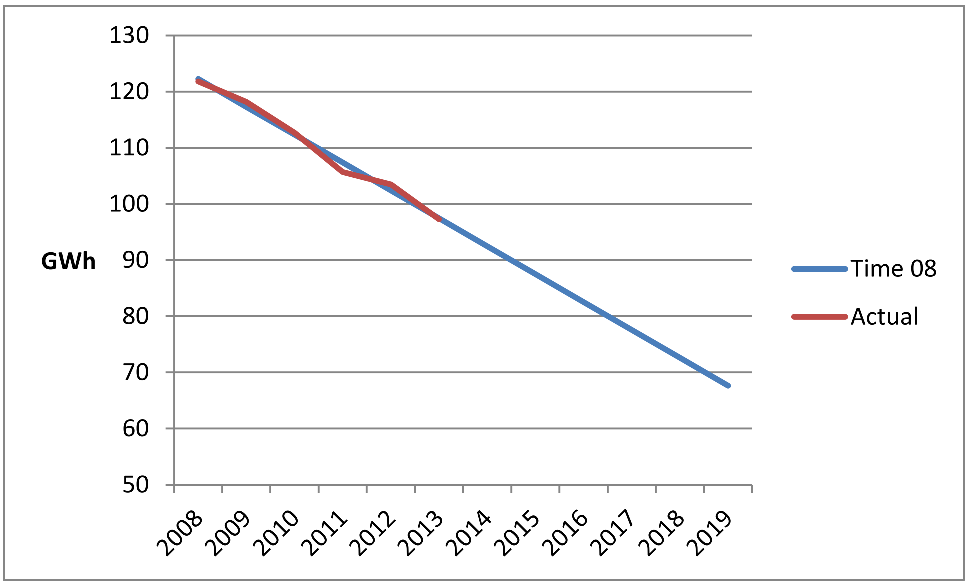
Figure 6.13 : Model R11 calculation of net energy (GWh)



6.2.2 Residential OP forecasts

The residential OP forecast based on the preferred Time 08 model is reproduced in Figure 6.14.

Figure 6.14 : Residential OP energy forecast



6.2.3 LV forecasts

The drivers included in the preferred LV models are listed in Table 6.3.

Table 6.3 : LV model drivers

Model	Drivers		
LV6*	Efficiency	SFD	Interest rate
LV7	Efficiency	GSP	Interest rate

*Best model fit

LV forecasts for the preferred models are presented in Figure 6.15.

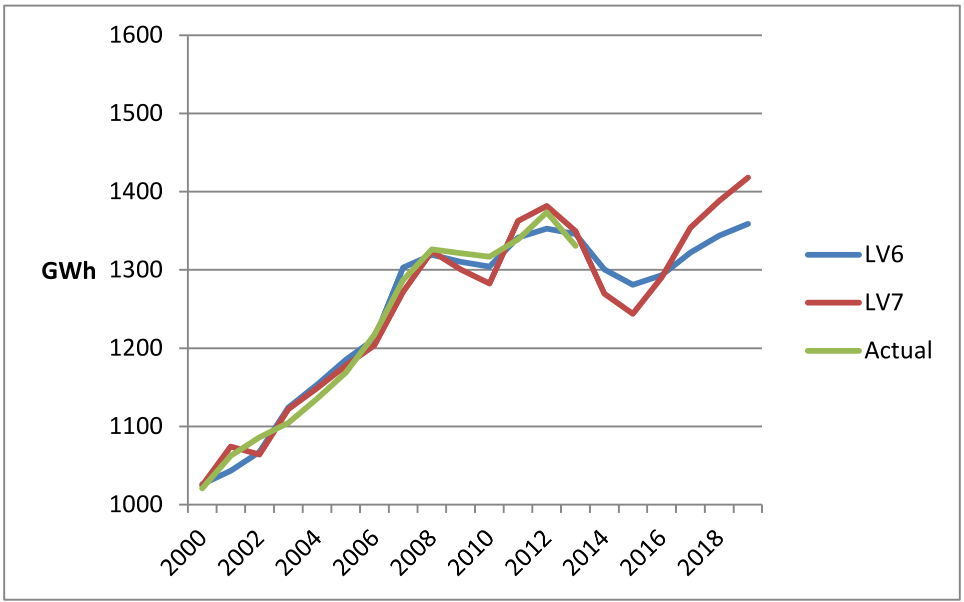
Analysis of the contribution of each driver to the growth between 2013 and 2019 yields the table below which shows that it is the GSP contribution which drives LV7 higher than LV6. The GSP contribution is caused by higher GSP elasticity in LV7 (compared to SFD elasticity in LV6) rather than the GSP forecast itself.

Table 6.4 : LV driver contributions to growth (GWh)

Model	Driver Contribution			
	GSP	SFD	Interest Rate	Efficiency
LV6*	0.0	117.6	8.6	-120.9
LV7	165.1	0.0	23.9	-121.2

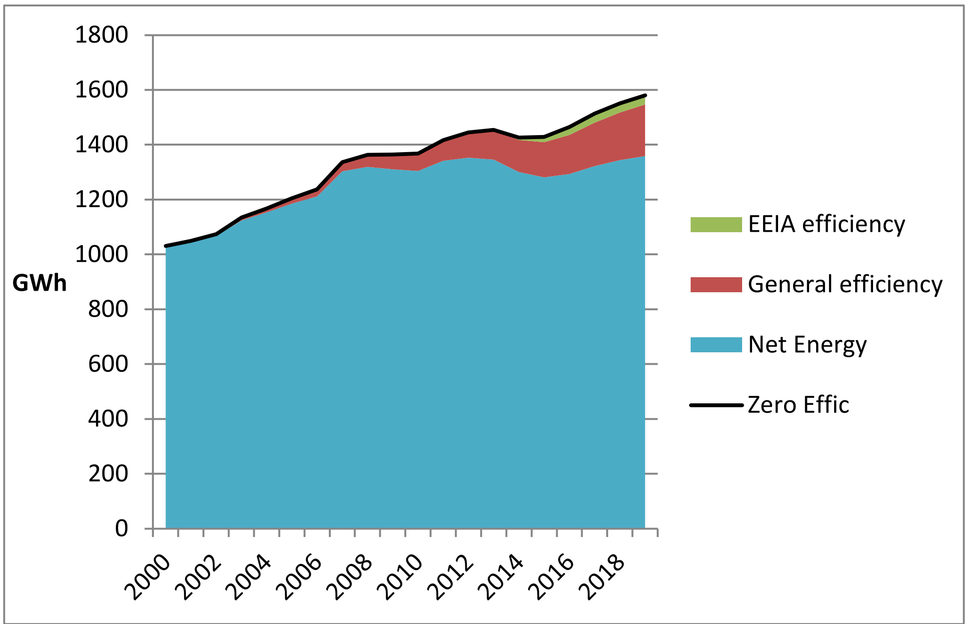
*Best model fit

Figure 6.15 : LV annual energy forecast



The recommended model based on fit is the zero efficiency LV6 model. Figure 6.16 illustrates how the net energy is calculated from the zero efficiency LV6 model by subtracting general efficiency growth and efficiency due to the EEIA.

Figure 6.16 : Model LV6 calculation of net energy (GWh)



6.2.4 HV forecasts

The drivers included in the preferred HV models are listed in Table 6.5.

Table 6.5 : HV model drivers

Model	Drivers		
HV6*	Efficiency	SFD	
HV7	Efficiency	GSP	Interest rate

*Best model fit

HV forecasts for the preferred models are presented in Figure 6.17.

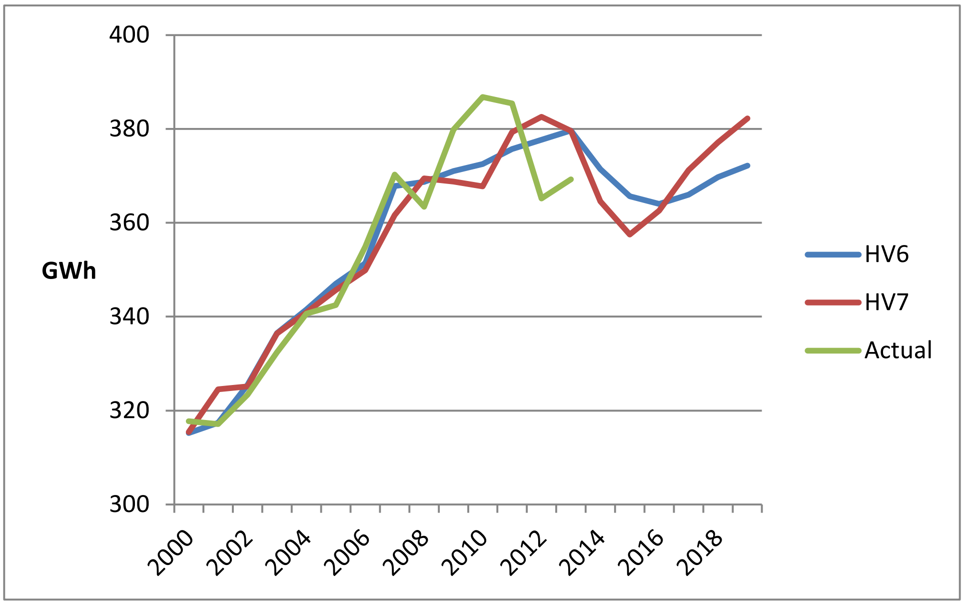
Analysis of the contribution of each driver to the growth between 2013 and 2019 yields the table below which shows that it is the GSP contribution which drives HV7 higher than HV6. The GSP contribution is caused by higher GSP elasticity in HV7 (compared to SFD elasticity in HV6) rather than the GSP forecast itself, exactly as in the LV forecasts.

Table 6.6 : HV driver contributions to growth (GWh)

Model	Driver contribution			
	GSP	SFD	Interest rate	Efficiency
HV6*	0.0	22.9	0.0	-34.1
HV7	31.4	0.0	3.0	-34.2

*Best model fit

Figure 6.17 : HV annual energy forecast

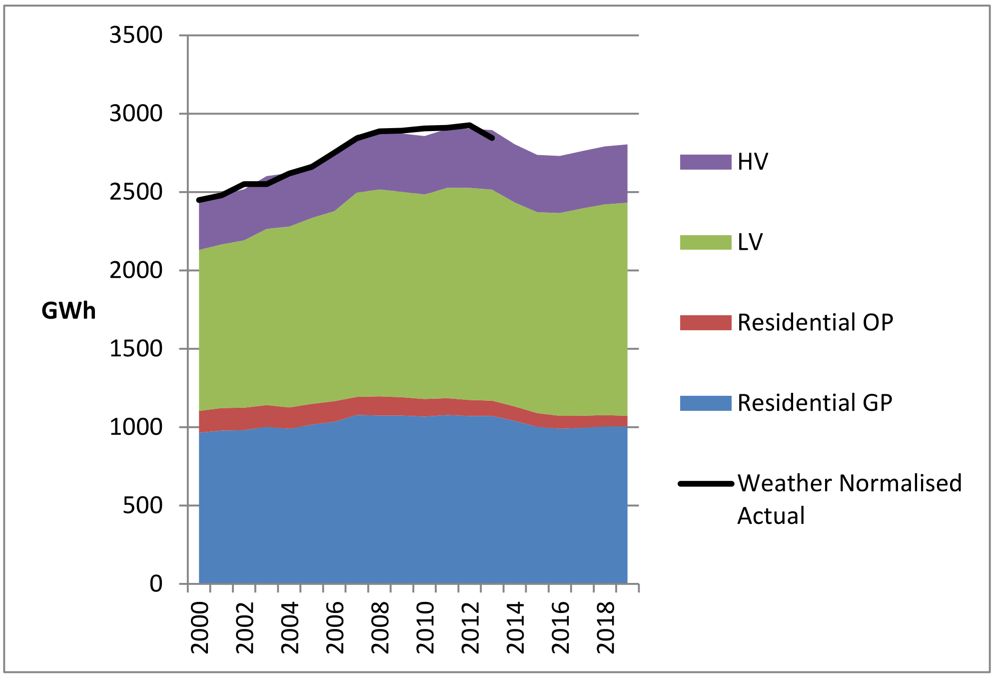


The recommended model based on fit is the HV6 model.

6.2.5 Total energy forecasts

The total energy forecasts for the ActewAGL network at the net energy level are illustrated below for the recommended residential GP, LV and HV forecasts (R11, LV6 and HV6).

Figure 6.18 : Total energy forecast



Appendix A. Preliminary weather normalisation analysis of Residential billings data

The same CDD and HDD measures are used for Residential GP load as for OP. Preliminary weather normalisation analysis of billings data provided by ActewAGL, presented in Table A.1, revealed anomalous results over different periods.

Table A.1 : Regression of Residential billing against Residential CDD and Residential HDD

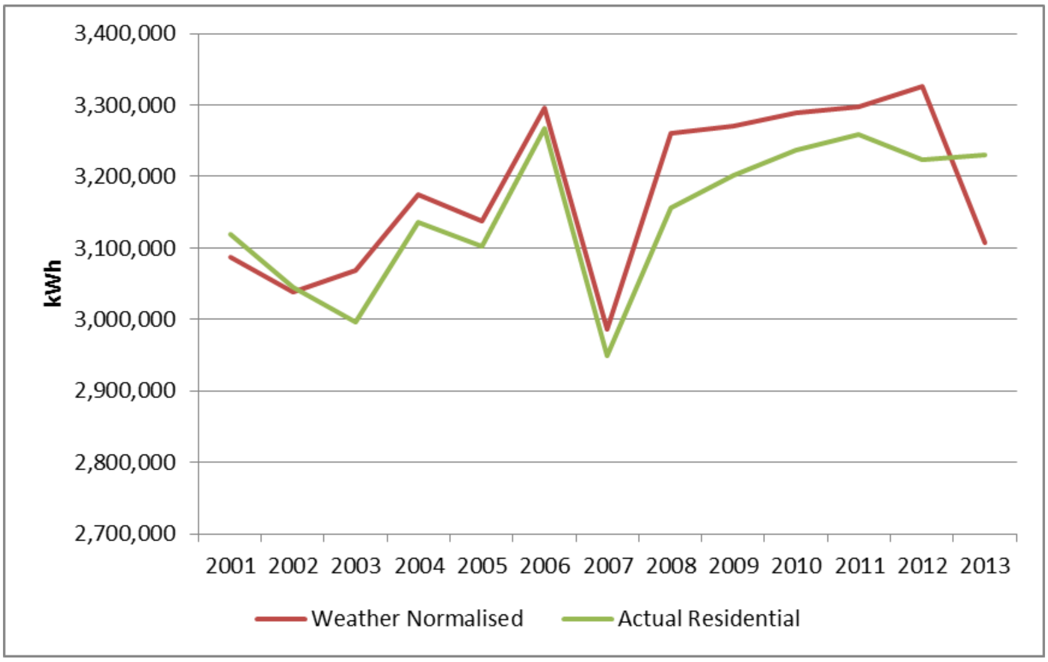
	2001	2002	2003	2004	2005	2006
Constant	2,250,451	2,508,208	2,948,526	2,819,189	2,179,740	2,250,884
HDD Residential	144,392	111,944	63,736	95,793	169,716	181,724
CDD Residential	77,652	-71,829	-242,620	-168,108	61,847	88,040
Standar Error	585,231	620,095	578,650	705,761	621,658	688,477
R-Sqr	0.497	0.429	0.547	0.448	0.530	0.456
T-Stat Constant	3.155	3.166	3.922	2.720	2.459	2.463
T-Stat HDD Residential	1.762	1.169	0.714	0.766	1.609	1.590
T-Stat CDD Residential	0.301	-0.162	-0.925	-0.441	0.164	0.328

	2007	2008	2009	2010	2011	2012	2013
Constant	1,658,557	1,972,899	1,796,966	1,784,421	80,782	1,632,474	1,208,412
HDD Residential	216,226	230,434	249,041	253,048	427,089	255,566	295,129
CDD Residential	198,404	73,733	166,442	177,292	1,050,120	374,538	367,648
Standar Error	389,384	366,333	246,469	103,468	629,492	269,329	232,899
R-Sqr	0.765	0.851	0.929	0.984	0.719	0.920	0.946
T-Stat Constant	3.496	3.451	6.198	12.127	0.097	3.548	3.907
T-Stat HDD Residential	3.762	3.287	7.006	13.807	4.347	4.963	8.568
T-Stat CDD Residential	1.309	0.297	1.542	4.078	2.795	1.006	3.144

The key outcome of this analysis is the poor fit of the regressions (low R2 of about 0.4 to 0.5) up to 2006 and the relatively good fit from 2007. We understand this is due to the pre-2007 data being estimated residential sales (billings adjusted to reflect actual energy consumption in the period), rather than billings per se, and consequently not as well related to the billing CDD and HDD values. The impact of the definitional change shows up clearly as a discontinuity in both actual and weather normalised trends (Figure A.1). Rather than use this data series we have used a substitute, described in section 0, which provides more reliable estimates of residential energy usage trends.

Although taking four months weighted average of CDD and HDD can incorporate the billing period for residential customers, it is also worth noting that it can also potentially smooth out the effect of temperature. Especially for the CDD as CDD do not occur as often as HDD during the year, taking the average over three month will make the CDD less obvious. This is also demonstrated by the low CDD T-stat in Figure A.1.

Figure A.1 : Weather normalised Vs actual Residential billings



The change in billing definitions in 2007 shows up clearly in Figure A.2.

Figure A.2 : Total billing Vs total energy