ACIL ALLEN CONSULTING

REPORT TO
ENERGY QUEENSLAND
15 MAY 2018

REVIEW OF SYSTEM MAXIMUM DEMAND AND ENERGY

REVIEW OF ENERGEX'S AND ERGON ENERGY'S APPROACH TO SYSTEM MAXIMUM DEMAND AND ENERGY DELIVERED

ACIL ALLEN CONSULTING PTY LTD
ABN 68 102 652 148

LEVEL NINE
60 COLLINS STREET
MELBOURNE VIC 3000
AUSTRALIA
T+61 3 8650 6000
F+61 3 9654 6363

LEVEL ONE
50 PITT STREET
SYDNEY NSW 2000
AUSTRALIA
T+61 2 8272 5100
F+61 2 9247 2455

LEVEL FIFTEEN
127 CREEK STREET
BRISBANE QLD 4000
AUSTRALIA
T+61 7 3009 8700
F+61 7 3009 8799

LEVEL ONE
15 LONDON CIRCUIT
CANBERRA ACT 2600
AUSTRALIA
T+61 2 6103 8200
F+61 2 6103 8233

LEVEL TWELVE, BGC CENTRE
28 THE ESPLANADE
PERTH WA 6000
AUSTRALIA
T+61 8 9449 9600
F+61 8 9322 3955

167 FLINDERS STREET
ADELAIDE SA 5000
AUSTRALIA
T +61 8 8122 4965

ACILALLEN.COM.AU

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EXECUTIVE SUMMARY

Introduction and project scope

ACIL Allen Consulting (ACIL Allen) has been appointed by Energy Queensland to review the forecasting methodologies of Ergon Energy and Energex with respect to system maximum demand and energy delivered. This review will assist Energy Queensland in the preparation of its submission to the AER (Australian Energy Regulator) covering the regulatory period from 1 July 2020 to 30 June 2025.

As part of this review ACIL Allen has:

- Reviewed the existing forecasting processes against best practice principles outlined in the AERs Better Regulation Explanatory Statement with a particular emphasis on:
  - Transparency and repeatability
  - Accuracy and unbiasedness
  - Incorporation of key drivers
  - Model validation and testing
  - Use of most recent and consistent inputs into the forecasting process
  - Any other attributes considered important
- Reviewed the various approaches used in forecasting maximum demand with an analysis of the strengths and weaknesses of the various approaches
- Assessed the appropriateness of the key inputs and drivers including:
  - Demographic, economic, weather and calendar variables
  - Electric vehicles, PV and battery storage post model adjustments
- Evaluated and assessed the model logic and structure and whether the resulting forecasts are reasonable
- Recommended improvements to the forecasting methodologies
- Demonstrated the value and materiality of the recommendations with supporting analysis and data

We recognise that there are differences in the forecasting methodologies between Energex and Ergon and that these differences have been accounted for in the review.

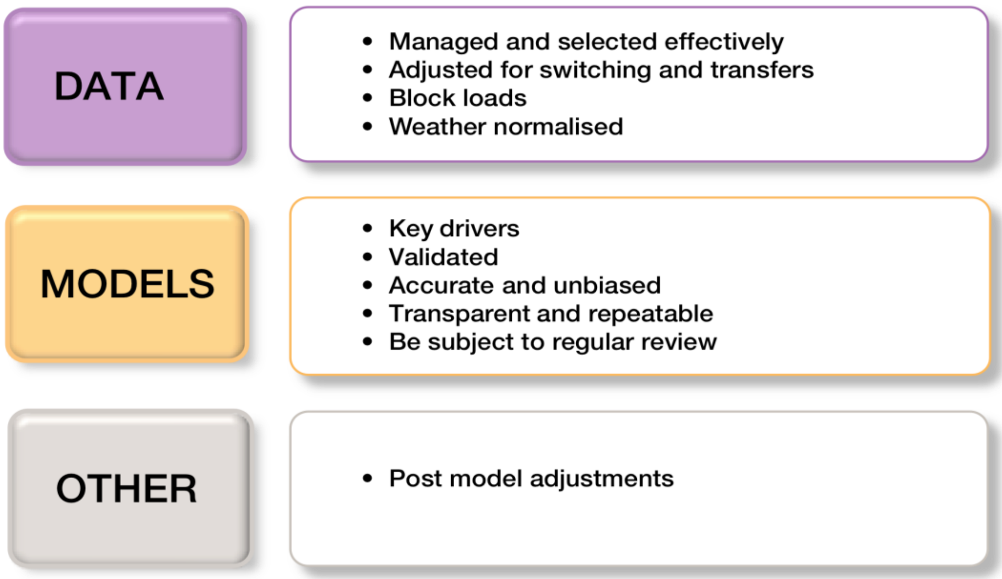
In consultation with Energy Queensland, ACIL Allen has adopted a higher level approach to reviewing the forecasting methodologies and procedures. Rather than focussing on the lower level details, ACIL Allen has evaluated the forecasts and associated methodologies against the AERs view of what constitutes forecasting best practice.

Best practice forecasting

In November 2013, the Australian Energy Regulator (AER) in its 'Better Regulation Explanatory Statement- Expenditure Forecast Assessment Guideline' set out the main principles of best practice demand forecasting. These were essentially a reproduction of the principles put forward by ACIL Allen in its report to the Australian Energy Market Operator (AEMO) entitled "Connection Point Forecasting- a nationally consistent methodology for forecasting maximum electricity demand"[1].

These principles are presented in **Figure ES 1** below.

FIGURE ES 1 BEST PRACTICE FORECASTING PRINCIPLES



SOURCE: ACIL ALLEN CONSULTING

Energy delivered- Ergon Energy

Previous reviews

Ergon Energy's energy delivered and customer numbers forecasting methodologies have been subject to a number of reviews, the first of which dates back to 2009[2]. This section details the major findings of these reviews and outlines how Ergon's methodology has changed over time to meet the requirements and recommendations of these reviews.

In 2009, Ergon's approach to forecasting energy and customer numbers could be described as a combination of trend analysis and the application of local area knowledge and expertise. The forecasts were split by different tariff classes and customer segments. Trend based forecasts for total customer numbers and total energy usage per segment were obtained for three separate regions, West, East and Mt Isa.

In its review of the methodology, ACIL Tasman considered that the trend based approach was reasonable for short run growth, but that in the long run, the key drivers of energy delivered were likely to change over time and result in significant changes from the short term trend.

ACIL Tasman suggested the adoption of a multiple regression approach, with the analysis split by customer segment. The forecasts would be based on estimates relating energy delivered to its main drivers, such as Queensland GSP and population growth.

[1] Available from http://www.aemo.com.au/Electricity/Planning/Forecasting/AEMO-Transmission-Connection-Point-Forecasting

[2] Common Network Demand and Energy Forecasting, Prepared for Energex and Ergon Energy December 2009.

In April 2010, ACIL Tasman produced a set of System Energy guidelines.[3] These guidelines introduced a set of best practice forecasting principles, and they were subsequently introduced to and adopted by the AER. The suggested model specifications for energy delivered and customer numbers formed the basis of Ergon Energy's current approach to forecasting energy and customer numbers.

Current approach to forecasting

Following the previous independent reviews, Ergon Energy has adopted a multiple regression approach to forecasting system energy delivered and customer numbers within its distribution network.

The multiple regression approach estimates the historical relationship between energy delivered and customer numbers and their drivers. Forecasts of the individual drivers are used in conjunction with the estimated models to generate the forecasts. The forecasts are produced by customer class for each of Ergon's six regions.

The relationship between energy delivered and its main economic, demographic and weather drivers will differ across each of the major customer classes. By splitting the data into separate customer classes, Ergon is able to better capture the characteristics of each customer class. Moreover, the behaviour of energy consumption across each of Ergon's six region is also likely to differ. Ergon's network is very large with divergent characteristics.

Major recommendations of the review

As a result of this review, ACIL Allen recommends the following:

- Currently, Ergon does not remove the impact of rooftop PV from its historical data before model estimation. Ergon Energy should net off the impact of rooftop PV from the historical data before model estimation commences for the domestic component of the model, and for the commercial component in those regions where the take up of commercial rooftop PV has become significant
- In light of an increased sample size, Ergon should re-consider the variables used in the econometric models. It is possible that key drivers that were previously found to be statistically insignificant or had a nonsensical coefficient will perform better in a re-formulated model
- Ergon should introduce a post model adjustment by scenario, for the impact of each of the following:
  - Rooftop PV
  - Electric vehicles
- Ergon should attempt to include the impact of the retail price of electricity within the base econometric model rather than through a post model adjustment using externally sourced elasticities

Energy delivered- Energex

Previous reviews

Energex's energy forecasting methodology has evolved significantly over time in response to a series of reviews dating back to the Joint Workings project of 2009. Like Ergon, Energex's energy forecasting methodology could be described as bottom up using a combination of time series analysis and experience.

Forecasts were created by customer class, with total customer numbers and energy usage per customer separately forecast for each segment, and the two sets of forecasts combined to provide the total forecast for each segment. The models did not contain any explicit relationship between system energy and the underlying economic and demographic variables that drive it. Moreover, there were no weather inputs used in the modelling process. Energex's fitting of trends to the historical data often involved the fitting of complex polynomial functions which tended to behave erratically in the projection period and were often overwritten by hard coded adjustments for which there was little or no justification.

[3] System Energy Forecast Models and Guidelines, Common Forecasting Methodology, Prepared for Energex and Ergon Energy, April 2010.

In the System Energy Guidelines document released the following year in April 2010, ACIL Tasman recommended the creation of a set of top down econometric models that related energy delivered for each customer segment to each of the underlying drivers that drove the long run trends in consumption for each segment.

In December 2013, Energex's system energy and customer numbers forecasting were reviewed again, this time by Frontier Economics[4]. In this review it is clear that Energex had made some progress towards a more top down econometric approach to forecasting energy and customer numbers. The energy and customer numbers forecasts were a combination of trend extrapolation and top level econometric models, which involved the use of key drivers to generate the forecasts.

Frontier reviewed the models for each customer segment and made a number of additional criticisms:

- The sample used to estimate the trends did not always use the most up to date information and no explanation was provided as to why this was the case
- The quadratic and cubic trends were prone to producing unrealistic forecasts
- Hard-coded and ad-hoc post model adjustments were made to the forecasts with little or no explanation

Current approach to forecasting

Energex currently adopts an econometric approach to forecasting energy delivered, which links energy sales to a set of key economic, demographic and weather drivers. Previous practices such as the fitting of quadratic and cubic trends and ad-hoc adjustments have now been discontinued. The current approach first estimates a base case model which excludes the impact of emerging technologies such as Electric Vehicles and Battery storage systems. These are estimated separately and then added to the forecast as a post model adjustment.

Energy sales forecasts are produced under separate high, medium and low scenarios. The forecasts are produced to cover a 10 year forecasting horizon. Energex splits its energy forecasts into separate customer classes. Post model adjustments for rooftop PV, battery storage and electric vehicles were sourced from and provided by an external consultant.

Major recommendations of the review

As a result of this review, ACIL Allen recommends the following:

- Energex should remove all variables from its base econometric specifications that are not statistically significant at the 1% or 5% significance level, except for GSP and Gross State Income which should be retained on theoretical grounds
- Energex should consider replacing the GSP variable in the non-domestic model with GSP per capita. This is because the dependent variable is energy per customer, so this would put both the explanatory variable and dependent variable on the same basis
- Energex have applied the NIEIR low case GSP forecast to produce its medium or base case forecast. ACIL Allen considers that the NIEIR low case is too pessimistic based on recent history and the forecasts of other independent experts. Our recommendation is for Energex to use the NIEIR medium case as the basis for its base or medium case forecasts. These are more consistent with historical economic activity after the GFC
- Energex should consider shifting to a fundamentally driven model of rooftop PV uptake that is based on forecasts of the major drivers such as the cost if installation, changes in feeds in tariffs and other subsidies, and electricity prices, rather than relying on a method of extrapolation along an S curve
- Energex could improve the transparency and repeatability of its forecasts by adding detail to its documentation on the methodology used to forecast the uptake of PV, battery storage and electric vehicles
- Energex's energy forecasting documentation should include a short section on the domestic energy and customer numbers models. These are important contributors to the total energy delivered, yet they are not detailed in any meaningful way in the documentation

[4] Review of Energex's customer numbers and energy demand forecasting procedures. A report prepared for Energex, December 2013.

System maximum demand- Ergon Energy

Previous reviews

In December 2009 as part of the Joint Workings project, ACIL Tasman conducted the first formal review of Ergon's approach to forecasting system maximum demand within its network.

At that time Ergon Energy produced its system maximum demand forecast by aggregating bulk supply/connection point forecasts up to the region level and then again up to the system level using historical coincidence factors for the purpose.

The lower level bulk supply/connection point forecasts were calculated through the extrapolation of historical trends. The review identified a number of deficiencies of the methodology and made a set of recommendations to rectify these. These were:

- That it was not possible to incorporate trend changes into the forecasts
- That there was no formal weather normalisation procedure
- That forecasts at the spatial level were subject to a high degree of noise and randomness
- That there was likely to be double counting of block loads, because block loads were added to the trend forecast without the applying any form of threshold for smaller block loads
- That the methodology was not transparent due to a lack of documentation
- That there was no formal reconciliation with an independently produced system level forecast

As a result, ACIL Tasman recommended that Ergon shifted to a regression based system level methodology which incorporated the key economic and demographic drivers of daily maximum demand, seasonal and calendar effects and weather effects.

ACIL Tasman also recommended the new system level methodology employ a weather correction methodology which utilised a sufficiently long weather series to allow accurate calculation of 50% POE and 10% POE demand forecasts.

In March 2012, Ergon's approach to forecasting system maximum demand was reviewed by ACIL Tasman again. The findings of that review were that Ergon Energy had made considerable progress in the development of its system demand forecasting methodology and had to a significant degree addressed the concerns raised in previous assessments and reviews.

The main methodological improvements were that:

- Ergon had developed an independent system maximum demand methodology that could be used to reconcile spatial forecasts
- Ergon had developed a methodology that allowed for variation in key economic, demographic, appliance and weather factors
- Ergon applied a weather normalisation process to its forecasting process
- Ergon had documented its processes and methodology where previously documentation was sparse

Current approach to forecasting

Ergon estimates separate regression models for system maximum demand for both summer and winter.

The models are estimated using daily maximum demand. The main drivers used in the modelling process are Queensland GSP, the number of air-conditioning systems and daily maximum and minimum temperature data from three weather stations in Gladstone, Cairns and Townsville.

Major recommendations of the review

After reviewing Ergon Energy's system maximum demand methodology ACIL Allen recommends the following:

- Ergon should consider developing separate regional maximum demand models to allow better targeted reconciliation between its spatial level and higher level demand forecasts

- Ergon should shorten the long run weather time series used in the weather normalisation process to include only the period from around 1980 onwards. This reflects the fact that summer average temperatures have increased over the long term, and is in effect a judgement call that the structural shift in Queensland temperature is permanent rather than temporary
- Ergon should recalibrate its preferred model based on the most up to date data available, and re-introduce variables that were tried previously and found to be statistically insignificant, such as price
- Ergon should introduce post model adjustments for battery storage and electric vehicles

System maximum demand- Energex

Previous reviews

The basis of Energex's current methodological approach to forecasting System maximum demand dates back as far as 2009, when it was reviewed as part of the Joint Workings project conducted by ACIL Tasman.

In that review, Energex had essentially applied an approach that was developed by ACIL Tasman in earlier work for Energex dating from April 2008. This methodological approach adopted as a result of the Joint Workings project forms the backbone of Energex's current methodology, although many of the details have now changed.

At this time, Energex modelled daily summer maximum demand using an econometrically based time series regression approach.

In December 2013, Energex's peak demand methodology was reviewed by Frontier Economics. The main findings of this review were:

- That Energex needed to further develop its documentation to improve the methodology's transparency and repeatability
- That Energex's models include all the major drivers of system maximum demand but that further analysis was required to determine the exact form that these variables enter the model
  - In particular, Frontier recommended that where Energex uses interaction terms in its model specification, it should also include the main effect as well
- That there was significant evidence that the model was mis-specified based on a very low value for the Durbin-Watson statistic
- That Energex should consider using multiple weather stations for inclusion into the modelling and the weather normalisation procedure
- That Energex should consider including a price variable and dummy variables for day of the week effects directly into the estimated model

Energex has adopted the recommendations of Frontier Economics December 2013 review.

Current approach to forecasting

Energex's current approach to forecasting System maximum demand is a top down econometric model which uses daily system maximum demand as the dependent variable. The latest estimated regression is calibrated using data from November 2008 through to March 2017.

The model incorporates the main drivers of demand such as temperature, GSP and electricity prices. Also included as explanatory variables are a dummy variable for a structural break from 2011 onwards as well as calendar related variables such as separate dummies for weekends and public holidays, Fridays, Sundays, a dummy variable for Christmas day and for the Christmas period, normally defined as the three period around Christmas.

Energex apply five separate post-model adjustments to their base econometric forecasts. These are for:

- Battery storage
- Rooftop PV
- Network demand management

- Electric Vehicles
- Block Loads

Energex's rooftop PV, battery storage and Electric Vehicle forecasts are obtained externally from the consultancy Energeia.

Major recommendations of the review

As a result of this review, ACIL Allen recommends the following:

- Energex have applied the NIEIR low case GSP forecast to produce its medium or base case system maximum demand forecast. ACIL Allen considers that the NIEIR low case is too pessimistic based on recent history and the forecasts of other independent experts. Our recommendation is for Energex to use the NIEIR medium case as the basis for its base or medium case forecasts. These are more consistent with historical economic activity after the GFC
- Energex should consider shifting to a fundamentally driven model of rooftop PV uptake that is based on forecasts of the major drivers such as the cost if installation, changes in feeds in tariffs and other subsidies, and electricity prices, rather than relying on a method of extrapolation along an S curve
- Energex could improve the transparency and repeatability of its forecasts by adding detail to its documentation on the methodology used to forecast the uptake of PV, battery storage and electric vehicles

1 INTRODUCTION

1.1 Project scope

ACIL Allen Consulting (ACIL Allen) has been appointed by Energy Queensland to review the forecasting methodologies of Ergon Energy and Energex with respect to system maximum demand and energy delivered. This review will assist Energy Queensland in the preparation of its submission to the AER (Australian Energy Regulator) covering the regulatory period from 1 July 2020 to 30 June 2025.

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  - Accuracy and unbiasedness
  - Incorporation of key drivers
  - Model validation and testing
  - Use of most recent and consistent inputs into the forecasting process
  - Any other attributes considered important
- Reviewed the various approaches used in forecasting maximum demand with an analysis of the strengths and weaknesses of the various approaches
- Assessed the appropriateness of the key inputs and drivers including:
  - Demographic, economic, weather and calendar variables
  - Electric vehicles, PV and battery storage post model adjustments
- Evaluated and assessed the model logic and structure and whether the resulting forecasts are reasonable
- Recommended improvements to the forecasting methodologies
- Demonstrated the value and materiality of the recommendations with supporting analysis and data

We recognise that there are differences in the forecasting methodologies between Energex and Ergon and that these differences have been accounted for in the review.

1.2 ACIL Allen's approach to the review

In consultation with Energy Queensland, ACIL Allen has adopted a higher level approach to reviewing the forecasting methodologies and procedures. Rather than focussing on the lower level details, ACIL Allen has evaluated the forecasts and associated methodologies against the AERs view of what constitutes forecasting best practice.

ACIL Allen interviewed the key personnel within Energy Queensland responsible for producing the system maximum demand and energy forecasts. From these interviews we were able to gain a good overall understanding of the methodologies and procedures employed, and were able to seek clarification on any questions that arose in the course of the review.

ACIL Allen was provided with a number of files and spreadsheets to be reviewed. These included spreadsheet files of Energex's and Ergon's base energy and system maximum demand models. Moreover, we were provided with several documents describing the methodology and process of model selection and validation from both the Energex and Ergon for both system maximum demand and energy.

ACIL Allen was also provided with access to several previous reviews of Energex's maximum demand and energy conducted Frontier Economics, as well as a number of previous reviews performed by ACIL Allen's predecessor firm, ACIL Tasman.

1.3 Structure of this report

This report as structured as follows:

— Section 2 describes the AERs principles of best practice forecasting
— Section 3 reviews Ergon Energy's approach to energy delivered
— Section 4 reviews Energex's approach to energy delivered
— Section 5 reviews Ergon Energy's approach to system maximum demand
— Section 6 reviews Energex's approach to system maximum demand

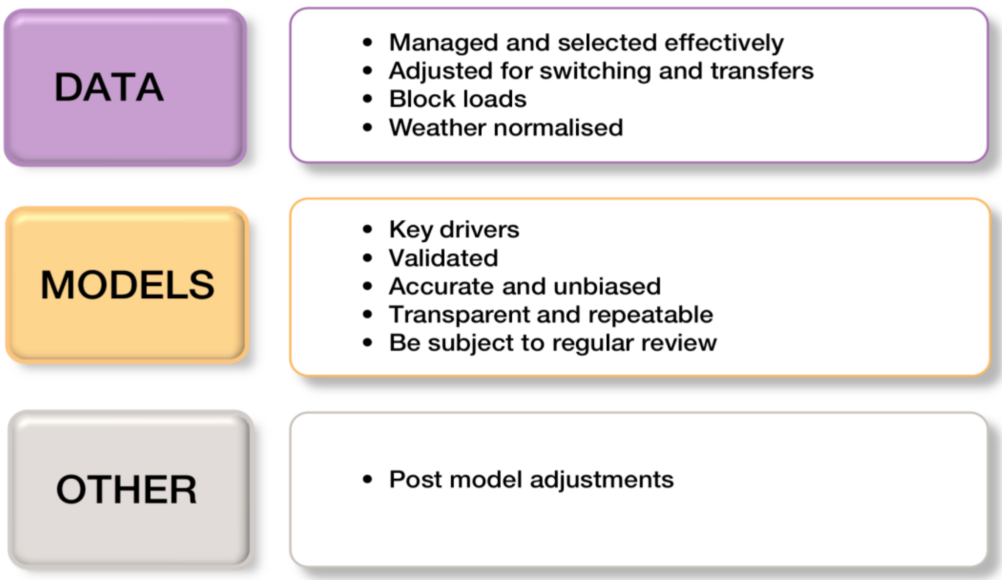
2 BEST PRACTICE FORECASTING

2.1 Attributes of a best practice methodology

In November 2013, the Australian Energy Regulator (AER) in its 'Better Regulation Explanatory Statement- Expenditure Forecast Assessment Guideline' set out the main principles of best practice demand forecasting. These were essentially a reproduction of the principles put forward by ACIL Allen in its report to the Australian Energy Market Operator (AEMO) entitled "Connection Point Forecasting- a nationally consistent methodology for forecasting maximum electricity demand"[5]

These principles are presented in **Figure 2.1** and described in more detail in the section that follows.

FIGURE 2.1 BEST PRACTICE FORECASTING PRINCIPLES



SOURCE: ACIL ALLEN CONSULTING

5 Available from http://www.aemo.com.au/Electricity/Planning/Forecasting/AEMO-Transmission-Connection-Point-Forecasting

2.2 Incorporating key drivers

The forecasting methodology should incorporate the key drivers of maximum demand and energy, either directly or indirectly. These may include[6]:

1. Economic growth
2. Electricity price
3. Population growth and/ or growth in the number of households
4. Temperature, humidity and rainfall/wind data
5. Any seasonal and calendar effects
6. Growth in the number of air conditioning systems
7. Growth in the number of heating systems
8. Growth and change in usage of key appliances and other relevant technological changes
9. Uptake and impact of Electric vehicles
10. Uptake and impact of battery storage systems
11. Uptake and impact of rooftop PV systems

2.3 Weather normalisation

Electricity demand is well known to be sensitive to weather. The stochastic nature of weather means that any comparison of historical demand is only meaningful if the historical data are adjusted to standardised weather conditions. If this is not done, the analysis becomes, at least partly, an analysis of historical weather rather than electricity demand.

Another issue is that electricity demand forecasts prepared for regulatory purposes are not intended to forecast what electricity demand will be in any given year. Rather, they are intended to forecast what demand *would be* under normal weather conditions. This cannot be estimated without accounting for the impact of weather on historical data appropriately.

For these reasons, any electricity demand forecasting methodology should incorporate weather normalisation, both within the system maximum demand and energy forecasting models.

In modelling system demand, only weather conditions on a single or a very small number of days are relevant in driving the peaks. However, for energy sales a single hot or cold day will make only a small contribution to energy sales over a whole year. Therefore, any measure of weather that attempts to explain energy sales needs to capture the degree to which the summer and winter seasons have been hot or cold on average rather than on a single or small number of days.

This is often done by introducing the concept of heating degree and cooling degree days. These measures capture not only the number of cold or hot days within a given year, but also their extent.

For heating degree days (HDD), the measure works by summing up the total number of degrees Celsius over the year, where the temperature was below some threshold. On days where the temperature is above the threshold, that day contributes zero to the number of heating degree days. Heating degree days therefore capture the extent to which a given season was cold on average.

Cooling degree days (CDD) measure the extent to which a given year experienced hot weather conditions on average. It is defined in precisely the opposite way from heating degree days. CDD is defined as the sum of all the degrees over an entire year where the temperature exceeded some threshold. Days which have a temperature below the threshold contribute zero to the total number of cooling degree days. The most appropriate threshold to use in the calculation of HDD and CDD is usually determined through a process of empirical testing, with those threshold levels providing greater explanatory power in the estimated models being preferred over those providing less explanatory power.

6 This is a list of drivers that may be applicable, but it does not necessarily follow that the ideal forecasting methodology will automatically incorporate all of these drivers. Whether individual drivers should be used in a given forecasting methodology is partly an empirical question and depends on data availability.

2.4 Accuracy and unbiasedness

All forecasting models will include errors by nature of the fact that they are an approximation of the real world. Those errors will limit the model's accuracy. Nonetheless, any credible forecasting methodology must produce forecasts that are reasonably accurate and whose accuracy can be measured objectively.

Assessing a model's accuracy should include both in-sample and out-of-sample tests. Poor performance on these tests could typically be traced to shortcomings in the modelling approach or to deficiencies in the data used. Whichever is the case, these should be addressed until the model performs satisfactorily.

Similarly, models should be free of bias, meaning that they should be no more likely to produce high than low forecasts. An unbiased forecast is one which does not consistently over or under-predict the actual outcomes the methodology is trying to forecast. Forecasting bias can be avoided or at least minimised by careful data management (e.g. removal of outliers, data normalisation etc.) and forecasting model construction (choosing a parsimonious model which is based on sound theoretical grounds and which closely fits the sample data).

In the event that a forecasting methodology consistently results in biased forecasts, it may be possible to adjust the forecasts by the amount of the estimated bias to remove the bias from the forecasts.

2.5 Transparency and repeatability

A transparent forecasting process is one that is easily understood and well documented and, if it was repeated by another forecaster, would produce the same result. It is generally incumbent on a forecaster who intends that their forecasts be used for regulatory or similar purposes to be able and willing to explain how they were prepared and the assumptions that were made in preparing them.

Forecasting electricity demand will inherently include subjective elements, exposing it to the judgement of individual forecasters. This is not inappropriate and 'judgement' should not be considered a less robust forecast method in this context.

However, the use of judgement increases the importance of transparency. In cases where judgement is used, those judgements should be documented and reasons explained, either as a process or individually.

To achieve this any documentation needs to set out and describe clearly the data inputs used in the process, the sources from which the data are obtained, the length of time series used, and details of how the data used in the methodology are adjusted and transformed before use.

The functional form of any specified models also need to be clearly described, including:

- The variables used in the model
- The number of years of data used in the estimation process
- The estimated coefficients from the model used to derive the forecasts
- Detailed description of any thresholds or cut-offs applied to the data inputs
- Details of the forecast assumptions used to generate the forecasts

The process should clearly describe the methods used to validate and select one model over any others. Any judgements applied throughout the process need to be documented and justified. Adjustments to forecasts that are outside of the formal modelling process that are not documented with a clear rationale justifying that course of action should be avoided.

The methodology should be systematic so that any third party that follows a series of prescribed steps will be able to replicate the results of the forecasting methodology.

2.6 Estimated models should be validated

Models derived and used as part of any forecasting process need to be validated and tested. This is done in a number of ways:

— Assessment of the statistical significance of explanatory variables
  – One of the key issues concerning statistical significance that is generally poorly understood is that a statistically significant result does not necessarily imply that the inclusion of a particular variable will have a sizeable impact on the model outcomes. Often in large sample sizes, statistically significant results are identified which are of little of no economic consequence.
— Theoretical coherence of the size and sign of the estimated model coefficients
— In sample forecasting performance of the model against actual data (goodness of fit)
— Diagnostic checking of the model residuals
  – The residuals are the differences between the actual value of each observation and its fitted value and are derived from the in-sample forecasts above. A valid model should produce residuals that do not exhibit patterns or trends and the expected value of the residuals should equal zero.
— Out of sample forecast performance

These should be done after forecasts are prepared and an attitude of continuous improvement should be applied to the forecasting methodology.

2.7 Effective management and selection of data

The forecasting methodology requires effective management of data used in the process. This means keeping a central repository of all the data series used in the forecasting methodology in one or more electronic databases. The importance of the data collected implies that these databases need to be developed such that the management and collection of data is auditable and has integrity.

Ideally a number of electronic databases would be constructed which would split the data into categories depending on the type of data involved (for example demographic, economic, demand and temperature data) and the extent to which it has been processed.

Selection of which data series to use will depend on factors such as their:

— Reliability and accuracy
— The reputation of the data source
— The degree of completeness of the data and the absence of significant gaps
— The consistency of the data series through time
— The extent to which they cover a sufficiently long time series

2.8 Use of the most recent information

Maximum demand and energy forecasts should use the most recent input information available to derive the forecast. As new information becomes available it should be incorporated into the forecasts.

2.9 Regular review

The forecasting process should be subjected to review on a regular basis to ensure that the data inputs have been collected and utilised adequately and that the applied methodology meets the above principles.

The review should also focus on forecast performance and consider the possible causes of any divergence of observed maximum demand and energy from the forecasts. The causes of the divergence could relate to factors such as differences between forecasts of the explanatory variables and the actual levels observed, or could be due to structural issues with the way the models are constructed.

3 ENERGY DELIVERED - ERGON ENERGY

3.1 Previous reviews of Ergon Energy energy delivered and customer numbers forecasting

Ergon Energy's energy delivered and customer numbers forecasting methodologies have been subject to a number of reviews, the first of which dates back to 2009[7]. This section details the major findings of these reviews and outlines how Ergon's methodology has changed over time to meet the requirements and recommendations of these reviews.

In 2009, ACIL Allen's predecessor firm, ACIL Allen, was appointed jointly by Energex and Ergon Energy to review the DNSPs existing energy and system maximum demand forecasting methodologies, as well as propose recommendations and a set of guidelines for the development of a consistent methodology across both businesses.

In 2009, Ergon's approach to forecasting energy and customer numbers could be described as a combination of trend analysis and the application of local area knowledge and expertise. The forecasts were split by different tariff classes and customer segments. Trend based forecasts for total customer numbers and total energy usage per segment were obtained for three separate regions, West, East and Mt Isa.

In its review of the methodology, ACIL Tasman considered that the trend based approach was reasonable for short run growth, but that in the long run, the key drivers of energy delivered were likely to change over time and result in significant changes from the short term trend.

ACIL Tasman suggested the adoption of a multiple regression approach, with the analysis split by customer segment. The forecasts would be based on estimates relating energy delivered to its main drivers, such as Queensland GSP and population growth.

In April 2010, ACIL Tasman produced a set of System Energy guidelines.[8] These guidelines introduced a set of best practice forecasting principles, and they were subsequently introduced to and adopted by the AER. The suggested model specifications for energy delivered and customer numbers formed the basis of Ergon Energy's current approach to forecasting energy and customer numbers. These guidelines introduced a top down econometric approach which incorporated the key drivers of energy delivered:

— Population growth, household formation
— Economic Growth
— Growth in the number of air conditioning systems

[7] Common Network Demand and Energy Forecasting, Prepared for Energex and Ergon Energy December 2009.
[8] System Energy Forecast Models and Guidelines, Common Forecasting Methodology, Prepared for Energex and Ergon Energy, April 2010.

— Weather drivers

The guidelines also stressed the importance of statistical methods of model validation such as model fit, statistical significance and the out of sample forecasting performance of the models.

3.2 Ergon Energy current approach to energy forecasting

Following the previous independent reviews, Ergon Energy has adopted a multiple regression approach to forecasting system energy delivered and customer numbers within its distribution network.

The multiple regression approach estimates the historical relationship between energy delivered and customer numbers and their drivers. Forecasts of the individual drivers are used in conjunction with the estimated models to generate the forecasts.

The forecasts are produced by the main customer classes:

— Domestic
— Commercial
— Industrial
— Rural

The forecasts are produced separately across Ergon's six regions:

— Capricornia
— Far North Queensland
— Mackay
— North Queensland
— South West
— Wide Bay

The models provided are all calibrated using quarterly data dating from the September quarter of 2009 to December 2015. In our view, Ergon's current approach of splitting its forecasts into four customer classes and across its six regions is a reasonable one. The relationship between energy delivered and its main economic, demographic and weather drivers will differ across each of the major customer classes. By splitting the data into separate customer classes, Ergon is able to better capture the characteristics of each customer class. Moreover, the behaviour of energy consumption across each of Ergon's six region is also likely to differ. Ergon's network is very large with divergent characteristics.

The main advantage of the econometric approach is that it allows the forecaster to incorporate their view about the future course of the drivers and their impact on the variable of interest. This is the main advantage of the econometric approach over less sophisticated methods like trend analysis which assumes that the historical relationship between energy delivered and its key drivers remains constant into the future. This approach may be acceptable if the environment in which the forecasts are constructed are stable or if it is not possible to establish meaningful statistical relationships.

3.2.1 Domestic models

In the case of the domestic sector, Ergon estimate two separate econometric models, one for customer numbers and one for average consumption per household.

The base model specification for the number of domestic customers is as follows:

$$Residential\ customers = \alpha + \beta_1 \times Population + \varepsilon$$

In the case of the customer model for Capricornia an additional dummy variable is included to capture a discontinuity in the time series in the second quarter of 2013.

Energy use per residential household is assumed to be driven by a time trend (incorporated to capture a large number of factors such as increasing efficiency, increasing energy prices, increasing solar PV and so on), weather effects as measured by cooling degree and heating degree days and three quarterly seasonal dummies.

The potential impact of hot weather in summer and cold weather in winter is measured by the CDD and HDD respectively.

$$\text{Energy per household}=\alpha+\beta_1\times\text{Time}+\beta_2\times\text{CDD}+\beta_3\times\text{HDD}+\varepsilon$$

Heating degree days where found to be significant only in the southern parts of the Ergon network, specifically in Wide Bay and the South West. This is not surprising as these regions experience colder conditions during the winter months, while the more northern parts of the network do not.

Total domestic energy delivered is therefore calculated as:

$$\text{Total energy}=\text{Energy per household}\times\text{No: of customers}$$

3.2.2 Commercial models

The model specification for the number of commercial customers is as follows:

$$Commercial\ customers=\alpha+\beta_1\times GSP+\varepsilon$$

An additional dummy variable for 2013 was included in the Capricornia, Far North and South West model to account for a one off discontinuity in the customer numbers time series in the second quarter of 2013.

The model used for forecasting average consumption per customer is:

$$\text{Energy per customer }=\alpha+\beta_1\times\text{Time}+\beta_2\times\text{CDD}+\varepsilon$$

In the case of the average energy use per customer model, seasonal dummies are included in the specification to capture seasonal variation in commercial energy delivered. Also, only the CDD weather variable is included in the models as a driver. The HDD variable was not found to add significantly to the explanatory power of the models.

3.2.3 Industrial models

The industrial sector of the Ergon network is largely driven by a small number of large customers. For this reason, it is difficult to formulate a viable econometrically driven model of industrial energy delivered. It is, in our view, better to build the industrial forecast up from the careful surveying of large customers.

In the absence of bottom up information, simple models using time trends to extrapolate both industrial energy delivered and customer numbers are used.

$$\text{Total Energy}=\alpha+\beta_1\times\text{Time}+\varepsilon$$

While no seasonal dummy was included for Capricornia and Mackay, the models for Far North, North and South West include a single dummy for the third quarter, and Wide Bay includes a dummy for both the second and third quarters.

Industrial customer numbers are modelled as a simple time trend. No seasonal effects were evident.

$$\text{Customer numbers}=\alpha+\beta_1\times\text{Time}+\varepsilon$$

3.2.4 Rural models

Total rural energy delivered is modelled as a linear function of a constant and a one quarter lag of rainfall.

$$\text{Total Energy}=\alpha+\beta_1\times\text{ Rainfall(-1)}+\varepsilon$$

The analysis could not detect any underlying trend in total rural volume, however there was a strong cyclical element driven by seasonality and by recent rainfall.

In the case of the North region, no seasonal dummy is included in the model, while Capricornia, Mackay and Far North displayed significant seasonal impacts in the third quarter of each year.

For South West, seasonal dummies for the first and second quarters were included in the model, while for Wide Bay, seasonal dummies were added for the first and third quarters.

Rural customer numbers are modelled as a simple time trend. No seasonal effects were evident.

$$\text{Customer numbers} = \alpha + \beta_1 \times \text{Time} + \varepsilon$$

3.2.5 Treatment of weather factors

The model assigns a specific weather station to each region within the Ergon network. This station is chosen according to a number of criteria:

— Proximity to major population centres in each region
— Sufficient time series length
— Quality of data, namely relatively few missing observations

The assigned weather stations are shown in **Table 3.1** below.

TABLE 3.1 WEATHER STATIONS ASSIGNED TO EACH REGION WITHIN ERGON NETWORK

Region	CDD/HDD	Rainfall
Capricornia	Rockhampton Aero (39083)	Rockhampton Aero (39083)
Far North Queensland	Cairns Aero (31011)	Cairns Aero
Mackay	Mackay MO (33119)	Mackay MO (33119)
North Queensland	Townsville Aero (32040)	Townsville Aero (32040)
South West	Amberley AMO (40004)	Oakey Aero (41359)
Wide Bay	Maryborough (40126)	Oakey Aero (41359)

SOURCE: BUREAU OF METEOROLOGY

The time series used dates back to the first quarter of 1965 for all weather stations, except Oakey whose time series commences from the third quarter of 1970.

Data used in the models is daily maximum and minimum which is used to derive the number of cooling degree days (CDD18) heating degree days (HDD18) for each year. Rainfall is also used in the model which determines the total irrigation energy consumption.

The CDD, HDD and rainfall data enter the model on a quarterly basis.

HDD is a measure designed to reflect the amount of energy required to heat a home or business, while the CDD is designed to reflect how much energy is required to cool a home or business.

The number of HDD in a given year is simply the sum of the difference between some measure of ambient room temperature which we define as 18 degrees Celsius and the average daily temperature on each day. Any given day makes a contribution to the total number of heating degree days only if the average temperature on that day is below 18 degrees. For example, if the average temperature today is 10 degrees Celsius, then the number of heating degree days contributed to the annual total from that day is 8 (e.g. 18-10).

If the average temperature exceeds 18 on a given day then that day contributes zero to the total number of heating degree days for the year. The higher the number of HDD for a given year, the colder that year is.

In the case of cooling degree days the concept is the same, but the formula takes the sum of degrees that exceed some benchmark (in our case 18 degrees Celsius) for each day. It is therefore an indication of how hot a given year is, with a higher number of CDD reflecting a hotter season.

Annual rainfall is expected to be a significant determinant of energy delivered for the rural customer class. Periods of below average rainfall are expected to correspond to an increased need to irrigate crops resulting in higher energy consumption. Conversely, in periods of above average rainfall, the need to irrigate crops is reduced and hence energy consumption associated with pumping to supply irrigation is also reduced.

3.2.6 Post model adjustments

Ergon Energy in its latest energy models does not make any post model adjustments to its base forecasts for the uptake of rooftop PV. By doing this, Ergon makes an implicit assumption that (ceteris paribus) rooftop PV uptake will continue to exhibit the same behaviour in the forecast period as it has in the past. The inclusion of scenarios for electric vehicles and battery storage provides alternative forecasts with a range of underlying assumptions for uptake. The use of scenarios help to maintain the robustness of the forecasts.

3.3 Assessment of Ergon's approach to energy forecasting

3.3.1 Suitability of econometric models

Sample size

When originally developed in 2013-14, Ergon Energy's energy delivered and customer numbers regressions were calibrated using quarterly data from September 2009 to June 2013, a total of just 16 observations. This was an IT systems related constraint, with customer and tariff level data being unavailable for the Ergon network prior to the third quarter of 2009.

Given such a small sample size, there is a considerable degree of uncertainty regarding the value and stability of the estimated regression coefficients. If the underlying data is normally distributed, then there is a common rule of thumb that approximately 30 observations are required to adequately characterise the true underlying data generating process.

In the set of forecasts provided, Ergon Energy has recalibrated the models using data to the end of the fourth quarter of 2015, an additional 10 observations, bringing the total observations to 26. This is a significant relative improvement in the sample size and is closer to the minimum level required to obtain reliable parameter estimates. Given that we are now into the second quarter of 2018, an additional 10 observations could be added to the sample size were the models to be re-estimated with the most up to date data. This would bring the total sample size to 36 and give us considerably more comfort about the reliability of the models to generate longer term energy forecasts.

Given the significant increase in the sample size, ACIL Allen recommends that the choice of explanatory variables in the base regression models should be re-examined and re-assessed. It is likely that some economically meaningful variables such as price, which were originally left out of the estimated models because the small sample size resulted in statistically insignificant coefficient values, can be re-evaluated with the larger data sets which are now available.

3.3.2 Inclusion of main drivers

Ergon Energy has included the main drivers of energy volumes and customer numbers into their models where the estimated coefficients were reliable, statistically significant and of the right sign. In the case of domestic and commercial customer numbers, the main drivers in the econometric models are population and GSP respectively. In our view, both of these are reasonable choices.

In the case of domestic energy volumes per customer, the main drivers are a time trend as well as quarterly seasonal dummy variables to capture seasonal variation in energy delivered. Where a significant relationship was able to be established, cooling degree days (CDD) and or heating degree days (HDD) were also added to the regressions. This was done for North Queensland, South West and Wide Bay. In the case of Capricornia, Mackay and Far North Queensland, no weather related variables were included in the regression, although the presence of the seasonal dummies would incorporate the impact of changing weather conditions to some degree.

The time trend in the domestic volume per customer regressions tends to be negative, mostly reflecting the impact of higher electricity prices and more rooftop PV systems being installed in the network. The extrapolation of the time trend therefore points to a continuation of the historical trend in rooftop PV systems and price rises, something which may change in the future.

The use of the time trend in per customer regression captures a number of factors such as rising household income or GSP, the uptake of PV or responses to price increases. It would be better if we could establish an econometric specification that includes each of these drivers separately, rather than lumped together inside a time trend. However, an important step to disaggregating each of these drivers is to strip out the impact of rooftop PV from the historical data before the domestic component of the models are estimated. By doing this first, it may be possible to identify a meaningful relationship between GSP/Income and electricity price and energy use per customer.

In the case of commercial volumes per customer, time trends, seasonal quarterly dummy variables and cooling degree days (CDD) (except for Capricornia) were used.

Price is not included as a separate variable in the model regressions. When the econometric models were originally calibrated, the price variable did not enter the models with the right sign or magnitude, leading to price being handled outside of the model through the application of a separate price elasticities of demand. In the latest set of forecasts, Ergon Energy does not assume any change in the real price of electricity going forward. This means that there is no adjustment required to the forecasts for price.

This result was not surprising given the small sample size that was available to calibrate the models. In our view, it may be appropriate to re-test the real price of electricity as a potential explanatory variable given the now expanded sample size. In fact, this should be done with all the underlying econometric models driving the forecasts.

3.3.3 Approach to model validation

Ergon Energy adopts three methods to model validation, namely assessing:

— The goodness of fit of the regression
— Theoretical justification of coefficients
— The statistical significance of the explanatory variables
— Consideration of the model residuals for any patterns or signs of autocorrelation

Theoretical basis

The choice of model parameters is based on theoretical considerations of key drivers to explain the measured variation in energy delivered. As a consequence, some sense of the likely size and direction of model coefficients is possible.

Where variables produced coefficient signs that were contrary to those expected by economic theory, they were discarded from the models.

Goodness of fit

The most commonly used measure of the goodness of fit of the regression model to the observed data is R^2. In the model validation process, the R^2 is considered as part of a suite of tools available. Emphasis is placed on the overall fit of the models as well as on the statistical significance of individual explanatory variables.

The goodness of fit of an estimated regression as measured by the R^2 provides an indication of how well the explanatory variables explain the variation in the dependent variable. A higher value for R^2 indicates that more of the historical variation in the dependent variable is explained by the main drivers included in the model.

Table 3.2 presents the model R^2's of each of the separate regressions estimated within Ergon's energy model. The table shows that there is a wide variation in the goodness of fit across the various models. First, it can be seen that better model fits can be obtained from the commercial and domestic models rather than the industrial or rural models. This is not surprising as the industrial and rural sectors tend to be more heterogeneous and driven by a more diverse array of factors which are not easily captured in the model.

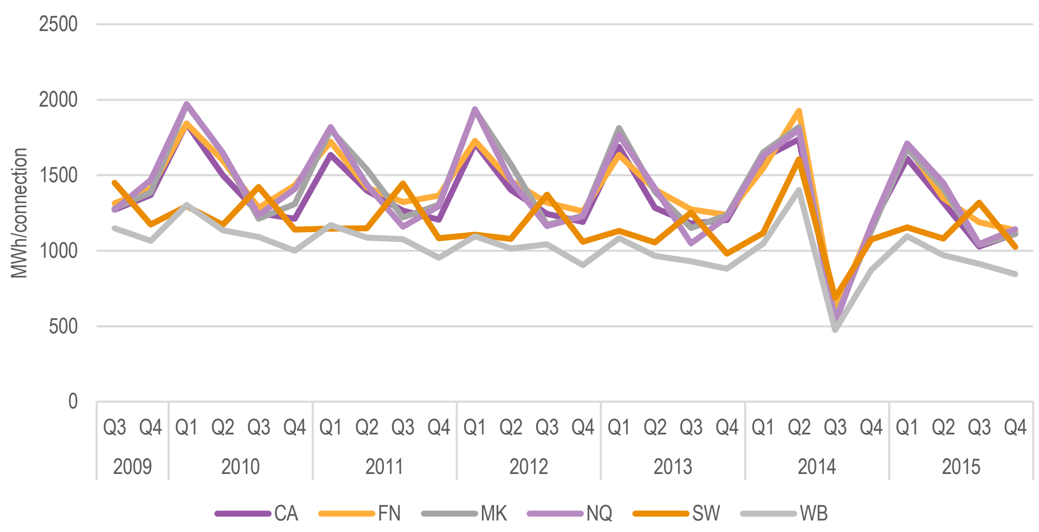
TABLE 3.2 MODEL R^2 BY CUSTOMER SEGMENT AND REGION

Region	Commercial (MWh/cust)	Domestic (MWh/cust)	Commercial customers	Domestic customers	Industrial (total)	Rural (total)
Capricornia	84.2%	75.8%	51.4%	93.4%	30.4%	50.1%
Far North	76.0%	66.1%	60.1%	92.2%	30.1%	43.2%
Mackay	87.4%	84.5%	72.8%	96.0%	72.7%	46.1%
North Queensland	73.3%	84.4%	66.0%	90.1%	83.4%	47.5%
South West	59.8%	32.4%	93.9%	98.5%	3.7%	45.7%
Wide Bay	63.9%	50.5%	37.3%	95.7%	35.5%	29.0%
Average	**74.1%**	**65.6%**	**63.6%**	**94.3%**	**42.6%**	**43.6%**

SOURCE: ERGON ENERGY

Further examination of the data also indicated that there is a possible outlier observation in the domestic energy segment. **Figure 3.1** shows the domestic energy use per customer across each of Ergon's six regions from 2009 to 2015. It appears that there is a major decline in energy use per customer in the 3rd quarter of 2014 that lies outside the bounds of plausibility relative to the rest of the values observed across the time period. It appears that the 3rd quarter of 2014 is an outlier, whose influence needs to be removed from the estimated models or accounted for in some other way.

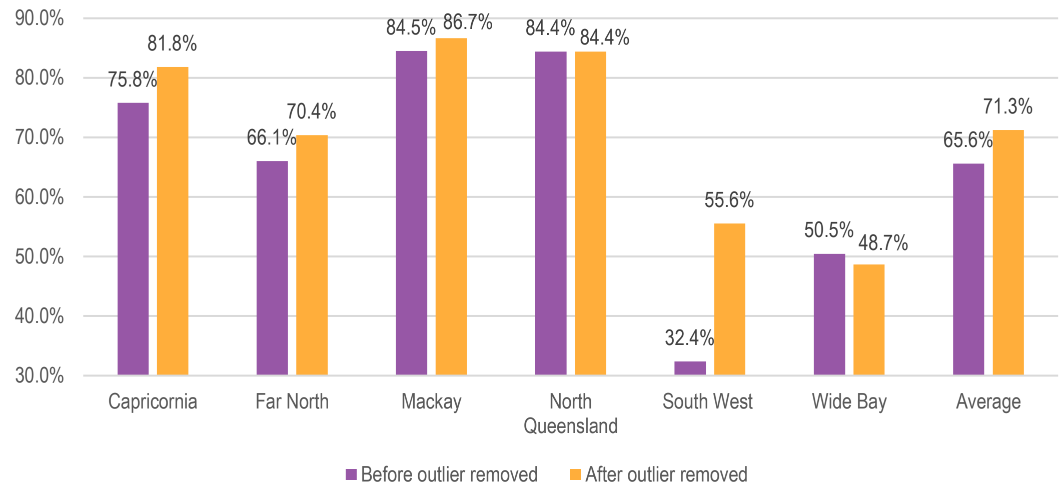
FIGURE 3.1 DOMESTIC ENERGY USE PER CUSTOMER, Q3 2009 TO Q4 2015 BY REGION



SOURCE: ERGON ENERGY

When we remove the influence of the suspicious data point we observe a significant increase in the R^2 of the domestic energy use per customer models (see **Figure 3.2**). This is particularly the case for the Wide Bay region, whose model R^2 increased from 32.4% to 55.6%. The average R^2 across all the regions increased from 65.6% to 71.3% when the influence of the outlier is removed.

FIGURE 3.2 DOMESTIC ENERGY MODEL R^2 BEFORE AND AFTER OULIER REMOVAL



SOURCE: ERGON ENERGY

Statistical Significance

Because of the relatively small sample size, achieving statistical significance for all variables was not always possible. Ergon Energy's approach was to allow the inclusion of some statistically insignificant variables if the estimated coefficients were reasonable and did not diverge significantly from expectations set through other empirical studies and economic theory.

Up until now, the use of formal statistical testing in Ergon's energy delivered methodology has been limited due to the small sample size available for the model estimation. In this situation, many formal statistical tests lack power and the probability of the test reaching an erroneous conclusion is high. Despite this limitation, we consider that Ergon Energy has made appropriate use of formal statistical tests to assist in model specification, however, where appropriate, Ergon has opted to over-ride some of the test results. Where supported by economic theory we consider that this is an appropriate course of action, given the limited sample size.

The problem of small sample size should be mitigated over time as additional data is added to the historical data set driving the models.

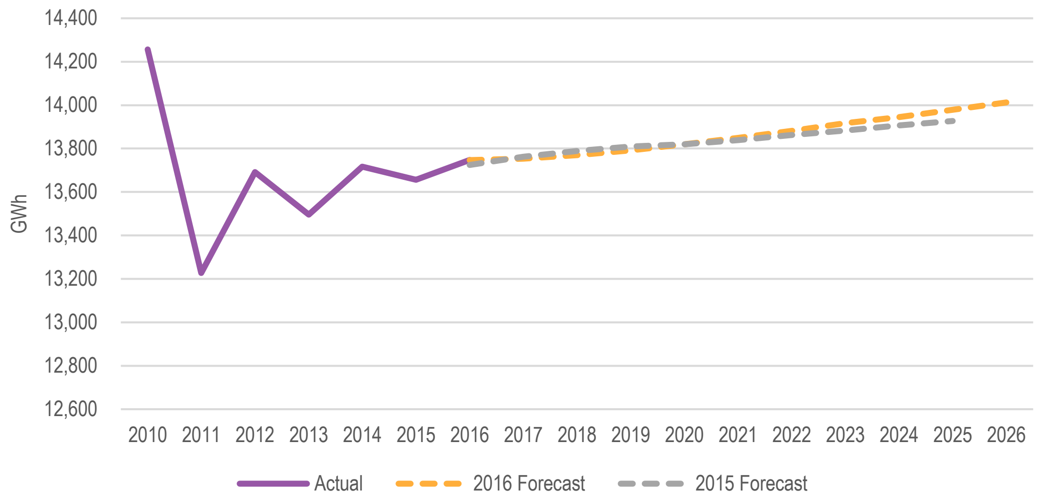
3.3.4 Reasonableness of the forecasts

One of the first and simplest methods the AER will use to assess the energy and maximum demand forecasts submitted by a DNSP is to compare the submitted forecasts against the historical behaviour of the series of interest. The main focus is to compare the projected growth rates against those observed historically to identify any discontinuities or unusual changes in trajectory which have not been explained by changes in main drivers or some other underlying factor.

Figure 3.3 presents Ergon Energy's energy delivered forecasts (produced in 2015 and 2016), as well as the historical series from 2010 to 2016.

Ergon's 2016 forecast for the next 10 years shows a very modest rate of growth of 0.19% per annum. This is consistent with very low historical growth over the last five years within the Ergon Energy network. In this sense, we consider that the energy forecasts produced by Ergon are reasonable and consistent with the historical behaviour of the network.

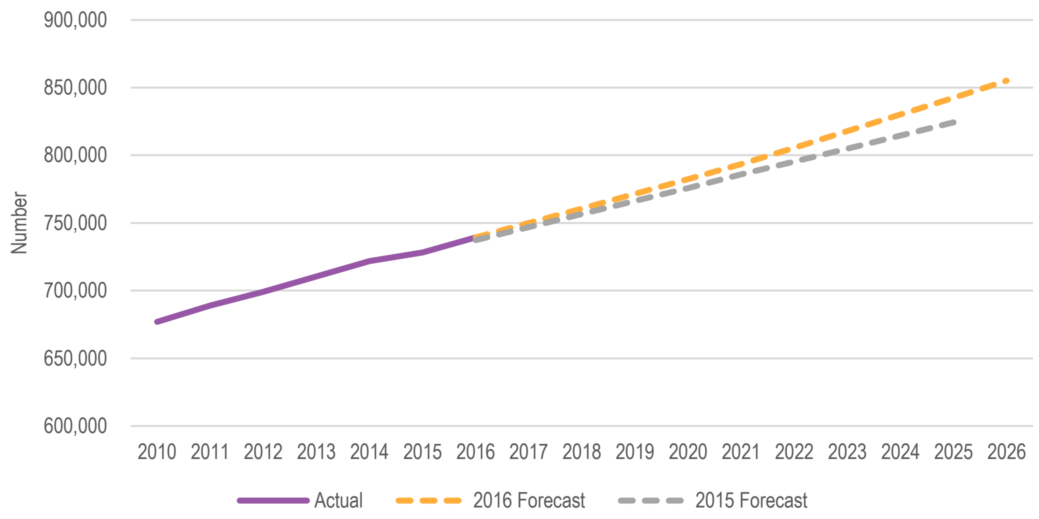
FIGURE 3.3 ENERGY DELIVERED, HISTORICAL AND FORECAST



SOURCE: ERGON ENERGY

In the case of customer numbers, Ergon's 2016 projection is for a rate of growth of 1.47% over the 10 years to 2026. This compares to an average annual rate of growth of 1.48% from 2010 onwards. In our view, it is reasonable to expect that customer numbers continue to grow in line with recent history.

FIGURE 3.4 CUSTOMER NUMBERS, HISTORICAL AND FORECAST



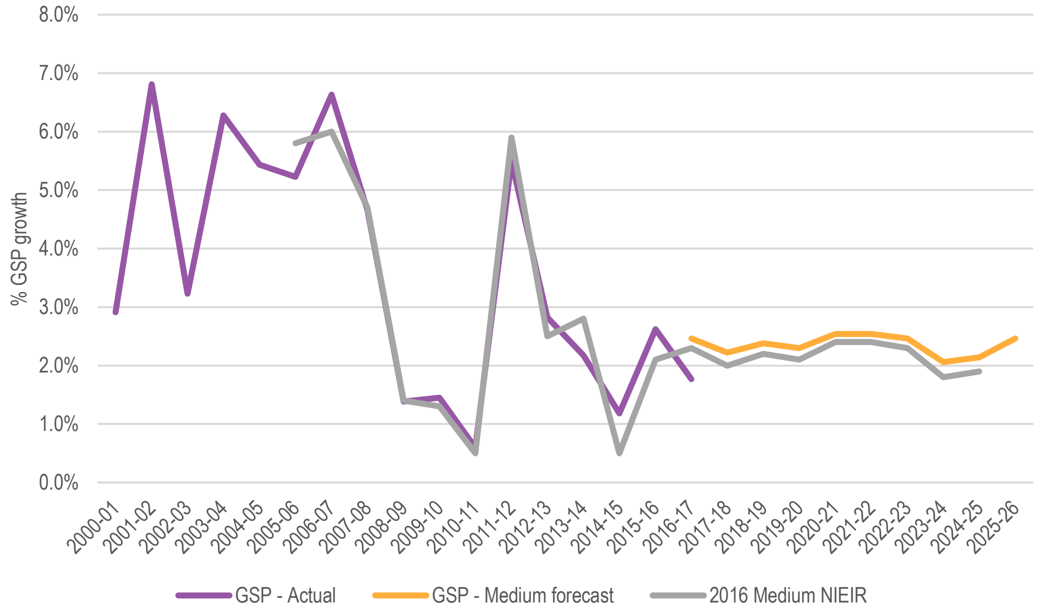
SOURCE: ERGON ENERGY

3.3.5 Assessment of key inputs

Gross State Product

A key input into Ergon's energy models is Queensland GSP. **Figure 3.5** shows Ergon's medium scenario GSP growth forecast against the historical rate of growth as well as NIEIRs 2016 set of GSP growth forecasts. It can be seen that Ergon is projecting an average annual rate of growth in GSP of 2.4% over the forecast horizon. This is slightly above the 5 year historical average of 2.1%, and in line with the 10 year historical average of 2.4% per annum. In our view, Ergon has taken a reasonable and conservative approach to forecasting GSP growth.

FIGURE 3.5 ERGON ENERGY GSP MEDIUM FORECASTS VERSUS ACTUAL



SOURCE: ERGON ENERGY

Population

Ergon Energy utilises estimated resident population data by LGA obtained from Queensland Treasury's Office of Economic and Statistical Research (OESR) to construct its regional population series. The OESR also provides forecasts of regional Queensland population growth. ACIL Allen considers that these forecasts are fit for purpose to be applied within Ergon Energy's forecasting models.

Weather inputs

Ergon Energy calculates quarterly HDD and CDD values for inclusion into the energy regressions. As mentioned previously, data from six regional weather stations is utilised for this purpose:

— Cairns
— Townsville
— Mackay
— Amberley
— Rockhampton
— Maryborough

These weather stations were chosen because they correlated best with energy variation in each of Ergon's six regions and they also closely matched the main population centres across Ergon's distribution network. ACIL Allen considers that these weather stations are suitable for use within Ergon's energy models. However, we did observe that the long run CDD and HDD values that were used to apply within the forecast period were calculated on weather data that ceased at the end of the second quarter of 2013. It is our view that the CDD and HDD values should be updated to include all the available data.

3.3.6 Accuracy and bias

In this section we analyse Ergon Energy's 2016 energy delivered and customer numbers forecasts against the observed energy delivered in 2015-16, the first year of the forecast period. Given the long forecasting horizon that is estimated and the relative newness of the forecasting methodology, it is not possible to evaluate the accuracy of the forecasts beyond only a single year.

Table 3.3 shows the 2016 actual against the forecast for that year made in 2015. The table also shows the error measured as both a quantity and percentage. It can be seen that the Ergon forecasts were remarkably accurate over a 1 year horizon. While this is a good sign, we are unable to make any concrete judgements on the performance of the forecasting models over the longer term, which is of greater importance. Nevertheless, we cannot draw any negative conclusions on the accuracy of the forecasts based on this somewhat limited evidence.

TABLE 3.3 COMPARISON OF ACTUALS WITH ERGON FORECASTS

	2016 Actual	2016 Forecast (in 2015)	Error (Qty)	Error (%)
Energy	13,747	13,725	-23	-0.17%
Customer numbers	739,354	737,329	-2,024	-0.27%

SOURCE: ERGON ENERGY AND ACIL ALLEN CONSULTING

3.3.7 Transparency and repeatability

In our view Ergon Energy has taken a very transparent approach to forecasting energy delivered. The forecasting model is self- contained with a clear separation of the model inputs, calculations and outputs. The model contains formulas, rather than hard coded numbers, and where inputs do enter the calculations as hard-coded numbers they are clearly labelled and the data source is well identified. The energy model has a detailed and comprehensive manual, outlining:

- The modelling approach and model structure
- The model inputs and data sources, including:
  - Energy delivered and customer numbers data
  - Economic and demographic data (both historical and forecast)
  - Weather data
  - Electricity prices
- Detail on each regression model specification estimated
- The approach adopted to validate the models
- Quarterly and annual forecast outputs by region and customer class
- Details on how to conduct scenario analysis

The Excel based model follows a logical structure and can be followed easily by someone with intermediate level spread sheeting skills. The transparent and logical structure of Ergon's spreadsheet and associated documentation means that it is not difficult to replicate Ergon's results if necessary. It is ACIL Allen's view therefore, that Ergon's forecasting process satisfies the AER's requirements for transparency and repeatability.

3.3.8 Post model adjustments

Rooftop PV and battery storage

Ergon Energy has not made any adjustment for the uptake of rooftop PV systems in its most recent domestic forecasts. By not making any explicit adjustment for rooftop PV, Ergon Energy is implicitly assuming that the impact of rooftop PV will on average be similar in the future to that observed in the past. While this assumption might be appropriate under certain conditions, such as under high degree of stability, it is our view that this assumption may no longer be valid for a number of reasons:

1. The historical period includes a period of very rapid relative uptake which has now slowed considerably and is unlikely to be repeated again.
2. The historical uptake demonstrates a highly non-linear pattern, with an initial period of very slow growth followed by a rapid ramp up, before the commencement of a period of slower but quite solid growth. The econometric models being linear by construction, will incorporate the average effect of rooftop PV, which may not be reflective of the future course of the take-up of rooftop PV.

3. The historical period was characterised by significant rebates and subsidies, many of which are no longer available or have been significantly reduced over time.
4. Changes in the fundamental drivers of rooftop PV uptake are likely to be very different in the forecast period compared to the past.
   a) For example, the installation price of a new rooftop PV systems declined very rapidly over the historical period, but is now likely to have reached a period of diminishing returns, with the price decline expected to continue, albeit at a considerably slower pace.
   b) The retail price of electricity has undergone a very major upswing over the last 8 years or so, which has led to a significant improvement in the payoff from installing rooftop PV systems. Future electricity price rises are very unlikely to match those observed in the historical period.

In ACIL Allen's view, Ergon Energy would be better served in the future from separately removing the impact of rooftop PV from the historical domestic component of the dataset, before calibrating the econometric models, and then deducting the projected impact of rooftop PV from the base forecasts obtained from the econometric models.

Projected uptake of rooftop PV should be derived from a model which is able to capture the changing fundamental drivers over time and to estimate their impact on rooftop PV uptake. A simple way of doing this this is to estimate the financial payoff over time from installing a new rooftop PV system, a good measure of which is the Net Present Value (NPV) of the future financial benefits relative to the upfront purchase and installation cost. A regression could then be estimated between using the uptake as the dependent variable and the NPV payoff from installing a new rooftop PV systems over time. This approach has the added advantage in that it allows the forecaster to incorporate changing or dynamic views about the future course of the fundamental drivers of rooftop PV uptake. By allowing the influence of rooftop PV to remain embedded in the energy delivered data, the forecaster does not have the flexibility to treat rooftop PV differently, from the average behaviour of the dataset. This is OK only if the future behaviour of the uptake of rooftop PV is expected to resemble the past. It is ACIL Allen's view that this is no longer likely to be the case.

Electric vehicles

In their most recent energy forecasting process, Ergon Energy have not made any adjustments for the possible uptake of electric vehicles, although they have produced scenarios which can be potentially incorporated as post model adjustments. In ACIL Allen's view, this is unlikely to matter materially in the first half of the forecasting horizon, say up to the year 2025. This is because the current economics of electric vehicles are still such that the upfront cost of the vehicles are still very high relative to internal combustion engine (ICE) vehicles and the range disadvantage relative to ICE vehicles means that it will still be some time before electric vehicles are competitive based on financial terms.

However, ACIL Allen believes that the uptake of electric vehicles after the early 2020's will begin to accelerate as the cost of the battery technology declines, leading to a lower upfront purchase price for electric vehicles. It is our position therefore, that a post model adjustment should be made for the uptake of electric vehicles in Ergon Energy's distribution network and added to the base line model as a scenario.

Retail electricity prices

The impact of real price changes on energy delivered is calculated separately from the base econometric forecasts. The retail price impact is determined separately and the forecasts are then adjusted accordingly. The price impact is then converted into an impact on energy delivered via a set of assumed price elasticities.

The responsiveness of each customer class to higher electricity prices will depend on their own price elasticity of demand. The price elasticity of demand is defined as the percentage change in energy consumption resulting from a 1% change in the price of electricity. Most studies of the price elasticity of demand for energy have found energy demand to be price inelastic, implying a price elasticity with a value less than 1.

The study, from which the price elasticities of demand to be applied were obtained was conducted by NIEIR in June 2007[9]. The long run own price elasticities by sector recommended by this NIEIR report are shown in the following table. These are the price elasticities adopted in this study to determine the adjustment in consumption as a result of increases in the retail electricity price.

TABLE 3.4 ASSUMED PRICE ELEASTICITIES BY SECTOR

Heading	Heading
Residential	-0.25
Commercial	-0.35
Industrial	-0.38

SOURCE: NIEIR

These elasticities can be interpreted as follows:

— A 1% increase in the residential retail tariff results in a 0.25% reduction in the residential sector's demand for energy

— A 1% increase in the commercial retail tariff results in a 0.35% reduction in the commercial sector's demand for energy

— A 1% increase in the industrial retail tariff results in a 0.38% reduction in the industrial sector's demand for energy

As expected, the commercial and industrial sectors are more responsive to price changes in electricity due to the energy intensity of these sectors relative to the domestic sector, in which energy costs have traditionally comprised only a very small proportion of the total household budget.

In its most recent energy forecasts, Ergon Energy has assumed that the real price of electricity will remain unchanged throughout the forecast period. This means that there is no post model adjustment for the effect or price. In our view, it would be better to incorporate the views of an expert, such as NIEIR, rather than to assume no change in the real price.

Moreover, as the sample size of the dataset available expands, it is better to estimate the price elasticity within the econometric modelling rather than as a post-model adjustment. In our view, if the estimated coefficient form the model is of a reasonable size and of the right sign, then the estimated price elasticity should be used, rather than those estimated externally, by NIEIR. These estimated elasticities are now over a decade old, and are in our view out of date, given the major changes that have occurred in the electricity sector over this period.

3.4 Key recommendations summary

— Ergon Energy should net off the impact of rooftop PV from the historical data before model estimation commences for the domestic component of the model, and for the commercial component in those regions where the take up of commercial rooftop PV has become significant

— In light of an increased sample size, Ergon should re-consider the variables used in the econometric models. It is possible that key drivers that were previously found to be statistically insignificant or had a nonsensical coefficient will perform better in a re-formulated model

— Ergon should remove the impact of a possible outlier in the domestic regression models corresponding to the 3rd quarter of 2014

— Ergon should introduce a post model adjustment by scenario, for the impact of each of the following:
  - Rooftop PV
  - Electric vehicles

— Ergon should update the quarterly CDD and HDD weather data to utilise the latest available information within the forecasting process

[9] The own price elasticity of demand for electricity in NEM regions, A report for the National Electricity Market Management Company, Prepared by the National Institute of Economic and Industry Research, June 2007

— Ergon should attempt to include the impact of the retail price of electricity within the base econometric model rather than through a post model adjustment using externally sourced elasticities

4 ENERGY DELIVERED - ENERGEX

4.1 Previous reviews of Energex's approach to energy forecasting

Just like Ergon Energy, Energex's energy forecasting methodology has evolved significantly over time in response to a series of reviews dating back to the Joint Workings project of 2009. Like Ergon, Energex's energy forecasting methodology could be described as bottom up using a combination of time series analysis and experience.

Forecasts were created by customer class, with total customer numbers and energy usage per customer separately forecast for each segment, and the two sets of forecasts combined to provide the total forecast for each segment. The models did not contain any explicit relationship between system energy and the underlying economic and demographic variables that drive it. Moreover, there were no weather inputs used in the modelling process. Energex's fitting of trends to the historical data often involved the fitting of complex polynomial functions which tended to behave erratically in the projection period and were often overwritten by hard coded adjustments for which there was little or no justification.

In the System Energy Guidelines document released the following year in April 2010, ACIL Tasman recommended the creation of a set of top down econometric models that related energy delivered for each customer segment to each of the underlying drivers that drove the long run trends in consumption for each segment. The report also recommended that any forecasts based on professional judgements should be clearly documented and explained, thus increasing the robustness and transparency of the methodology.

In December 2013, Energex's system energy and customer numbers forecasting were reviewed again, this time by Frontier Economics[10]. In this review it is clear that Energex had made some progress towards a more top down econometric approach to forecasting energy and customer numbers. The energy and customer numbers forecasts were a combination of trend extrapolation and top level econometric models, which involved the use of key drivers to generate the forecasts.

It was only in the case of separate models for commercial customer numbers and industrial customer numbers that an econometric model was estimated using GSP and population for commercial customers and GSP only for industrial customers. All the other forecasts, for domestic customers and average energy usage for domestic, commercial, industrial and rural segments were based on the extrapolation of trends, either linear for domestic, or quadratic and cubic for commercial and industrial respectively. The review also identified that there was no attempt made to control for weather variation in the models, so that the effect of an unusually cold or warm year could lead to biases in the estimated trends.

[10] Review of Energex's customer numbers and energy demand forecasting procedures. A report prepared for Energex, December 2013.

Frontier reviewed the models for each customer segment and made a number of additional criticisms:

- The sample used to estimate the trends did not always use the most up to date information and no explanation was provided as to why this was the case
- The quadratic and cubic trends were prone to producing unrealistic forecasts
- Hard-coded and ad-hoc post model adjustments were made to the forecasts with little or no explanation

Frontier correctly stated that Energex would not meet the AERs requirement of transparency and repeatability based on what they had seen. They recommended the need for better documentation that outlined all of the ad-hoc and hard-coded adjustments.

Frontier correctly identified that Energex was still in the process of transitioning from a methodology based on simple trend extrapolation towards the development of econometric models. Frontier strongly encouraged the move away from trend extrapolation to the use of more sophisticated econometric models.

Frontier recommended that Energex also needed to adopt a more systematic approach to model validation and testing in order to produce more robust forecasts. In particular, they recommended that Energex visually inspect the residuals of all the estimated models and identify any remaining patterns. They also recommended testing to identify non-stationarity and cointegration, structural breaks, functional form and dynamic specification.

It is evident in the section that follows that Energex has moved away substantially from the methodology reviewed by Frontier Economics in 2013.

4.2 Energex current approach to energy forecasting

Energex adopts an econometric approach to forecasting energy delivered. The approach first estimates a base case model which excludes the impact of emerging technologies such as Electric Vehicles and Battery storage systems. These are estimated separately and then added to the forecast as a post model adjustment. Given, the fact that there is very little historical data on which to base forecasts of EVs and battery storage, we consider it reasonable to estimate these separately and incorporate their respective impacts into the forecasts as post model adjustments. The EV and battery storage impacts are provided by the external consultants Energeia.

Energy sales forecasts are produced under separate high, medium and low scenarios. The forecasts are produced to cover a 10 year forecasting horizon.

Energex splits its energy forecasts into separate customer classes and adopts a different methodology for each. The separate customer classes are:

- ICC customers (Large customers)
- CAC customers (Large customers)
- SAC customers (small to medium sized businesses)
- Domestic customers

4.2.1 ICC energy sales

In the case of the ICC customers, each customer was forecast individually on the basis of historical data and anticipated operational changes based on the local area knowledge of the asset managers. Average monthly load profiles were created for each customer which were the used to generate an annual energy forecast for each ICC customer.

Forecasts of maximum demand for each customer are generated by applying a set of load factors and power factors to the energy forecasts.

4.2.2 CAC energy sales

In the case of the CAC customers, the first 2 years of the forecast are based on the aggregate totals of the individual CAC customers. In the last 8 years of the forecast, Energex have opted to apply a rate of growth of 0.5% for the 4000's tariff class and 0.25% per annum for the 8000's tariff class.

The documentation provided by Energex does not go into any further detail on how these growth rates were derived. In our view, this makes the forecasting process appear to be quite arbitrary. ACIL Allen considers that the description of the methodology should include some detail of how these growth rates were determined.

4.2.3 SAC energy sales and customer numbers

In the case of the SAC customers, Energex have adopted an econometric model which can relates the average daily use per customer to a range of fundamental drivers. The model uses monthly data and covers the period from March 2008 to June 2017, a total of 112 observations. Prior to estimation, the contribution of rooftop PV is netted out of the historical data. It is then added back later as part of the post model adjustment.

The main explanatory variables used in the regression are:

- A constant term
- Average temperature
- Accumulated cooling degree days for summer
- Accumulated heating degree days for winter
- Accumulated heating degree days for the rest of the year
- The presence of rain on a given day in summer
- The presence of rain on a given day in winter
- Presence of rain on a particular day in the rest of the year
- Relative humidity in summer
- Log of commercial prices
- Difference between monthly GSP and same month 12 months ago
- Dummy variable for the week of Christmas
- Dummy variable for the week of Easter
- Dummy variable for weekends and other public holidays
- Dummy variable for the global financial crisis covering the period from October to December 2008
- Dummy variable for the impact of the Brisbane floods in January and February 2011

Table 4.1 shows the estimated model coefficient from Energex's preferred SAC model.

TABLE 4.1 SAC MODEL ENERGY DELIVERED PER CUSTOMER, MODEL COEFFCIENTS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	183.7360	7.0862	25.9287	0.0000
Average temp	2.7162	0.2134	12.7290	0.0000
Accumulated CDD summer	0.2372	0.0235	10.0987	0.0000
Accumulated HDD summer	0.2738	0.0246	11.1346	0.0000
Accumulated HDD rest of year	0.2528	0.0295	8.5815	0.0000
Rainfall summer	-0.2207	0.1582	-1.3954	0.1662
Rainfall winter	0.3008	0.3532	0.8516	0.3966
Rainfall rest of year	0.2417	0.2145	1.1272	0.2625
Relative humidity summer	0.1367	0.0620	2.2044	0.0299
Log of commercial price	-18.4221	2.2367	-8.2364	0.0000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Monthly difference in GSP	0.0015	0.0010	1.4924	0.1389
Christmas period dummy	-58.6550	7.0820	-8.2822	0.0000
Easter period dummy	-42.3063	6.7940	-6.2270	0.0000
Weekends/Public holidays	-38.2282	8.2894	-4.6117	0.0000
GFC dummy	-2.5324	1.3115	-1.9309	0.0565
Brisbane flood dummy	-3.4805	2.2631	-1.5379	0.1274
AR(1)	0.4941	0.1013	4.8787	0.0000

SOURCE: ENERGEX

The estimated regression contains the key economic drivers of average daily consumption, namely GSP and electricity prices. The weather impact is captured through the presence of average temperature and the cooling and heating degree day variables. Some additional explanatory power is also provided through the inclusion of a variable for relative humidity. The presence of rainfall in summer is expected to have a positive impact on commercial energy delivered on the basis that rainfall is associated with cloud cover which is expected to reduce the amount of electricity generated from rooftop PV systems. In the winter months, rainfall is expected to increase energy sales on the basis that rainy days feel colder compared to non-rainy or sunny days.

Seasonal effects are captured through the inclusion of dummy variables which capture the impact of weekends and other non-working days, Christmas and Easter.

The model also includes a first order autoregressive term whose purpose is to capture any remaining autocorrelation in the model residuals that is not already captured by the included explanatory variables.

The SAC model of customer numbers is a simple econometric model that relates the number of SAC customers to a time trend and Queensland GSP.

4.2.4 Domestic energy sales and customer numbers

In the case of domestic customers, an average daily consumption per customer regression was estimated covering the same historical period from March 2008 to June 2017. The regression included the main drivers of domestic energy consumption per customer. The main variables included were:

— Accumulated cooling degree days for summer
— Accumulated heating degree days for winter
— Accumulated heating degree days for the rest of the year
— The presence of rainfall in summer, winter and the rest of the year
— Average cumulative relative humidity
— Log of the residential electricity price
— Gross State Income per customer
— Dummy variable for weekends
— Dummy variable for the impact of the global financial crisis from October to December 2008
— The model also includes an autoregressive term and a seasonal adjustment factor

Table 4.2 presents the estimated coefficients from Energex's preferred domestic model.

TABLE 4.2 DOMESTIC MODEL ENERGY DELIVERED PER CUSTOMER, MODEL COEFFCIENTS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	21.9209	3.2768	6.6897	0.0000
Accumulated CDD summer	0.0626	0.0034	18.3657	0.0000
Accumulated HDD summer	0.0434	0.0041	10.5228	0.0000
Accumulated HDD rest of year	0.0515	0.0036	14.1383	0.0000
Rainfall summer	-0.0216	0.0290	-0.7462	0.4574
Rainfall winter	0.0759	0.0598	1.2682	0.2079
Rainfall rest of year	0.0500	0.0252	1.9819	0.0504
Average cumulative relative humidity	0.0154	0.0046	3.3404	0.0012
Log of residential price	-3.4199	0.5946	-5.7515	0.0000
Gross State Income per customer	0.0001	0.0004	0.3416	0.7334
Weekends dummy	0.5834	0.8475	0.6883	0.4929
Christmas period dummy	-0.1262	0.1808	-0.6978	0.4870
GFC dummy	-0.7315	0.4050	-1.8063	0.0741
Brisbane flood dummy	-0.3966	0.5629	-0.7046	0.4828
AR(1)	0.4638	0.1708	2.7151	0.0079
SAR(3)	0.3615	0.1171	3.0860	0.0027
MA(1)	0.1784	0.1670	1.0682	0.2882
SIGMASQ	0.1171	0.0164	7.1402	0.0000

SOURCE:

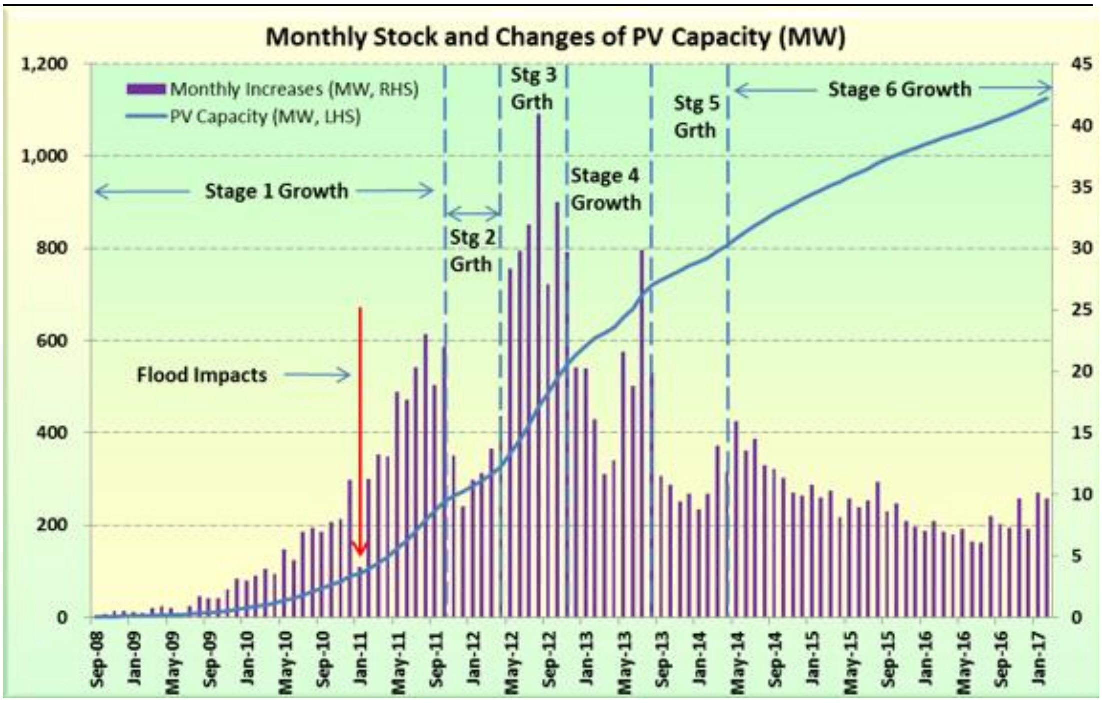
Energex also estimates a simple model of customer numbers that relates the domestic customers in its network to the population of South East Queensland.

4.2.5 Post model adjustments

Energex applies separate post model adjustments for Rooftop PV, Battery storage and Electric vehicles. These have been provided to Energex by the external consultant Energeia. ACIL Allen does not have sufficient information about the methodology applied to review the post-model adjustments in any great detail.

However, Energex's documentation suggests that the rooftop PV forecasts are made based on the identification of six stages of growth shown in **Figure 4.1** below.

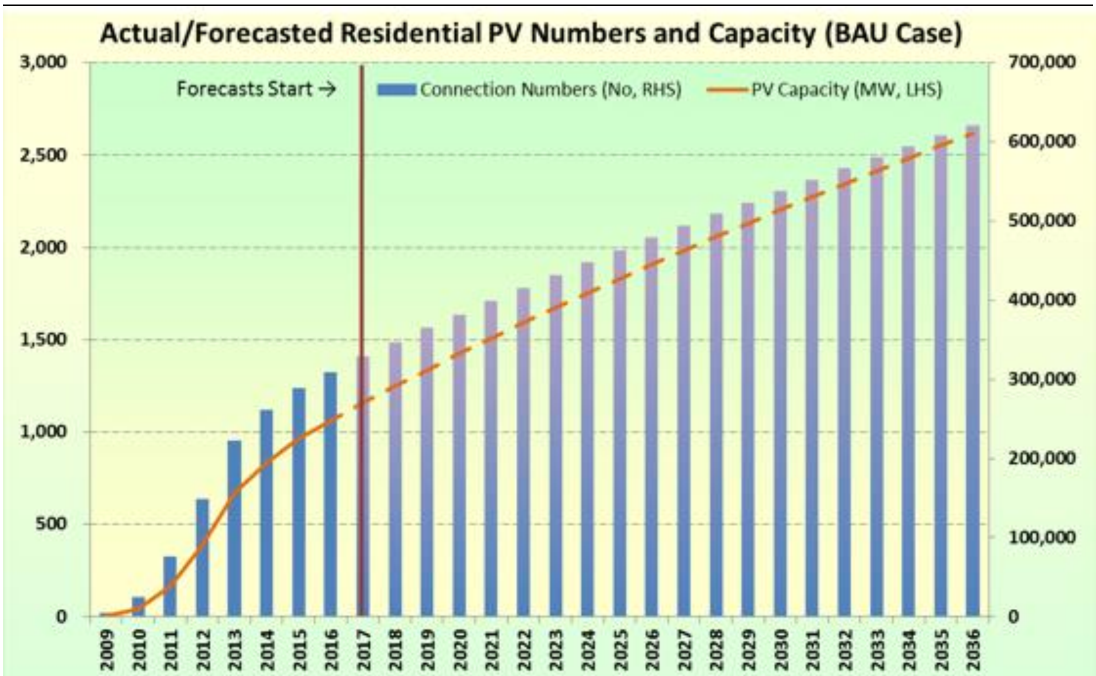
FIGURE 4.1 MONTHLY STOCK AND CHANGES OF PV CAPACITY



SOURCE: ENERGEX, NETWORK FORECASTING, CONSTRUCTING THE TEN YEAR FORECAST OF ENERGY DELIVERED, 2018 TO 2028

It appears that Energex then extrapolates the uptake of PV capacity based on the growth rate observed in Stage 6, identified as the period between May 2014 and June 2017. The resulting rooftop PV uptake forecasts are shown in **Figure 4.2** below.

FIGURE 4.2 ACTUAL AND FORECAST RESIDENTIAL PV NUMBERS AND CAPACITY



SOURCE: ENERGEX, NETWORK FORECASTING, CONSTRUCTING THE TEN YEAR FORECAST OF ENERGY DELIVERED, 2018 TO 2028

4.3 Assessment of Energex approach to energy delivered and customer numbers

4.3.1 Inclusion of key drivers

Energex's approach to energy and customer numbers forecasting includes all the important drivers of energy delivered and customer numbers.

Temperature drivers are captured through cooling and heating degree day variables as well as average temperature in the case of the SAC energy delivered model. Both of the SAC and the domestic energy models include separate rainfall variables for the summer, winter and rest of the year periods. These variables however, were found to be statistically insignificant at both the 1% and 5% significance levels. Also included in the model specification is relative humidity, which adds to energy delivered in both the commercial and domestic models.

Economic activity is captured through the inclusion of GSP and Gross State Income per customer in the SAC and domestic energy models respectively. Also included are real commercial and residential electricity prices in each of the SAC and domestic models respectively.

ACIL Allen notes that while the SAC average daily energy use model includes the monthly change in GSP from the previous 12 months as an explanatory variable, the dependent variable in the model is measured on a per customer basis. It is our view that for the sake of consistency the GSP variable be included on a per capita basis. Otherwise, the impact of increasing population, which contributes positively to GSP, is to increase average energy consumption per SAC customer. This may not be appropriate, given that GSP is used as a key driver in the SAC customer numbers model as well. At the very least, some further description in Energex's documentation to explain why it believes total GSP is preferable to per capita GSP should be provided.

The SAC model also contains variables to capture seasonal and calendar effects. These include dummy variables for the week of Christmas and the week including Easter. Additional dummy variables were included in the specification to capture the effect of the global financial crisis from October to December 2008 and the Brisbane floods from January to February 2011.

The domestic energy model also includes dummy variables for the global financial crisis and the Brisbane floods. The SAC model includes an additional autoregressive term to capture any remaining autocorrelation in the model residuals. In addition to the autoregressive component, the domestic model includes a seasonal adjustment term and a first order moving average component.

Energex also estimate separate models for SAC and domestic customers. SAC customer numbers are driven by GSP, while domestic customers are driven by SE Queensland population.

ACIL Allen considers that Energex's energy and customer numbers econometric models contain all of the key weather, economic, demographic, price, calendar and seasonal drivers of energy and customer numbers.

4.3.2 Approach to model validation

Energex has chosen to adopt a formal and rigorous testing approach to model validation. The first step in the process is to identify all of the potential target variables that may be useful as explanatory variables in the models.

The variables are then all thrown into the mix and their impact on metrics such as goodness of fit and their statistical significance is evaluated. Those variables that contribute little in terms of explanatory power and fail to satisfy the necessary condition of statistical significance are then progressively eliminated from the estimated model.

Formal stationarity tests are conducted on each variable as well as tests of cointegration such as the Johansen procedure. Without going into excessive technical detail, the existence of one or more cointegrating relationships between the dependent and explanatory variables of the model, means that there is an economic equilibrium relationship between the variables and that the risk of a spurious relationship between the dependent and the explanatory variables can be ruled out.

Additional diagnostic testing is then conducted to identify any residual serial correlation, or the presence of multicollinearity or heteroscedacity. Additional tests are conducted to identify any structural breaks in the series where it may appear that such a break has occurred.

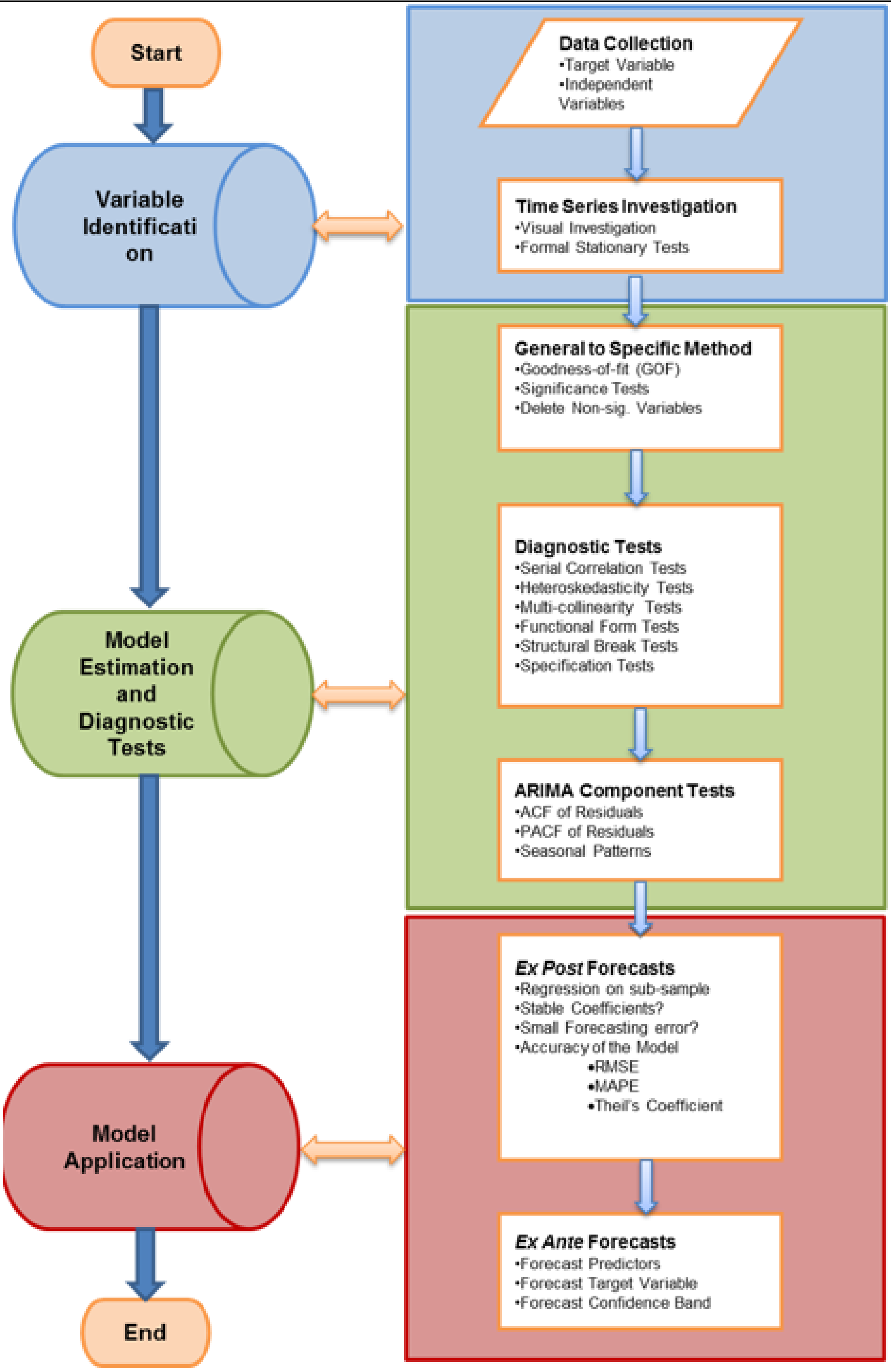
In the event of the presence of serial correlation in the residuals, additional tests are conducted to identify the nature of the autocorrelation in the residuals.

Further tests were conducted to estimate the stability of the model coefficients in response to subsetting of the sample. Out of sample forecasts were also produced, again by subsetting the sample, re-estimating the regression on the reduced sample, and then assessing the forecasts against the actual values from the omitted part of the sample.

All of these procedures can be considered good practice. By formalising the process, Energex are able to increase the level of rigour of their forecasting process. This helps to increase the credibility and transparency of the forecasts in the eyes of the regulator.

Figure 4.3 presents a flow chart of the econometric modelling process employed by Energex.

FIGURE 4.3 FLOWCHART OF ECONOMETRIC MODELLING PROCESS



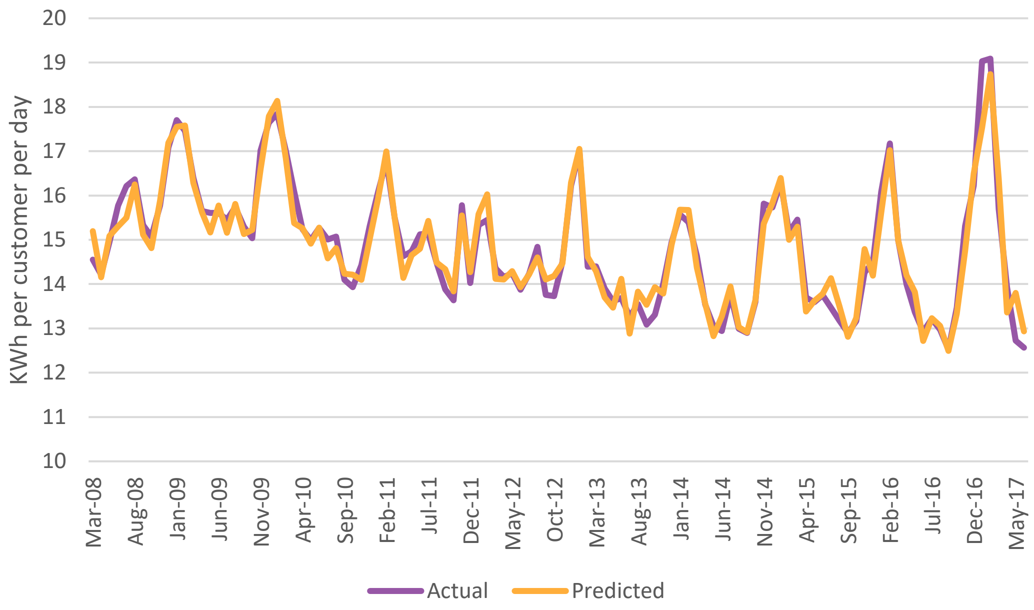
SOURCE: ENERGEX, NETWORK FORECASTING, CONSTRUCTING THE TEN YEAR FORECAST OF ENERGY DELIVERED, 2018 TO 2028

Goodness of fit

On the basis of model fit, Energex's SAC and domestic energy per customer models display exceptional explanatory power.

Figure 4.4 shows the in-sample fit of Energex's domestic model. The estimated model had an adjusted R^2 of 92.8%, reflecting the fact that over 92% of the variation in domestic average daily use per customer was captured by movements in the explanatory variables.

FIGURE 4.4 ACTUAL VERSUS PREDICTED DOMESTIC ENERGY PER CUSTOMER PER DAY



SOURCE: ENERGEX

In the case of the SAC customers' average daily usage, Energex's estimated model was able to achieve an adjusted R^2 of 97.7%.

When an econometric model achieves an R^2 of well in excess of 90% there may be some concern of overfitting. It is our view that given the rigorous and comprehensive diagnostic checking that Energex conducts, it is unlikely that this is the case.

It is ACIL Allen's view that these Energex has achieved an acceptable model fit for its estimated energy models.

Statistical significance

Energex applies the standard of statistical significance in the process of selecting between potential explanatory variables. The majority of the variables included in Energex's energy use models were found to be significant at the 1% or 5% significance levels. There are several exceptions, however. In both the SAC and domestic average daily energy use models, the rainfall variables fail the standard test of statistical significance at both the 1% and 5% levels. ACIL Allen recommends that these variables be removed from the preferred regression models.

Moreover, the GFC and Brisbane flood dummies also fail to achieve statistical significance at both the 1% and 5% levels of statistical significance. ACIL Allen recommends that these variables also be removed from the preferred econometric models.

In the case of the domestic model, there appear to be a number of results which are difficult to comprehend. These relate to the estimated coefficients on the weekends and Christmas period dummies. Both of these are statistically insignificant which is at odds with our experience of the behaviour of domestic energy users. Moreover, the coefficient on the weekend variable has a positive coefficient which again is at odds with our understanding of the theory of how domestic energy consumers behave. ACIL Allen recommends that Energex explore this anomaly further. It may indicate an error in the way the variable was constructed and included into the model. In the absence of any such errors, ACIL Allen recommends that the weekend and Christmas dummy variables be excluded from the preferred domestic energy model on the basis that they are not statistically significant.

Energex's preferred domestic model also mops up any remaining patterns in the model residuals through the inclusion of a first order autoregressive term, a seasonal adjustment term and a first order moving average term. It is ACIL Allen's view that any remaining pattern in the residuals is more than adequately soaked up by the autoregressive and seasonal terms. The moving average term (which is statistically equivalent to an infinite order autoregressive term) is overkill in our view. This is evidenced by the fact that the coefficient on the moving average term is not statistically significant. ACIL Allen recommends it be removed from the preferred specification.

Finally, Energex have included variables in the both the domestic and SAC energy regressions to capture the upward trend in average energy use due to economic drivers, namely GSP in the SAC regression and Gross State Income in the domestic regression. Despite these being found to be statistically insignificant, Energex have opted to retain these variables in the model specifications on the grounds of economic theory. ACIL Allen agrees with this view. Over the long run, rising household incomes and economic activity have clearly been a major driver of the take up of electrical appliances, household formation and energy use. For this reason, measures of economic activity and rising incomes should be retained within the preferred model specifications, even if they fail to achieve statistical significance, as long as the estimated coefficients are coherent.

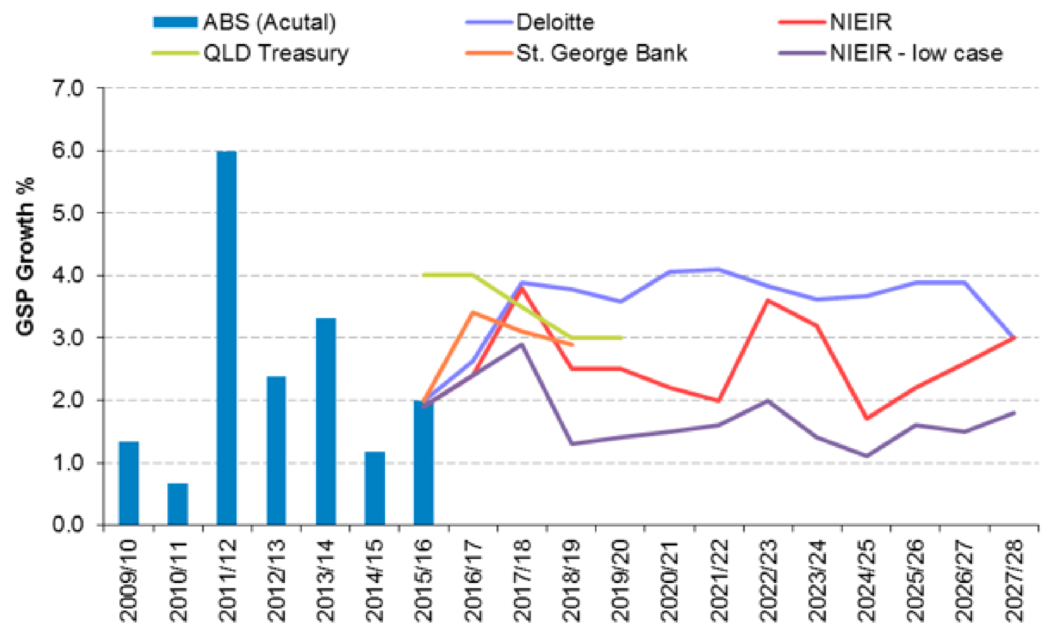
4.3.3 Assessment of key inputs

In this section we review the key inputs that Energex has used in the formulation of its energy forecasts.

Gross State Product

Figure 4.5 shows a number of GSP forecasts from a range of sources. Included in this chart are GSP forecasts for NIEIRs low and medium case scenarios.

FIGURE 4.5 SELECTED GSP FORECASTS, 2016-17 TO 2027-28

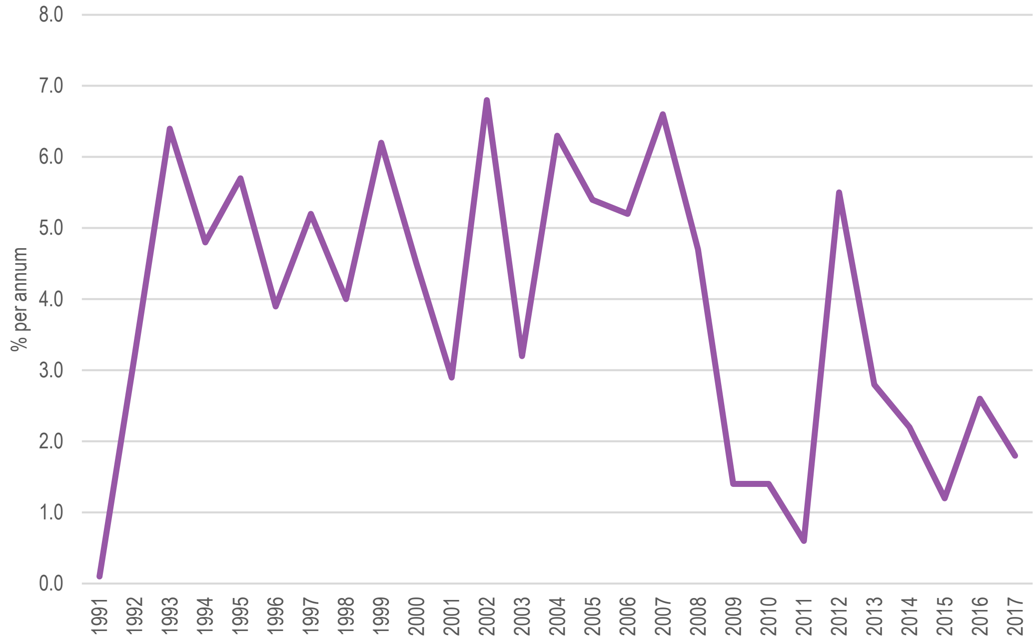


SOURCE: ENERGEX, NETWORK FORECASTING, CONSTRUCTING THE TEN YEAR FORECAST OF ENERGY DELIVERED, 2018 TO 2028

It is our understanding that Energex have adopted the NIEIR low case for their economic growth forecasts. In our view, the NIEIR low case numbers suggest that there will be a worsening of the subdued economic conditions that have persisted over the last two years in Queensland. The low scenario put forward by NIEIR is suggestive of an extended period of weak economic conditions.

Figure 4.6 below shows the long term historical growth in Queensland's GSP. It evident that while GSP growth has been quite variable, it has followed a significantly lower average growth trajectory in the period following the GFC in 2008.

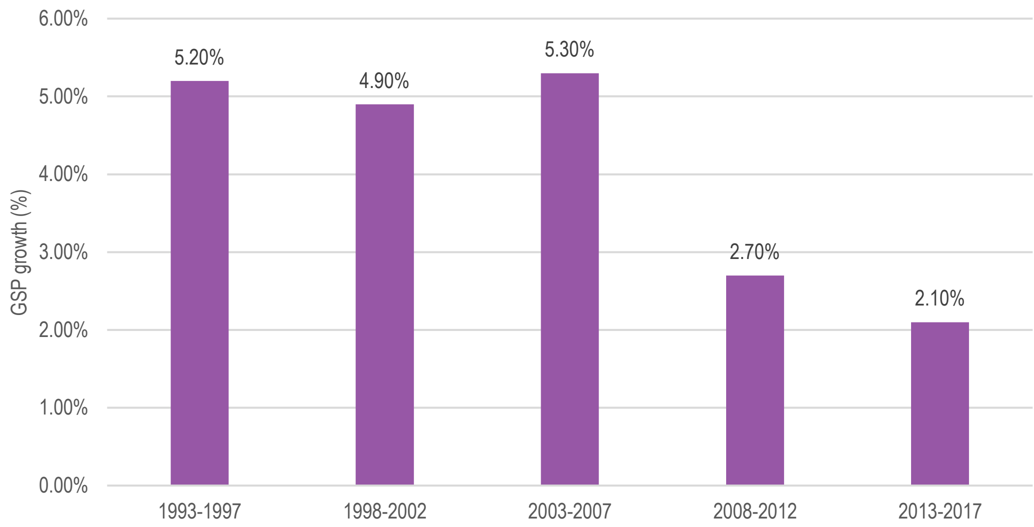
FIGURE 4.6 GROWTH IN QUEENSLAND GROSS STATE PRODUCT, 1991 TO 2017



SOURCE: ABS, 5220.0 AUSTRALIAN NATIONAL ACCOUNTS: STATE ACCOUNTS

This is even clearer in **Figure 4.7** which splits Queensland GSP growth into 5 year intervals. Between 2013 and 2017, GSP growth averaged only 2.1% per annum. In the five years prior to the most recent interval, Queensland GSP growth averaged only 2.7% per annum. This compares with average growth rates at or around 5% in the 15 year period from 1993 to 2007.

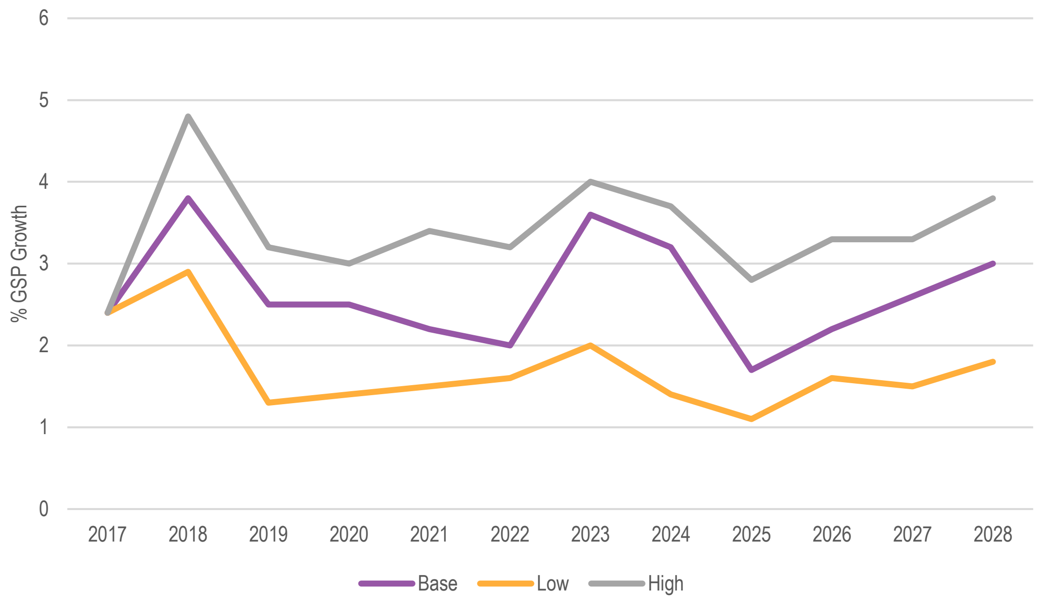
FIGURE 4.7 QUEENSLAND GSP GROWTH, AVERAGE GROWTH OVER FIVE YEAR INTERVALS



SOURCE: ABS, 5220.0 AUSTRALIAN NATIONAL ACCOUNTS: STATE ACCOUNTS

Figure 4.8 below shows NIEIRs forecast GSP growth rates under all three of its scenarios.

FIGURE 4.8 NIEIR GSP GROWTH FORECASTS, LOW, MEDIUM AND HIGH SCENARIOS



SOURCE: ENERGEX

Under the low scenario, NIEIR predicts an average rate of GSP growth of 1.65% per annum from 2018 to 2028. Under the medium scenario, NIEIR projects an average rate of GSP growth of 2.66% over the same period, while under the high case average GSP growth is projected to be 3.5%.

The NIEIR low case represents a significant worsening in economic conditions, evening compared against the last 5 and 10 years of below average GSP growth in Queensland. The NIEIR low case is also significantly at odds with GSP projections made by other forecasters (see **Figure 4.5**).

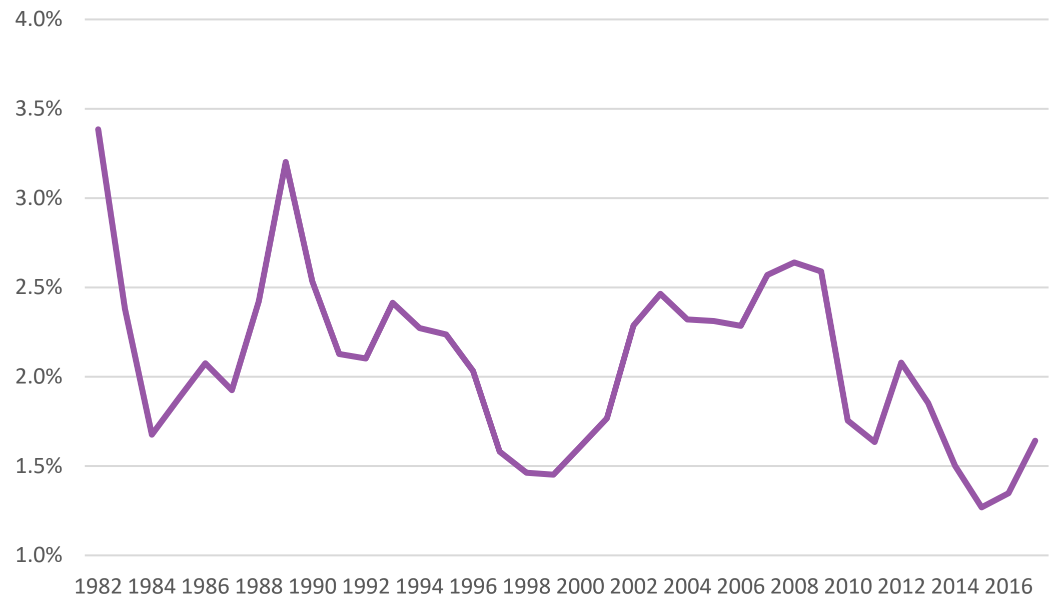
ACIL Allen considers that the use of the NIEIR low case as part of Energex's base case forecasting scenario is far too pessimistic based on recent history and the forecasts of other independent experts. We recommend that Energex revert to the use of the NIEIR base GSP forecasts which are consistent with economic activity similar to the post GFC period from 2008 to 2012.

Population

Energex's document 'Network Forecasting- Constructing the ten year forecast of energy delivered 2018 to 2028' indicates that the consensus view between ABS, AEMO, NIEIR and Deloitte is for population growth to be 1.6% in 2017-18, before gradually declining over the whole forecast period.

This projection is consistent with a continuation of the low population growth observed in Queensland over the post 2010 period (see **Figure 4.9**).

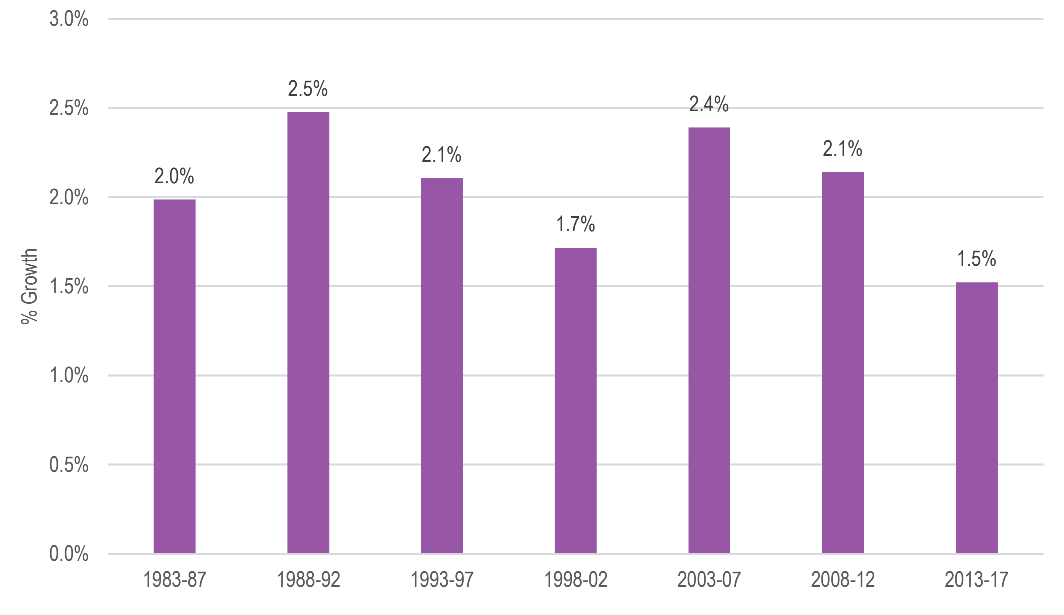
FIGURE 4.9 ANNUAL GROWTH RATES, ESTIMATED RESIDENT POPULATION, QUEENSLAND JUNE 1981 TO JUNE 2017



SOURCE: ABS, 3101.0 AUSTRALIAN DEMOGRAPHIC STATISTICS

Figure 4.10 shows the historical rate of growth in Queensland GSP on 5 year intervals. The figure shows that recent population growth in Queensland has averaged just 1.5% per annum. This is considerably lower than that observed in the previous two 5 year intervals where average population growth exceeded 2% per annum.

FIGURE 4.10 QUEENSLAND POPULATION GROWTH RATES OVER 5 YEAR INTERVALS

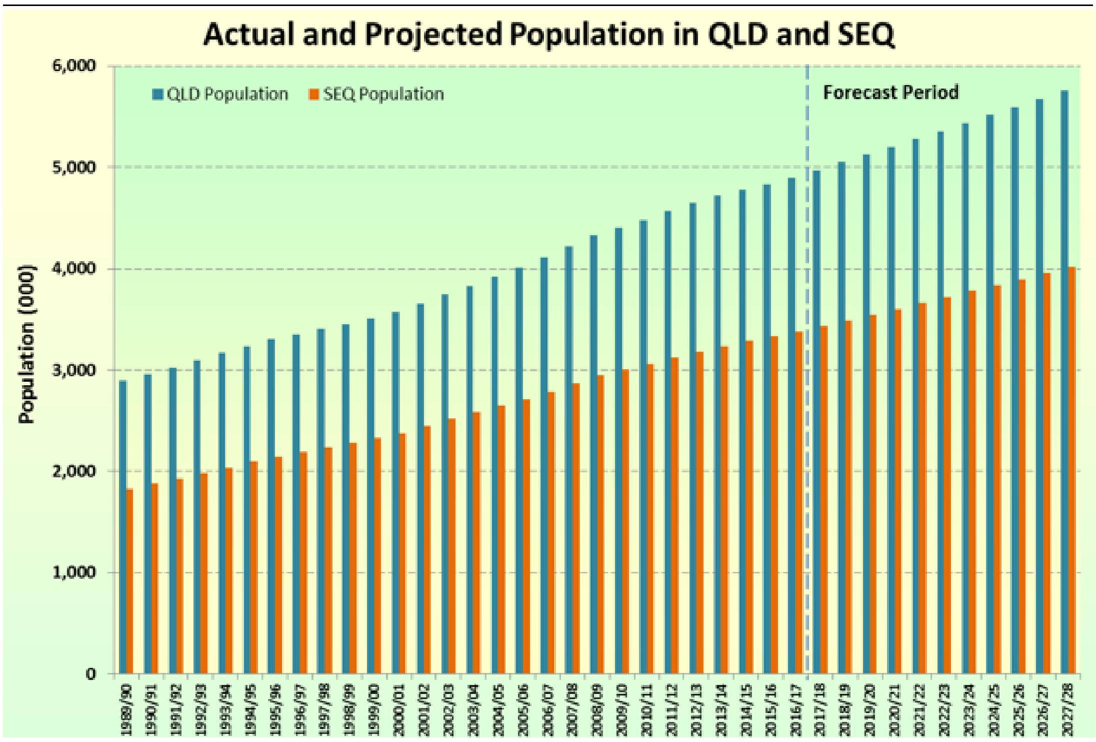


SOURCE: ABS, 3101.0 AUSTRALIAN DEMOGRAPHIC STATISTICS AND ACIL ALLEN CONSULTING

Figure 4.11 shows the population projections used by Energex to generate its forecasts. The forecasts follow a trajectory that is a continuation of the linear trend observed between 2010 and

2017. ACIL Allen considers that these are reasonable and credible forecasts of Queensland and South East Queensland population growth.

FIGURE 4.11 ACTUAL AND PROJECTED QUEENSLAND AND SOUTH EAST QUEENSLAND POPULATION



SOURCE: ENERGEX, NETWORK FORECASTING, CONSTRUCTING THE TEN YEAR FORECAST OF ENERGY DELIVERED, 2018 TO 2028

Weather inputs

The main weather inputs used by Energex within its energy forecasting models are heating and cooling degree days calculated using data from three separate weather stations:

— Amberley
— Archerfield and
— Brisbane Aero

The contribution of each weather station is weighted by the population living in its proximity. By doing this, Energex are better able to capture weather differences within its own network, especially considering that the weather station at Amberley is significantly inland and quite removed from the majority of the population living within the Energex network. ACIL Allen considers that this is an appropriate way to incorporate temperature into the models.

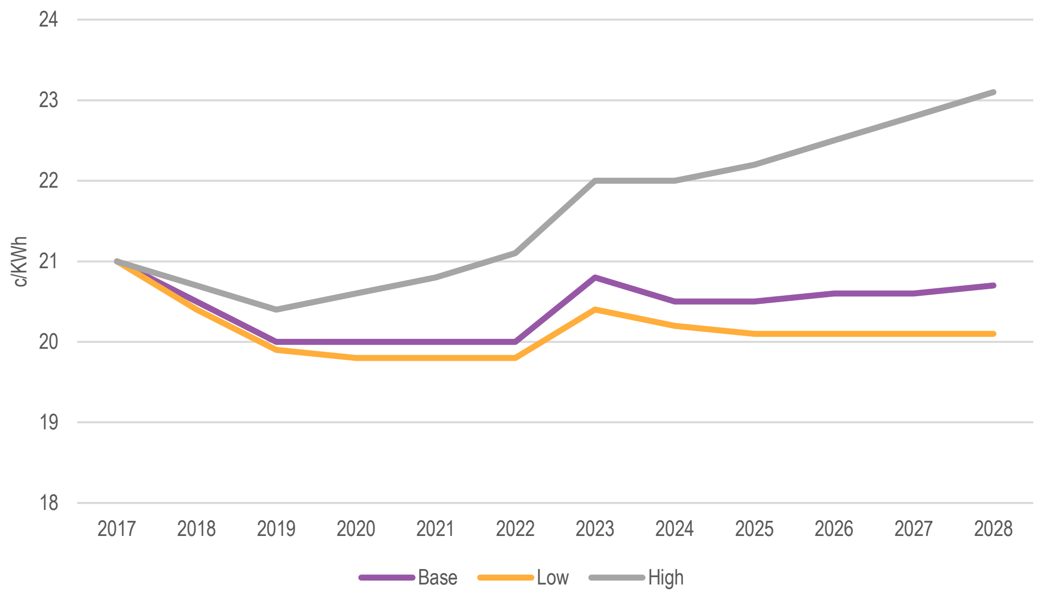
While the temperatures at the three weather stations are highly correlated, suggesting that most of the information content is captured by a single weather station, the use of three separate weather stations to create a combined temperature series should still perform better than using just one weather station in the modelling.

Real electricity prices

Energex use real electricity price forecasts from NIEIR in generating their energy forecasts.

Figure 4.12 shows NIEIRs electricity price forecasts under its three separate scenarios. Under the base case, electricity prices are projected to decline slightly over the next few years before stabilising and recommencing their ascent back up towards the 2017 price.

FIGURE 4.12 FORECAST REAL ELECTRCITY PRICES 2017 TO 2028



SOURCE: NIEIR

It is difficult to know how reasonable NIEIRs electricity price forecasts are in isolation. In December 2017, the Australian Energy Market Commission (AEMC) released the report '2017 Residential Electricity Price Trends'. This report provides some indicative forecasts of electricity price based on the cost components of the electricity supply chain that contribute to the price and the expected trends in each of the components from 2016-17 to 2019-20.

Based on its analysis, the AEMC predicts that electricity prices in South East Queensland:

— Increased by 3.4% from 2016-17 to 2017-18
— Are expected to decrease by 7.0% in 2018-19
— Are expected to decrease by 7.2% in 2019-20

By contrast, NIEIR under the base case predicts a total decline of 4.7% between 2016-17 and 2018-19. The AEMC predicts a total decline of 3.8% over the same period. However, after 2018-19, NIEIRs forecasts stabilise while the AEMC predicts an additional decline of 7.2% by 2019-20.

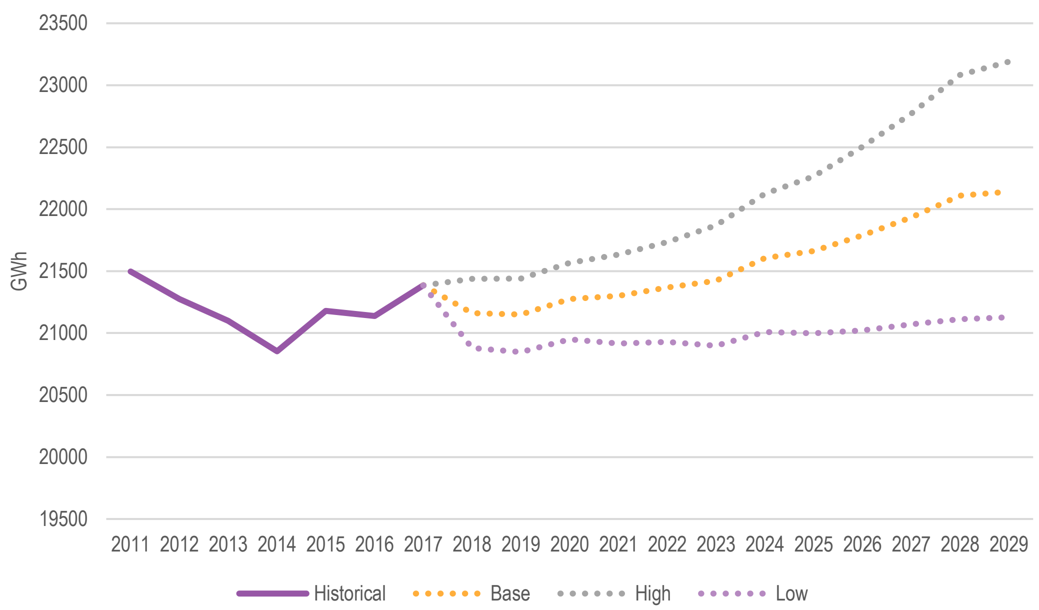
ACIL Allen considers that NIEIRs electricity price forecasts do not deviate sufficiently from those of the AEMC to warrant any serious concern. In our view, the electricity price inputs are reasonable and credible.

4.3.4 Reasonableness of the forecasts

Any forecast submitted to the AER will be assessed in terms of how realistic and reasonable it is. The simplest way to do this is to compare the energy forecasts against the historical behaviour exhibited by the series of interest.

Figure 4.13 shows Energex's total energy delivered forecasts under the three separate scenarios.

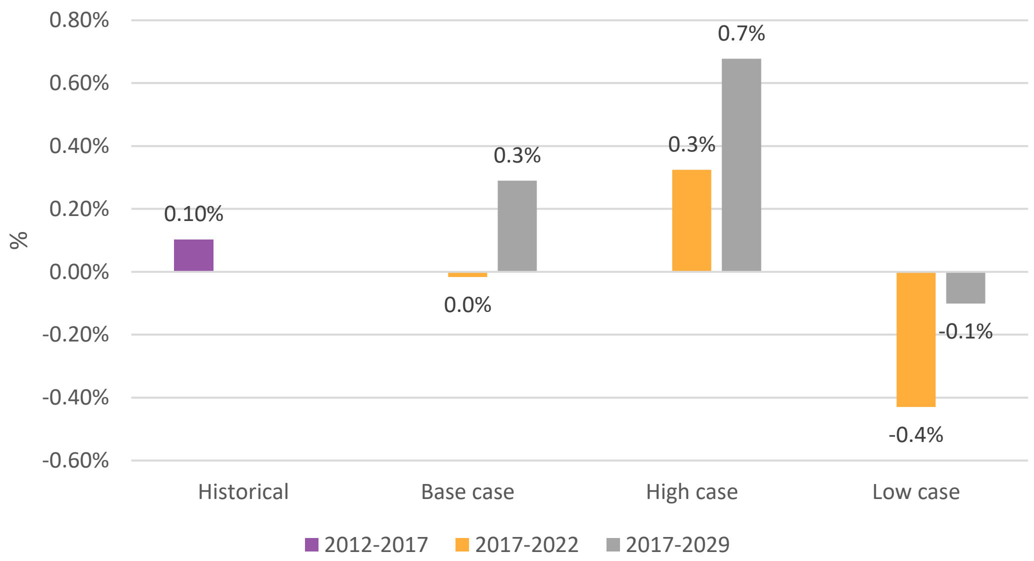
FIGURE 4.13 TOTAL ENERGY DELIVERED, ENERGEX, FORECAST AND HISTORICAL



SOURCE: ENERGEX, NETWORK FORECASTING, CONSTRUCTING THE TEN YEAR FORECAST OF ENERGY DELIVERED, 2018 TO 2028

Under the base case, total energy delivered in the Energex network is projected to grow at a rate of 0.3% per annum over the period from 2017 to 2029 (see **Figure 4.14**).

FIGURE 4.14 ANNUSLISED GROWTH RATE IN ENERGY DELIVERED, HISTORICAL AND FORECAST

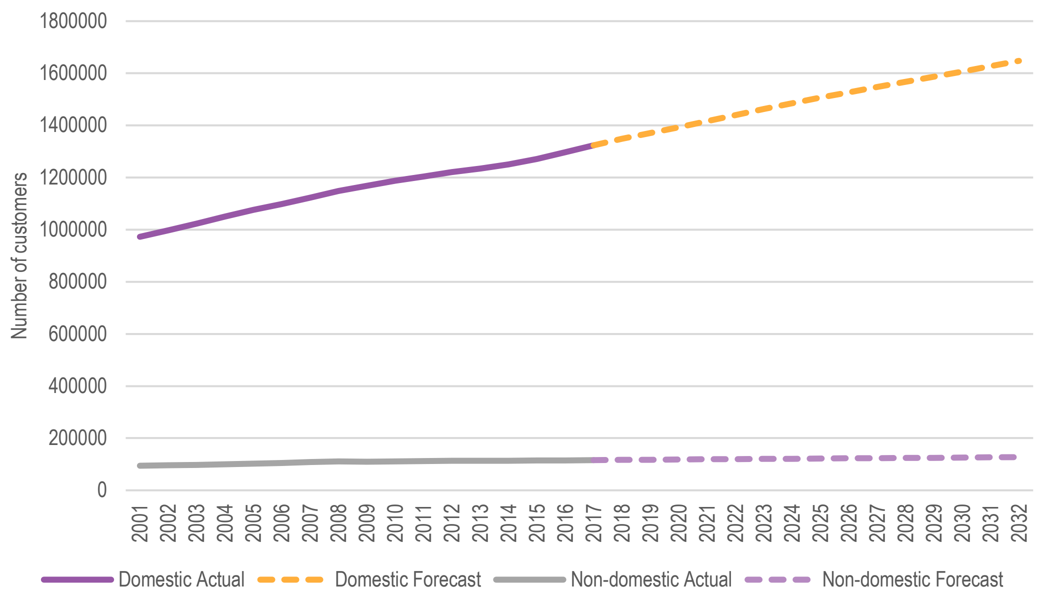


SOURCE: ENERGEX, NETWORK FORECASTING, CONSTRUCTING THE TEN YEAR FORECAST OF ENERGY DELIVERED, 2018 TO 2028

Over the first five years of the forecasting horizon, growth is projected to be zero. These rates of growth are more or less in line with that observed historically. Between 2012 and 2017, total energy delivered within the Energex network increased by just 0.1% per year. A combination of sluggish economic and population growth, and the contribution of rooftop PV have combined to produce this result. A continuation of these trends into the forecast period is consistent with the subdued GSP and population forecasts Energex is using as inputs into the forecasts. On this basis, ACIL Allen considers the forecasts to be reasonable and plausible.

Energex's historical and projected domestic and non-domestic customers are shown in **Figure 4.15** below.

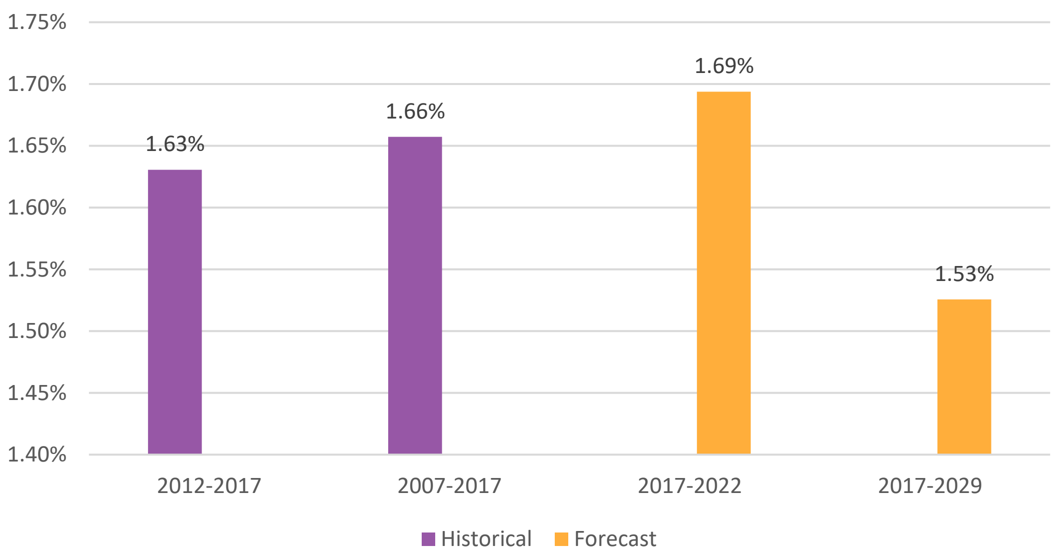
FIGURE 4.15 TOTAL DOMESTIC AND NON-DOMESTIC CUSTOMERS, ENERGEX, FORECAST AND HISTORICAL



SOURCE: ENERGEX

Figure 4.16 shows the historical and forecast growth in residential customer numbers over 5 and 10 years.

FIGURE 4.16 HISTORICAL AND FORECAST AVERAGE ANNUAL GROWTH RATES IN RESIDENTIAL CUSTOMER NUMBERS

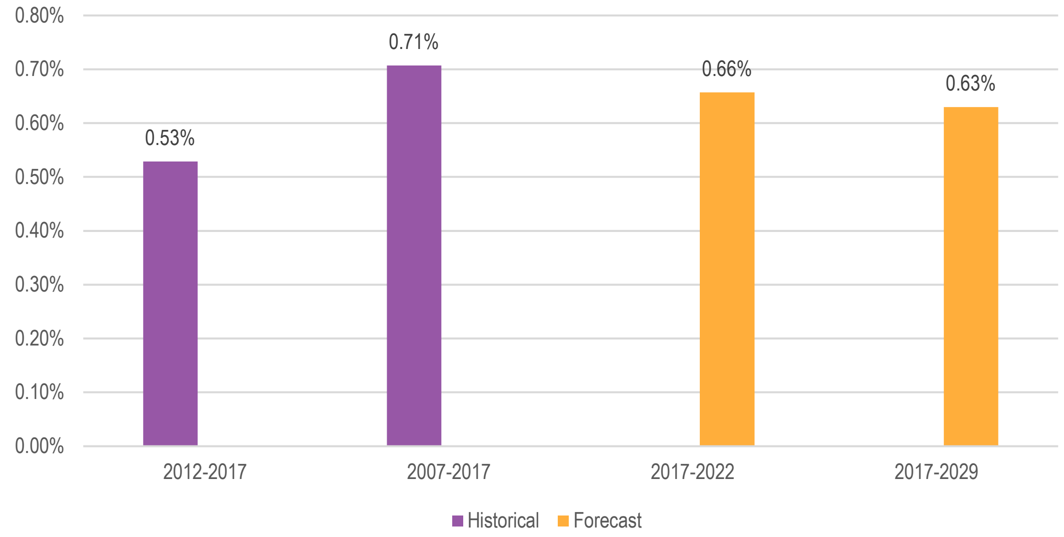


SOURCE: ENERGEX

The figure shows that near term growth in residential customer numbers closely follows that observed over the period from 2012-2017. It then declines slightly in the second half of the forecast period, which is broadly consistent with the population projections used to create the forecasts.

Figure 4.17 presents the historical and forecast growth rates of non-residential customer numbers. Over the longer term, non-residential customer numbers are projected to growth slightly below the long term historical growth rate.

FIGURE 4.17 HISTORICAL AND FORECAST AVERAGE ANNUAL GROWTH RATES IN NON-RESIDENTIAL CUSTOMER NUMBERS



SOURCE: ENERGEX

ACIL Allen considers Energex's forecasts of residential and non-residential customer numbers to be reasonable and plausible.

4.3.5 Post model adjustments

Rooftop PV

As mentioned previously, Energex appears to project the uptake of rooftop PV by imposing an S curve on the historical PV capacity time series. The S curve is split into six stages of growth, each representing a different segment of the S curve (see **Figure 4.1**). Energex then uses the trend line from the sixth stage of growth to extrapolate into the forecast period using a power index.

ACIL Allen does not consider this approach to be unreasonable. However, we are wary of the fact that rooftop PV uptake is driven by a range of fundamental drivers which are dynamic and changing over time. Moreover, the way in which they are expected to change within the forecast period are also likely to differ considerably from that observed historically.

The major drivers include:

— Costs of purchase and installation of PV systems
— Feed in tariff and other subsidies
— Electricity prices

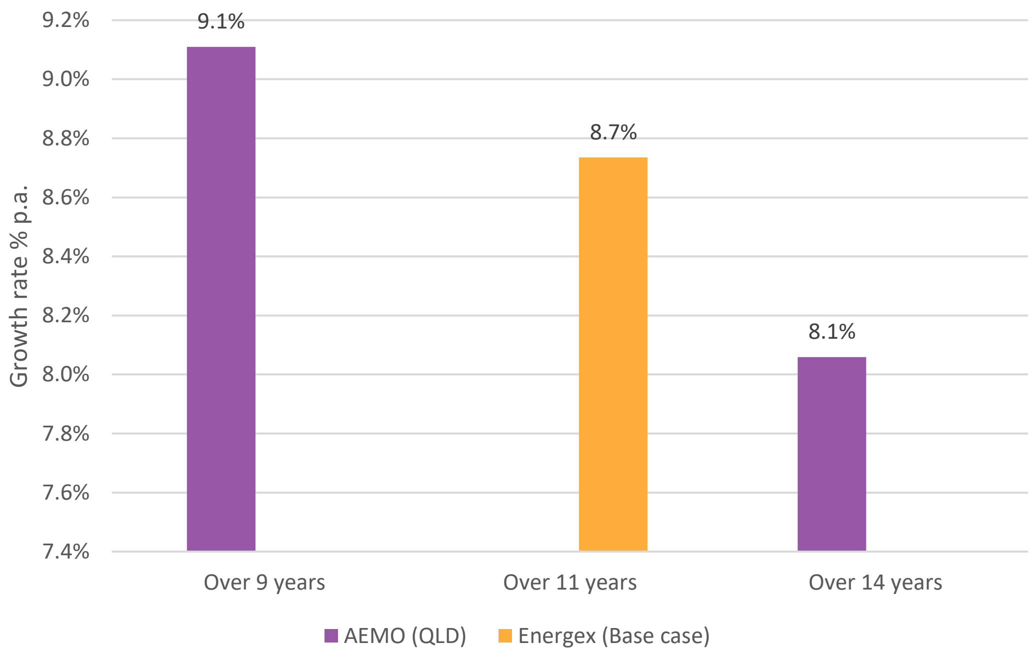
In the case of the system cost, rooftop PV is a technology that is reaching maturity and future price declines in the upfront cost of PV systems are likely to be more muted compared to that observed historically. Moreover, retail electricity prices are expected to show a period of real decline, compared to a historical period of consistently rising prices. Many of the subsidies available to the owners of PV systems have also been greatly reduced or phased out over time, leading to differences in the future compared to the past.

A similar criticism was made by Frontier Economics in its December 2013 review of Energex's customer numbers and energy demand forecasting procedures.

Another approach would be to adopt a modelling approach that relates the take up of rooftop PV systems to the financial payoff from installation over time. While ACIL Allen stops short of recommending that Energex adopts such as approach, we note that there are several independent consulting firms that have developed proprietary models that project rooftop PV in precisely this way and that a shift towards this approach would be an improvement on extrapolating along an S curve.

Figure 4.18 compares Energex's projected growth rate for rooftop PV capacity against those produced by AEMO for Queensland over several time periods. Under Energex's base case, solar PV capacity is projected to increase by 8.7% per annum from 2017 to 2028. This is compared to an average annual rate of growth for Queensland of 9.1% over 9 years and 8.1% over 14 years. The average of the two AEMO growth rates is 8.6% per annum. This is very similar to the growth rates predicted by Energex. On this basis, we can conclude that Energex's rooftop PV forecasts are reasonable and credible.

FIGURE 4.18 COMPARISON OF ENERGEX AND AEMO PROJECTED ROOFTOP PV CAPACITY



SOURCE: ENERGEX AND AEMO

Electric vehicles (EV)

Energex's forecasts of the impact of EVs on total energy delivered were sourced and obtained from an independent external consultant. We do not have any material describing the methodology in any detail. Consequently, we are unable to review the underlying methodology concerning the take up of electric cars.

Energex's documentation describing its methodology for constructing the 10 year energy delivered forecasts makes only a single statement regarding the uptake of EVs and plug-in hybrids (PHEVs), that the uptake of these vehicles will be slow and progressive and that there are many unresolved uncertainties concerning their take-up and retirement rates, their charging loads and diversity.

ACIL Allen considers that this is a reasonable statement, and that the assumption of a slow and progressive rate of uptake is reasonable.

Battery storage

Energex's forecasts of the impact of battery storage on energy delivered is also provided by an independent external consultant. As in the case of EVs we have not been able to review the methodology.

4.3.6 Transparency and repeatability

Energex's document, 'Network Forecasting: Constructing the 10 year forecast of energy delivered' describing its approach to forecasting system energy and customer numbers is of a high standard. The document describes the models estimated as well as the process involved in reaching the best model in some detail.

The document describes the process of data collection, model estimation and diagnostic checking and model validation very well.

There are some areas where we believe there is room for improvement. First, while the model selection and validation phase is explained in depth, there is very little discussion on the methodology used to produce the post model adjustments, namely rooftop PV, battery storage and EVs.

There is no discussion or coverage of how the forecasts of PV, battery storage and EV capacity or numbers translates into an impact on energy delivered. Also, while the base case impacts of each of the post model adjustments is provided in the document, the high and the low case are not present, even though the high and low case total energy delivered forecasts are presented.

ACIL Allen understands that the lack of detail regarding the post model adjustments is largely a result of the forecasts being outsourced to an external consultant. Despite this, the absence of this detail in a regulatory submission would be interpreted as a lack of transparency. ACIL Allen recommends that Energex address this by either adding further detail to the Network Forecasting document, or providing supplementary material from the independent consultant as part of its regulatory submission.

The document also omits any detail of the domestic and SAC customer numbers models, even though they are a key driver of the total domestic and SAC energy delivered. ACIL Allen recommends that Energex rectify this gap in the documentation by including a short section on the customer numbers model specifications.

4.4 Key recommendations summary

After reviewing Energex's approach to energy and customer numbers forecasting, ACIL Allen recommends the following:

— Energex should provide clarification in its documentation on how the growth rate of 0.5% per annum and 0.25% per annum were determined for the 4000s tariff class and 8000s tariff class respectively

— Energex should remove all variables from its base econometric specifications that are not statistically significant at the 1% or 5% significance level, except for GSP and Gross State Income which should be retained on theoretical grounds

— Energex should remove the rainfall variables and separate dummies for the GFC and Brisbane floods from its SAC and domestic model specification. These variables were found to be statistically insignificant and add little in terms of explanatory power

— Energex should closely examine why the weekends dummy and Christmas period dummy variables are statistically insignificant in the domestic energy model. This result seems counter intuitive as we would expect energy use over these periods to be below average. This result may be due to some underlying error

— Energex should remove the moving average term from its domestic model on the basis that it is statistically insignificant. It appears that nearly all of the remaining pattern in the model residuals are captured by the first order autoregressive term and seasonal term

— Energex should consider replacing the GSP variable in the SAC model with GSP per capita. This is because the dependent variable is energy per customer, so this would put both the explanatory variable and dependent variable on the same basis

— Energex have applied the NIEIR low case GSP forecast to produce its medium or base case forecast. ACIL Allen considers that the NIEIR low case is too pessimistic based on recent history and the forecasts of other independent experts. Our recommendation is for Energex to use the NIEIR medium case as the basis for its base or medium case forecasts. These are more consistent with historical economic activity after the GFC

— Energex should consider shifting to a fundamentally driven model of rooftop PV uptake that is based on forecasts of the major drivers such as the cost if installation, changes in feeds in tariffs and other subsidies, and electricity prices, rather than relying on a method of extrapolation along an S curve

— Energex could improve the transparency and repeatability of its forecasts by adding detail to its documentation on the methodology used to forecast the uptake of PV, battery storage and electric vehicles

— Energex's energy forecasting documentation should include a short section on the domestic and SAC customer numbers models. These are important contributors to the total energy delivered, yet they are not detailed in any meaningful way in the documentation

5 SYSTEM MAXIMUM DEMAND- ERGON ENERGY

5.1 Previous reviews of Ergon Energy's approach to System maximum demand

In December 2009 as part of the Joint Workings project, ACIL Tasman conducted the first formal review of Ergon's approach to forecasting system maximum demand within its network.

At that time Ergon Energy produced its system maximum demand forecast by aggregating bulk supply/connection point forecasts up to the region level and then again up to the system level using historical coincidence factors for the purpose.

The lower level bulk supply/connection point forecasts were calculated through the extrapolation of historical trends. The review identified a number of deficiencies of the methodology and made a set of recommendations to rectify these. These were:

- That it was not possible to incorporate trend changes into the forecasts
- That there was no formal weather normalisation procedure
- That forecasts at the spatial level were subject to a high degree of noise and randomness
- That there was likely to be double counting of block loads, because block loads were added to the trend forecast without the applying any form of threshold for smaller block loads
- That the methodology was not transparent due to a lack of documentation
- That there was no formal reconciliation with an independently produced system level forecast

As a result, ACIL Tasman recommended that Ergon shifted to a regression based system level methodology which incorporated the key economic and demographic drivers of daily maximum demand, seasonal and calendar effects and weather effects.

ACIL Tasman also recommended the new system level methodology employ a weather correction methodology which utilised a sufficiently long weather series to allow accurate calculation of 50% POE and 10% POE demand forecasts.

In March 2010, ACIL Tasman produced a set of system demand guidelines for Ergon Energy and Energex which served as the basis for Ergon's current approach to forecasting System maximum demand.

In March 2012, Ergon's approach to forecasting system maximum demand was reviewed by ACIL Tasman again. In that review, ACIL Tasman reviewed Ergon Energy's approach to forecasting system maximum demand, with a particular focus on the steps and measures adopted to alleviate the criticism and concerns that were raised in previous assessments by the AER and the recommendations by ACIL Tasman. The findings of that review were that Ergon Energy had made considerable progress in the development of its system demand forecasting methodology and had to a significant degree addressed the concerns raised in previous assessments and reviews.

The main methodological improvements were that:

- Ergon had developed an independent system maximum demand methodology that could be used to reconcile spatial forecasts
- Ergon had developed a methodology that allowed for variation in key economic, demographic, appliance and weather factors
- Ergon applied a weather normalisation process to its forecasting process
- Ergon had documented its processes and methodology where previously documentation was sparse

The most important recommendations made by ACIL Tasman in this review were that:

- That a module to account for the impact of rooftop PV on maximum demand within the Ergon network be further developed
- That consideration be given to amending the temperature normalisation procedure to increase the weighting on more recent weather data relative to more distant weather observations to better reflect long term warming trends
- That Ergon Energy should consider the development of separate regional models for each of its six regions, rather than treating the entire Ergon Energy network as a single entity
  - The Ergon network is somewhat disparate with different regions each with its own economic and industrial mix, demographic characteristics and climate. It would make more sense, especially when reconciling the spatial forecasts, to apply any formal reconciliation against a regional model rather than a single model for the entire network
- That at some point in the future, there would be a need to analyse and quantify the potential impact of electric vehicles on maximum demand within the Ergon network

The following section describes Ergon's current approach to forecasting System maximum demand for its entire network.

5.2 Ergon Energy approach to System maximum demand

Ergon estimates separate regression models for system maximum demand for both summer and winter. As Ergon Energy is a summer peaking distribution system, this review focuses on the modelling approach for summer system maximum demand.

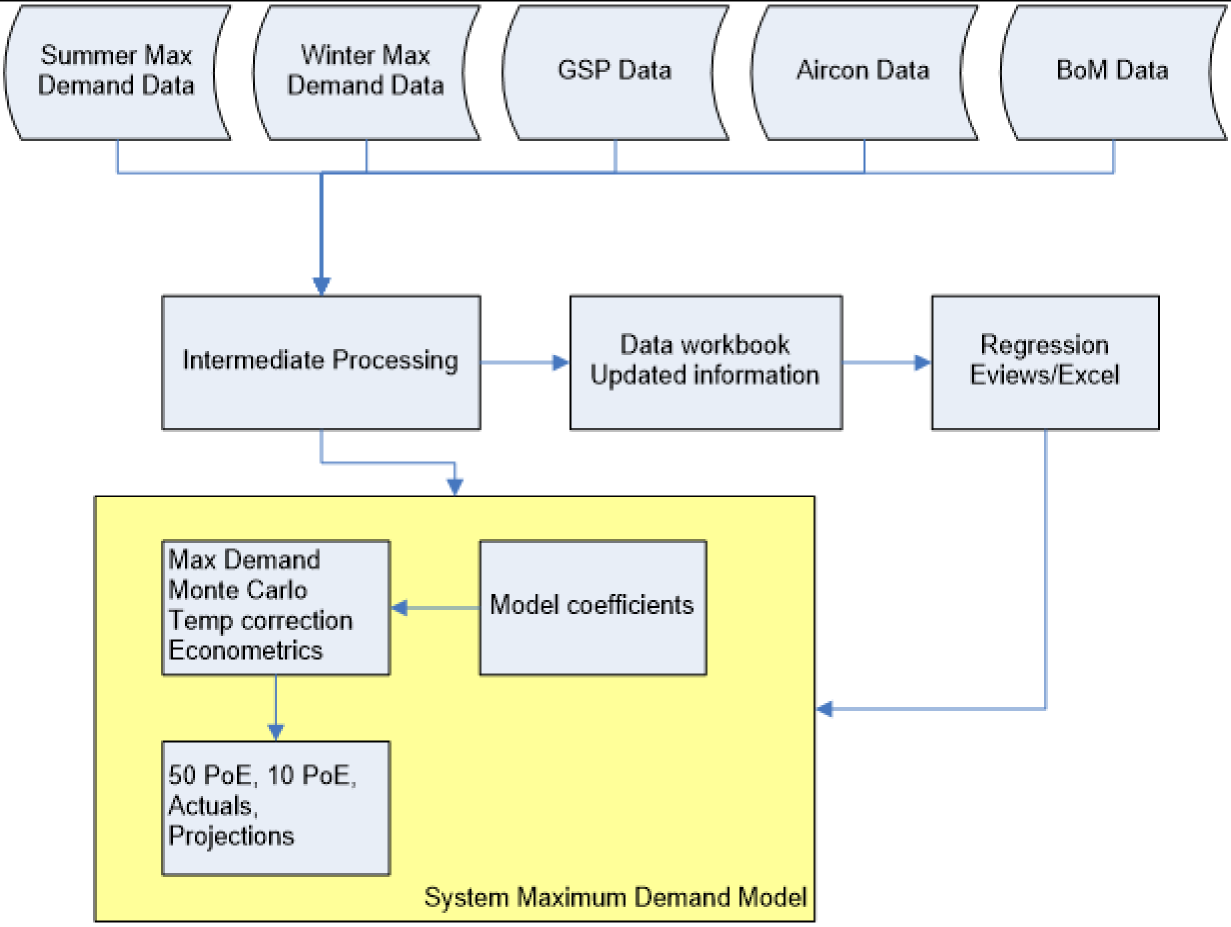
The models are estimated using daily maximum demand.

The first step in the methodology is data collection. Ergon collects data from a number of sources. This is followed by intermediate data processing and regression analysis within the econometric software package, Eviews, and Excel. Ergon then run a number of preliminary models in Excel before narrowing them down in number and applying more formal model diagnostic checking and model selection within the Eviews modelling software.

It is important to note that the intermediate processing and regression phases in the methodology are conducted outside of the system maximum demand model itself. The model coefficients and filtered data are then input into the system maximum demand model and used in the simulation phase of the process. Temperature correction of the historical data takes place during this phase and the forecasts are also calculated.

Figure 5.1 below presents the Ergon's system maximum demand process flow diagram. The diagram presents a schematic of all the key inputs and steps in the process required to produce weather normalized system maximum demand forecasts.

FIGURE 5.1 SYSTEM MAXIMUM DEMAND PROCESS FLOW DIAGRAM



SOURCE: 00188 LOAD FORECASTING MAXIMUM DEMAND REFERENCE DOCUMENT, ERGON ENERGY

5.2.1 Data requirements

Data requirements are daily summer and winter maximum demand data obtained from Ergon's internal systems. In addition, the methodology requires GSP time series data, daily maximum and minimum temperature time series data and air conditioner installation data. The temperature time series required for the modelling date back approximately 50 years and are sourced from the Bureau of Meteorology. The GSP time series data is sourced from the Australian Bureau of Statistics for historical data and from macroeconomic consultants for forecasts. The air-conditioner data is obtained from the consulting firm Energy Consult Pty Ltd.

5.2.2 Data processing

The collected data is then subject to intermediate processing before it can be used within the modelling process.

The main adjustments to the data are:

— Removal of weekends and non-working days from the dataset (only if a specification without the use of dummy variables to account for weekends and other non-working days is chosen)

— Removal of 2 week period around Christmas within the summer model

— Removal of cooler days from the summer model dataset (i.e. where average temperature is less than 23.5 degrees)

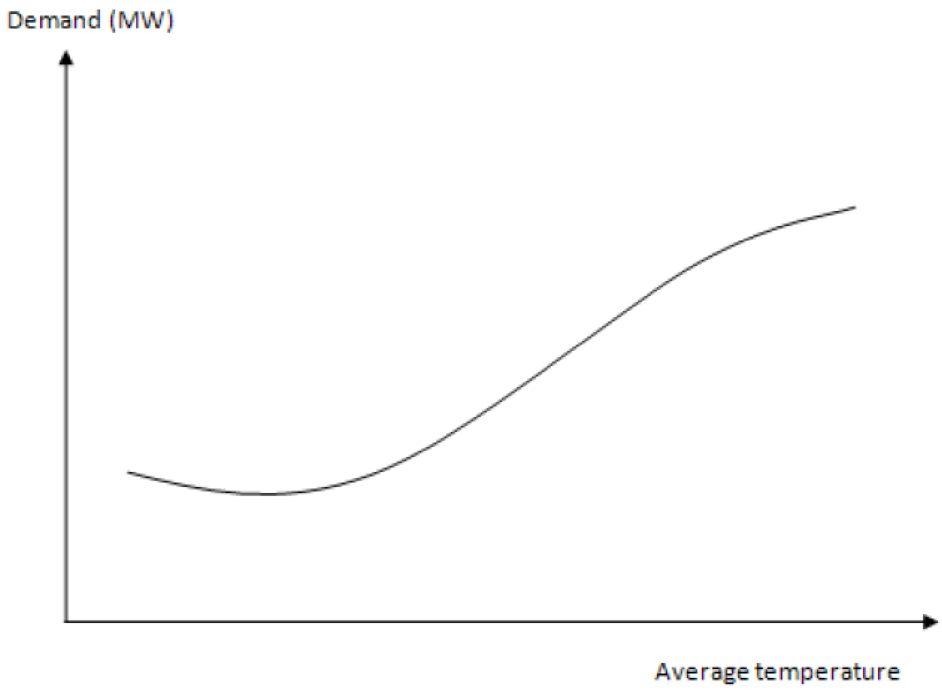
— Imputation of missing weather data points

The purpose of removing weekends and holiday periods from the model specification is because these days are generally not associated with peak system maximum demand days.

An alternative to removing weekends and non-working days from the dataset is to account for them explicitly through the use of dummy variables.

The same is true for cooler summer days within the season which are generally associated with lower peak demands. The removal of these days will also help to remove or minimise the bias arising from having a non-linear relationship between the daily maximum demand and temperature. By truncating the lower end of the curve shown in **Figure 5.2** Ergon imposes linearity on the relationship and can continue to use linear regression techniques to calibrate the models.

FIGURE 5.2 DAILY SUMMER MAXIMUM DEMAND VERSUS AVERAGE TEMPERATURE



SOURCE: ERGON ENERGY, LOAD FORECASTING SYSTEM MAXIMUM DEMAND REFERENCE DOCUMENT

5.2.3 Weather normalisation

There is no requirement to forecast future weather conditions in the methodology. The impact of weather is incorporated probabilistically by running the last 50 or so years of daily weather data from the Gladstone, Cairns and Townsville weather stations through the calibrated model. The maximum demands for each of the historical season peaks using the calibrated model forms the distribution from which the 10% and 50% POE demands are derived.

In addition, because the model estimates daily demand and the interest is in the peak of the season, the standard error of the regression is used to play a role in the simulation. While the calibrated models produce good fits, they are not able to capture all of the variation in the daily maximum demands. By accounting for the imperfect fit of the models, the tendency of the calibrated models to under predict the peak demand is reduced.

This is done by allowing each of the historical daily demands derived from the model to vary by a random draw from a normal distribution with a mean of zero and a standard deviation equal to the standard error of the calibrated model. The peak of each of the last thirty seasons is then calculated. One hundred trials are conducted calculating the peak of each historical season on each occasion. The 10% POE and 50% POE demand is then obtained from this expanded set of historical peaks which incorporates the uncertainty associated with the calibrated model.

5.2.4 Model validation

Ergon Energy in choosing the most appropriate model for the purpose of generating the forecasts has adopted the following model validation and testing procedures:

- Statistical significance of the model coefficients
- Theoretical justification of the inputs
- Overall fit of the model as measured by R^2
- Assessment of the degree of autocorrelation in the model residuals using the Durbin-Watson (DW) statistic

5.2.5 Post model adjustments

Ergon's system maximum demand methodology does not involve the application of any post model adjustments. The impact of increasing rooftop PV systems is included in the estimated regression. Other emerging technologies such as battery storage and electric vehicles are not considered. This is equivalent to a forecast of zero for these factors. Up until recently, this has not presented any problem as the uptake of battery storage and electric vehicles has been negligible. This is expected to change in the future, however, even over the next regulatory period the impact of storage and electric vehicles is not likely to be large.

5.3 Assessment of Ergon approach to system maximum demand

5.3.1 Econometric modelling approach

Ergon applies multiple regression techniques to estimate a daily time series model of system maximum demand. We consider that this approach if applied in conjunction with suitable model selection and diagnostic checking techniques will produce a model with unbiased and consistent coefficient estimates of the main drivers of daily demand.

Before any regression models are estimated, Ergon applies a number of filters to the data to ensure a linear relationship between maximum demand and the temperature variables. In the case of summer, days where the average temperature were below 23.5 degrees were excluded from the regressions. We understand that this threshold was determined by visually inspecting the relationship between daily maximum demand and average temperature and removing all the data points that lie on the non-responsive or flat part of the curve.

Also, in the case where the Christmas period and non-working days are nor accounted for explicitly within the model, then there is a requirement to filter these out from the dataset also.

Ergon Energy adopts a two stage process for model selection. Firstly, they estimate a larger number of potential candidates within Excel and narrow these down using standard diagnostic techniques such as R^2 and p values and t statistics before estimating a subset of these potential models within the Eviews econometric software which provides a broader suite of diagnostic checking tools such as the AIC and Durbin Watson (DW) statistic.

5.3.2 Inclusion of the main drivers

Ergon's final econometric specification modelled daily summer maximum demand as a function of:

- A constant term
- An interactive term between maximum temp (Gladstone) and GSP
- An interactive term between minimum temp (Gladstone) and GSP
- An interactive term between maximum temp (Gladstone) and air conditioner numbers
- An interactive term between maximum temp (Cairns) and GSP
- An interactive term between maximum temp (Townsville) and GSP
- An interactive term between a dummy to indicate a day where the max temp exceeds 33 and the number of air conditioning systems

The presence of the GSP variable captures the impact of increasing economic activity both due to increasing population and productivity within the Ergon network. The GSP variable enters the model only through the interactive terms with temperature. This leads to considerable difficulty in interpreting the estimated coefficients on the interactive terms. ACIL Allen does not consider this to be a significant issue.

In its review of the Energex system maximum demand methodology, Frontier Economics suggested that the main effect of GSP on its own should be included in the model specification alongside any interactive effects. This is not an unreasonable suggestion. It will however, in all likelihood introduce multicollinearity into the model, so there is a strong chance that the main effect of GSP will fail to pass the test of statistical significance. Again, this is not a serious concern as it has no serious implications for the model estimates. They are still unbiased, albeit with higher standard errors. In our view, it is better to include variables which introduce multicollinearity into a model, if the inclusion of that variable adds additional information content, rather than lose additional explanatory power to avoid statistically insignificant estimates. However, it is understood that the Ergon Energy model shows a high degree of multiplicative behavior rather than strictly linear processes.

The presence of maximum and minimum temperatures at Gladstone, and also maximum temperature variables at Cairns and Townsville capture the vast majority of weather related variation in daily maximum demand across the Ergon network. While other weather related variables like relative humidity might provide some additional explanatory power to the final specification, there is a major problem with obtaining humidity data of acceptable quality across regional Queensland. Humidity was therefore not included in the final model.

We also note that the model specification does not allow for higher demand resulting from several hot days in a row. This is easily incorporated through the use of lagged temperature variables. In particular, a very hot overnight minimum temperature or a high previous day's maximum might provide an additional boost to the next day's maximum demand.

It is our view that the model adequately captures the economic and weather related movement in maximum demand. We note however, that real electricity prices have been excluded from the preferred model specification. At the time the model was estimated and calibrated, real electricity prices were found to not exert a statistically significant influence on demand. As a result, price was not included in the model.

The absence of any calendar effects in the model specification reflects the fact that these were stripped out of the data in the data processing stage of the forecasting process.

Assessment of key inputs

The main inputs used in the modelling process are Queensland GSP, the number of air-conditioning systems and daily maximum and minimum temperature data from three weather stations in Gladstone, Cairns and Townsville.

GSP

For discussion of the GSP forecasts used in the system maximum demand forecasting process please refer back to section 3.3.5.

Air conditioners

Ergon Energy has previously obtained data on the number of air-conditioning systems within its network from the consulting firm Energy Consult Pty Ltd. As part of this review we have not been provided with any data on air conditioning systems. We understand that Energy Consult is a credible energy consulting business with a wide range of clients within the energy sector, and do not have any reason or basis to question the use of their forecasts. However, we also consider that accurately estimating the historical number of air conditioners across the Ergon network is also a difficult exercise that is likely to be prone to a high degree of error. Estimates of the number of air conditioners within the distribution network are likely to have been constructed using a combination of individual surveys, ABS data and possibly sales data from private sources.

Therefore, it may be preferable to use another more reliable variable as a proxy for the impact of increasing air conditioner numbers, such as population or GSP. Another advantage of using a more general measure of the size of the network is that it captures more than just the impact of increasing air conditioner numbers, but also the increase in the use and number of appliances in general.

Weather data

Ergon utilises daily maximum and minimum temperature data from weather stations located in Gladstone, Townsville and Cairns. These weather stations were chosen on the basis that they were more highly correlated with daily maximum demand than other possible alternatives. This is not surprising as these locations are spread along the Queensland coast where the majority of the population with Ergon's distribution network live.

They were also chosen on the basis that they had a sufficiently long time series available to facilitate the weather normalisation process and had only a very small proportion of missing data. ACIL Allen considers that these weather stations are suitable and fit for the purpose of inclusion into Ergon's system maximum demand model.

5.3.3 Weather normalisation

Ergon Energy's approach to weather normalisation is to use multiple regression to establish a relationship between the daily maximum demands over time and the weather conditions prevailing on each day in the sample. Rather than attempting to forecast weather drivers into the future for the purposes of forecasting demand, Ergon use a bootstrapping technique where they estimate daily maximum demands for each year in their historical and forecast period for each day in a long run time series starting from 1957. The daily peaks over the long history then form the basis of the annual distribution of maximum demands which are used to calculate the 10% and 50% POE demands.

The technique forms the basis of the temperature normalisation and is in accordance with the approach recommended by ACIL Allen's predecessor firm, ACIL Tasman as part of the Common Forecasting Methodology project. It is also now commonly applied by electricity DNSPs as is an integral part of many DNSPs methodology to forecast system maximum demand.

Climate change and global warming

One important aspect of weather normalization is to choose an appropriate length of time series of the temperature data to apply in the simulation. Because a 10% POE level of maximum demand is observed on average only 1 out of every 10 years by definition, the simulation needs a sufficient number of years to be able to adequately capture the 10 POE level of demand. The need for a longer time series is complicated by the fact that long term temperature patterns in Queensland exhibit an underlying rising trend.

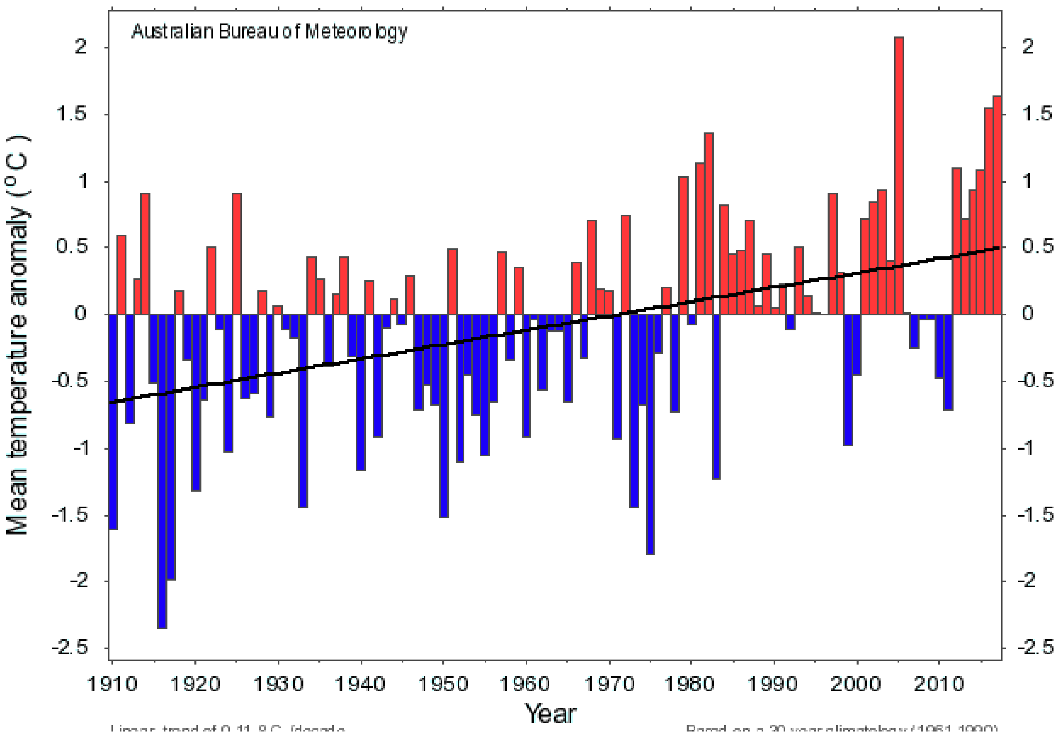
Figure 5.3 shows the summer mean temperature deviation from the long term average over the period from 1910 to 2017 period. The figure shows a persistent rising trend and seem to indicate that the period from about 1980 onwards marks the beginning of a structural shift towards warmer summer weather across Queensland.

Ergon Energy currently uses data from 1957 onwards as the basis of its weather normalization procedure. This encompasses the period of cooler than average temperatures in the 1960s and 1970s. By choosing such a long time series for the weather normalization procedure, Ergon takes an agnostic view about future weather conditions, and considers the possibility that long term weather patterns are cyclical, so that cooler temperatures are likely to return at some point. The longer the current trend continues, the greater the likelihood that it may be structural rather than cyclical. The notion of a structural shift in temperature is also consistent with the current general consensus of climate scientists.

ACIL Allen, therefore considers it to be reasonable for Ergon to limit the length time series used in its weather normalization procedure to the period extending from approximately 1980 onwards. By doing this, we remove the period of cooler conditions from the data set, and still retain 37 years of weather data for the simulation. In our view, 37 years is sufficient to adequately characterize the 10 POE level of maximum demand.

ACIL Allen recommends that Ergon Energy reduce the length of time series used in the weather normalization procedure.

FIGURE 5.3 SUMMER MEAN TEMPERATURE DEVIATION FROM LONG TERM AVERAGE, QUEENSLAND 1910 TO 2017



SOURCE: BUREAU OF METEOROLOGY

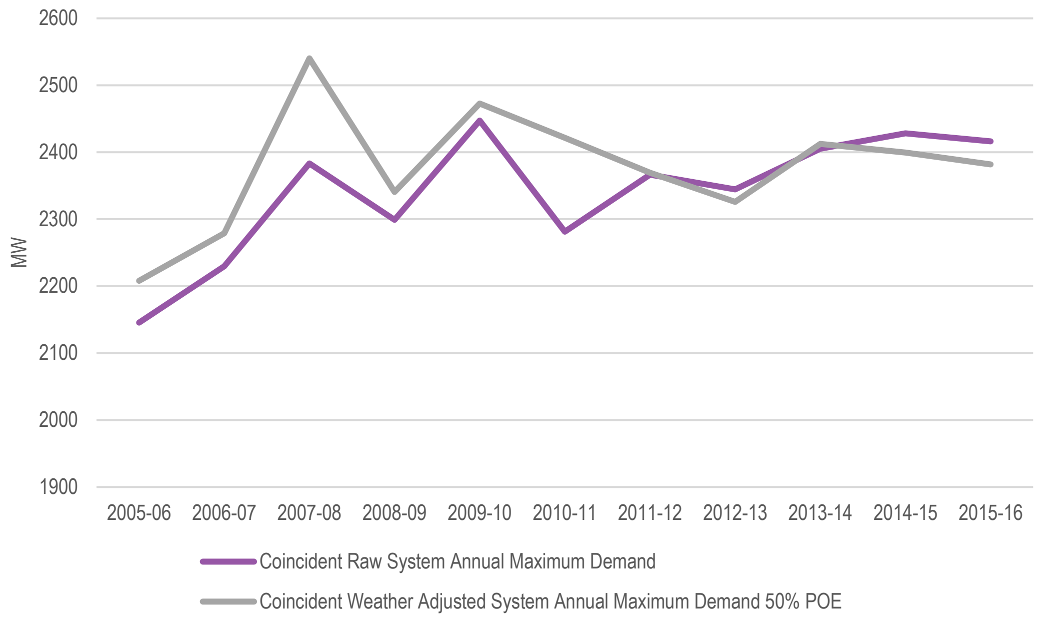
Historical maximum demand versus weather normalized (50 POE) demand

Figure 5.4 shows Ergon's historical weather normalized annual maximum demand against the actual observed maximum demand. Over a long enough time period, the observed maximum demand should spend approximately half of the time above and half of the time below the 50 POE level.

While the actual maximum demand spent the early part of the period above the weather normalised level of demand, it is difficult to conclude whether this is due to any inherent bias in the weather normalisation procedure or is simply the result of a run of cooler weather within the Ergon distribution network.

In fact, in **Figure 5.3** it is evident that the period from approximately 2005 to 2010 corresponds to a run of below average summer mean temperatures across Queensland which is consistent with Ergon's actual maximum demand lying below the weather normalised demand in this period. This observation provides us with some comfort that Ergon's weather normalisation procedure is adequate.

FIGURE 5.4 WEATHER NORMALISED 50 POE AND ACTUAL SYSTEM MAXIMUM DEMAND, ERGON



SOURCE: ERGON ENERGY

5.3.4 Model validation

As we have discussed in the previous section, Ergon uses a combination of in sample model fit, statistical significance, assessment of the theoretical coherence of the coefficients and diagnostic checking of the residuals to validate its models. **Figure 5.5** shows the estimated coefficients from Ergon's preferred model.

FIGURE 5.5 ESTIMATED COEFFCIENTS FROM 2014 SUMMER MAXIMUM DEMAND MODEL

Variable	Coefficient	Std. Error	t-Statistic	Prob
Constant	72.71857	66.64514	1.091131	0
Gladstone MAX*GSP	0.000175	1.08E-05	16.24062	2.53E-50
Gladstone MIN*GSP	4.95E-05	9.21E-06	5.381273	1.02E-07
Gladstone MAX*AIRCONS	-1.2E-05	8.81E-07	-13.9349	5.55E-39
Cairns MAX*GSP	3.77E-05	7.57E-06	4.985444	7.86E-07
Townsville MAX*GSP	8.04E-05	8.61E-06	9.345758	1.3E-19
MAXGT33*AIRCONS	3.36E-05	5.36E-06	6.269629	6.45E-10
R-squared	0.926124	Mean dependent var	1882.024	
Adjusted R-squared	0.925459	S.D. dependent var	290.0909	
S.E. of regression	79.20132	Akaike info criterion	11.592	
Constant	72.71857	66.64514	1.091131	0

SOURCE: 00188 LOAD FORECASTING MAXIMUM DEMAND REFERENCE DOCUMENT, ERGON ENERGY

Statistical significance

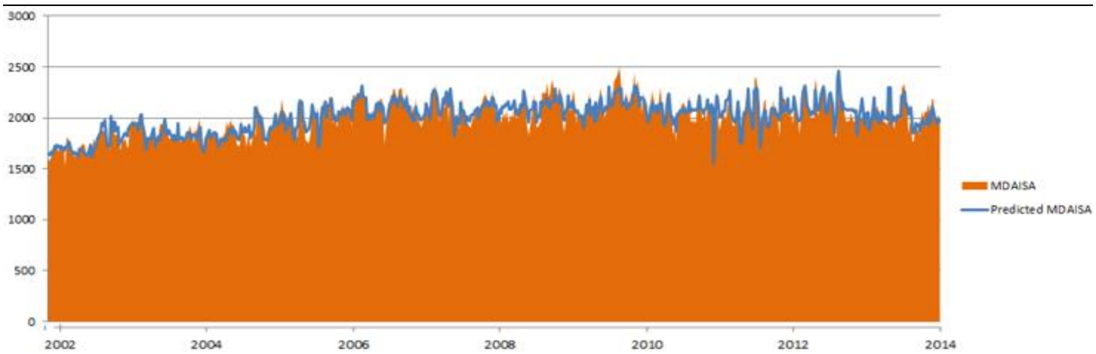
Ergon employs the concept of statistical significance when choosing between possible explanatory variables. **Figure 5.5** shows the key driver variables, apart from the constant term, are all statistically significant at the 1% significance level.

Goodness of fit

The adjusted R^2 of Energex's preferred estimated model is 92.5%. This represents a very high in-sample fit and is in our view reflective of the fact that the model's explanatory variables are able to adequately capture the vast majority of variation in daily maximum demand across the Ergon network.

The goodness of fit of the estimated regression model is shown in **Figure 5.6**. The figure shows the predicted and actual daily summer maximum demand, and is consistent with an estimated R^2 that is in excess of 90%.

FIGURE 5.6 PREDICTED VERSUS ACTUAL DAILY SUMMER MAXIMUM DEMAND



SOURCE: 00188 LOAD FORECASTING MAXIMUM DEMAND REFERENCE DOCUMENT, ERGON ENERGY

5.3.5 Need to re-calibrate models based on up to date data

It has now been several years since the Ergon summer system maximum demand was specified. We therefore consider, that the model needs to be updated and all the potential explanatory variables re-tested on an ongoing basis to establish their validity. While we do not expect the underlying structure to change markedly, it is possible that variables that were previously excluded from the modelling on the basis of statistical insignificance, such as price, may in fact add to the explanatory power of the model based on the most recent information.

5.3.6 Regionality and reconciliation of spatial forecasts to the system level

Ergon Energy has a very large and diverse electricity distribution network, whose regions have very different economies, populations and climates, ranging from tropical in the north to sub-tropical in the south. The network encompasses coastal regions as well as inland, rural and well as urban centres. This diversity makes it difficult to capture all the differences across the network in a single model.

One of the important uses of the system level forecasts, is for the purpose of reconciling and anchoring the lower level spatial forecasts to the higher level system forecasts. Because of the sheer geographic scale of the Ergon network, the practice of reconciling specific zone substation forecasts to a system level number is a very crude and blunt instrument.

In our view, the reconciliation process could be made more accurate through the development of lower level regional maximum demand models, similar to the regions used in the energy delivered methodology. ACIL Allen recommends that Ergon consider the development of separate regional maximum demand models for:

— Capricornia
— Far North Queensland

- Mackay
- North Queensland
- South West
- Wide Bay

5.3.7 Transparency and repeatability

Ergon Energy has developed two separate documents relating to their system maximum demand forecasting methodology.

The first entitled 'Load Forecasting: System Maximum Demand Reference Document' outlines the main concepts behind the methodology. This document provides an explanation of the methodology at a more conceptual level covering issues such as:

- The relationship between maximum demand and its drivers, including weather
- Model construction and form
- Model validation techniques applied
- Discussion of data sources and their location within Ergon's data repositories
- Detail of the nature of forecasts produced

The second document, entitled 'Load forecasting: System Maximum Demand User Document' covers issues more closely relating to the operation of the spreadsheet model itself. This document includes:

- Process flow diagrams
- Descriptions of the contents of each of the models worksheets
- Description of the calculations underlying the main worksheet where the forecasts are generated
- Description of the models run process to generate forecasts

Together these documents provide a good understanding of the forecasting methodology.

ACIL Allen considers that Ergon Energy has produced documentation that is largely adequate and suitable for presentation to the regulator to provide a description of the overall methodology applied to generate system maximum demand forecasts.

5.3.8 Post model adjustments

Ergon Energy currently makes an explicit adjustment for rooftop PV systems by estimating the rooftop PV demand at the time of day peak and treating this as a separate variable. This, combined with energy efficiency are combined as a unifying index and included as a separate variable in the baseline models. For the last three years peak demand for the system has been in the evening, resulting in a diminishing overall effect of this index.

Because rooftop PV is included as a separate variable within the baseline model, Ergon Energy does not make a post model adjustment for rooftop PV, although a separate scenario is produced for the uptake of battery storage and electric vehicles.

Moreover, the impact of battery storage up until very recently has been negligible and there was no reason to make any adjustment to the base model for it. However, it is very likely that this will change in the future as the price of new battery storage systems continues to decline relatively quickly and leading to significant improvement in the economic payoff from the installation of new battery storage systems. The rise of battery storage will enable households to store their excess electricity generated during the middle of the day, and consume it later on in the late afternoon and evening when their demand for electricity increases. This has the effect of reducing the late afternoon and early evening peaks and flattening out the daily load curve.

ACIL Allen therefore recommends that Ergon Energy adopts a formal method to forecast the increasing impact of battery storage systems on maximum demand by scenario, and included its impact on maximum demand through a post model adjustment. This model could be developed in-house, or a suitable external provider could be commissioned to provide a set of independent and robust forecasts.

In the case of electric vehicles (EVs), the impact on energy delivered is well understood. However, in the case of their impact on maximum demand, there is a strong likelihood that new tariffs will be created to incentivise owners of EVs to charge their vehicles during off peak periods. Consequently, we consider that the vast majority of vehicles will be charged at night when the car is garaged and the impact of maximum demand will not be very large, at least for the foreseeable future.

5.4 Key recommendations

After reviewing Ergon Energy's system maximum demand methodology we recommend the following:

— Ergon should consider developing separate regional maximum demand models to allow better targeted reconciliation between its spatial level and higher level demand forecasts

— Ergon should consider switching from the use of the number of air-conditioners as a variable in its model, to more reliable proxies such as GSP or population. These are produced by Australia's official statistical agency, while the air conditioner numbers come from a private vendor, whose reliability cannot be verified, and of which there is limited understanding of how the data series is constructed

— Ergon should shorten the long run weather time series used in the weather normalisation process to include only the period from around 1980 onwards. This reflects the fact that summer average temperatures have increased over the long term, and is in effect a judgement call that the structural shift in Queensland temperature is permanent rather than temporary

— Ergon should recalibrate its preferred model based on the most up to date data available, and re-introduce variables that were tried previously and found to be statistically insignificant, such as price

— Ergon should introduce post model adjustments for battery storage and electric vehicles

6 SYSTEM MAXIMUM DEMAND - ENERGEX

6.1 Previous reviews of Energex's approach to System maximum demand

The basis of Energex's current methodological approach to forecasting System maximum demand dates back as far as 2009, when it was reviewed as part of the Joint Workings project conducted by ACIL Tasman.

In that review, Energex had essentially applied an approach that was developed by ACIL Tasman in earlier work for Energex dating from April 2008. This methodological approach adopted as a result of the Joint Workings project forms the backbone of Energex's current methodology, although many of the details have now changed.

At this time, Energex modelled daily summer maximum demand using an econometrically based time series regression approach.

The model specification included the following variables:

— A constant term
— Queensland Gross State Product (GSP) level
— Daily maximum temperature
— Daily minimum temperature
— Friday dummy variable
— Saturday dummy variable
— Sunday dummy variable

Energex excluded cooler days from the regression dataset, where the average temperature was below 23.5 degrees. This constrained the relationship between daily maximum demand and temperature to be linear. Also excluded from the modelling dataset were the 3 week period around Christmas, where demand was significantly below the summer average.

For the purpose of weather normalisation and the derivation of 10, 50 and 90 POE demand, the weather history from the Amberley weather station for each summer from 1955 onwards was passed through calibrated model to obtain a frequency distribution of annual peak demands for the entire forecast period.

In December 2013, Energex's peak demand methodology was reviewed by Frontier Economics. The main findings of this review were:

— That Energex needed to further develop its documentation to improve the methodology's transparency and repeatability

- That Energex's models include all the major drivers of system maximum demand but that further analysis was required to determine the exact form that these variables enter the model
  - In particular, Frontier recommended that where Energex uses interaction terms in its model specification, it should also include the main effect as well
- That there was significant evidence that the model was mis-specified based on a very low value for the Durbin-Watson statistic
- That Energex should consider using multiple weather stations for inclusion into the modelling and the weather normalisation procedure
- That Energex should consider including a price variable and dummy variables for day of the week effects directly into the estimated model

Energex has made significant progress in meeting the recommendations of Frontier Economics December 2013 review.

6.2 Energex approach to System maximum demand

Energex's current approach to forecasting System maximum demand is a top down econometric model which uses daily system maximum demand as the dependent variable. The latest estimated regression is calibrated using data from November 2008 through to March 2017.

The model incorporates the main drivers of demand such as temperature, GSP and electricity prices. Also included as explanatory variables are a dummy variable for a structural break from 2011 onwards as well as calendar related variables such as separate dummies for weekends and public holidays, Fridays, Sundays, a dummy variable for Christmas day and for the Christmas period, normally defined as the three period around Christmas.

Prior to estimation, the impact of rooftop PV and Network Demand Management (NDM) is added back to the realised daily maximum demand to strip out the impact of these factors. These effects are then re-incorporated into the forecasts via post model adjustments which are made externally to the base econometric model. In addition to PV and NDM, additional post model adjustments are made for the contribution of battery storage and electric vehicles (EVs).

Energex have refined their model since the Frontier review of December 2013, by making a number of changes. First, they have created a single weather index based on data from three weather stations rather than just one. While previously, they used data from Amberley only, Energex have now created a population weighted maximum and minimum temperature index based on data from Amberley, Archerfield and Brisbane Airport. This alleviates a long standing concern that the weather station at Amberley, which is located some distance from Brisbane, may not be fully capturing weather behaviour along the coast where the majority of the population in Energex's network live.

Energex use data from the beginning of November to the end of March to define their summer. This is a common practice among DNSPs to capture the possibility that the peak demand for a given season could end occurring outside the conventional definition of summer.

The regression also excludes milder days from the estimation, which resolves the problem of having to fit a complex non-linear function to the temperature variables in the regression to account for the part of the relationship where daily maximum demand is unresponsive to incremental changes in the temperature variable. Energex use two separate criteria to filter the milder days out of the sample. If the weighted daily maximum temperature is less than 28.5 degrees or if the weighted daily minimum temperature is less than 22 degrees Celsius then the day is omitted from the regression. This, in our view, is a reasonable approach to take.

Once the base econometric model is estimated, Monte Carlo simulations are conducted around the long run historical weather to establish a frequency distribution of peak demands from which the 10POE, 50 POE and 90 POE maximum demands can be extracted. This approach has now become standard practice in the electricity industry. The simulation uses weather data from the three chosen weather stations dating back to 1985. In our view this is a sufficient length of time to create the weather normalised forecasts.

The estimated coefficients from Energex's most recent preferred system maximum demand model are shown in the table below.

TABLE 6.1 PREFERRED ENERGEX SYSTEM MAXIMUM DEMAND MODEL

Variable	Coefficient	Standard Error	T statistic	Prob.
Constant	-3623.766	408.28	-8.88	0.000
Weighted Daily Maximum Temp	149.978	3.17	47.26	0.000
Weighted Daily Minimum Temp	34.282	2.98	11.50	0.000
Total Electricity Price	-30.608	13.55	-2.26	0.024
GSP	0.116	0.02	4.84	0.000
3 Continuous Hot Days dummy	68.378	18.34	3.73	0.000
Weekend or Public Holiday dummy	-563.866	13.10	-43.03	0.000
Friday dummy	-32.938	14.44	-2.28	0.023
Sunday dummy	-44.148	14.81	-2.98	0.003
Structural Break Started 11/12 dummy	-325.026	45.78	-7.10	0.000
Christmas Season dummy	-248.442	23.93	-10.38	0.000
Christmas Day dummy	-219.282	109.66	-2.00	0.046
AR(1)	0.449	0.03	14.10	0.000
SIGMASQ	21092.087	966.00	21.83	0.000
Constant	-3623.766	408.28	-8.88	0.000

SOURCE: ENERGEX

Energex generate forecasts under three separate scenarios, Low, Medium and High. Forecasts of GSP and electricity prices under the three separate scenarios were obtained externally from the economic consultancy NIEIR.

6.3 Assessment of Energex approach to System maximum demand

6.3.1 Econometric approach

Energex's approach has a number of very desirable attributes. First, it is based on the main economic, demographic, weather drivers and calendar effects. These drivers are able to change over time to reflect the dynamic nature of the key variables that drive system maximum demand.

Energex has moved completely away from the extrapolation of trends which imply a continuation from the historical period into the future period of the key drivers of maximum demand.

ACIL Allen consider that the econometric approach taken by Energex is reasonable and in accordance with the regulators best practice forecasting principles outlined in an earlier section of this document.

6.3.2 Inclusion of main drivers

The main drivers used in the econometric model are:

— Weighted daily maximum and minimum temperatures
— A dummy for when there are three consecutive hot days
— Electricity prices
— GSP
— Calendar effects such as:

  - Dummy variables for lower demand on Fridays and Sundays
  - Dummy variables to capture lower demand during the Christmas season and Christmas day
  - Dummy variables to capture lower demand on weekends and public holidays
- A dummy variable to capture the presence of a structural break in 2011-12

It is our view that this model specification captures the main demographic and economic, price, weather and calendar effect drivers of system maximum demand.

6.3.3 Key inputs

The key inputs used in the base forecasting model are GSP, temperature and electricity prices. These are discussed below.

Gross State Product

Energex have opted to use GSP forecasts from NIEIR to use in developing their system maximum demand forecasts. Specifically, Energex have chosen to apply NIEIRs low case GSP forecast as part of its base case forecast. An analysis of NIEIRs GSP forecasts was presented in section 4.3.3. In this section we suggested that the NIEIR low case was not consistent with the forecasts of other official agencies, other independent experts or the recent historical behaviour of Queensland GSP.

Moreover, using the NIEIR low case for GSP, should necessitate the use of the NIEIR low case for any of the other input variables such as price. Otherwise the forecasts of the input variables are inconsistent with each other. We therefore recommended that Energex should revert to using the NIEIR base or medium case as its base case GSP forecast.

Weather variables

Energex employ weather data from three separate weather stations, Amberley, Archerfield Aero and Brisbane Aero. Data from each of the weather stations is weighted by population to create a single weighted daily maximum and daily minimum temperature series. ACIL Allen considers that this is a reasonable approach to constructing the temperature variables to be input into the regression model.

Electricity price

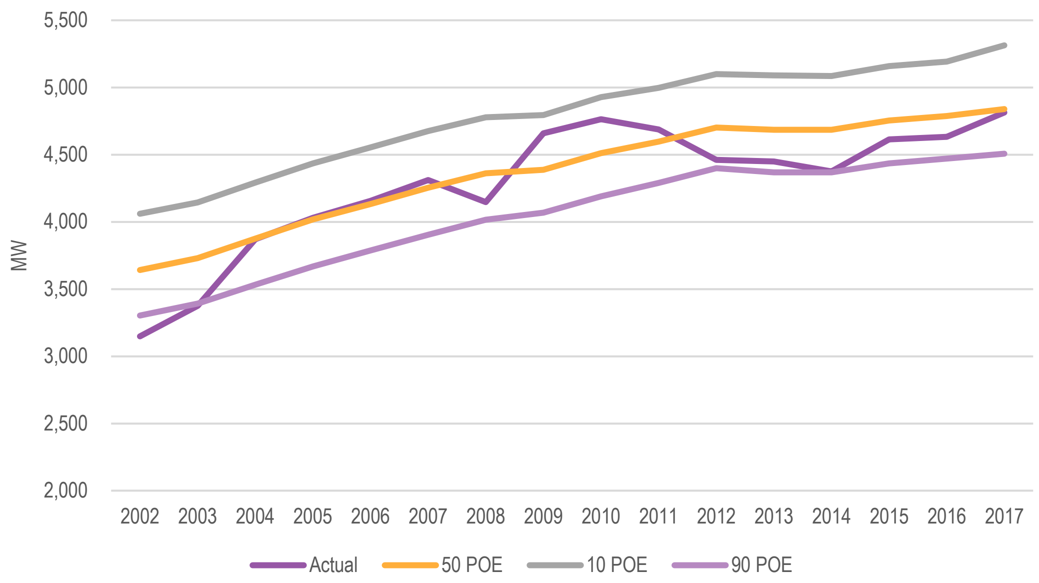
In section 4.3.3 ACIL Allen reviewed NIEIRs electricity price forecasts which are used as an input into both the energy delivered and summer maximum demand models. This section compared NIEIRs forecasts against those produced recently by the AEMC. We concluded that NIEIRs real electricity price forecasts were reasonable.

6.3.4 Weather normalisation

Energex apply a Monte Carlo simulation approach to weather normalisation, similar to that employed by Ergon Energy. A long run historical weighted temperature series is constructed back to 1985 and used to create a long term frequency distribution of annual system maximum demands from which the 10 POE, 50 POE and 90 POE forecasts can be derived. This approach to weather normalisation has become common practice in the Australian electricity industry, and is in our view the most appropriate approach to weather normalisation available. It represents a significant improvement on earlier approaches which linked the maximum demand to a specific average temperature, and then sought to weather normalise the actual maximum by moving along a line representing the relationship between maximum demand and average temperature

Figure 6.1 shows Energex's historical weather normalised maximum demands and actual peaks for the period from 2002 to 2017. Based on this figure, the actual historical maximum demand is securely anchored within the 10 POE and 90 POE demand, spending roughly half the time above the 50 POE as it does below the 50 POE. This is precisely what we would expect from a weather normalisation process that has no inherent biases.

FIGURE 6.1 HISTORICAL ACTUAL AND WEATHER NORMALISED SYSTEM MAXIMUM DEMANDS



SOURCE: ENERGEX

Assessment of the temperature sensitivity coefficients over time

In Frontier's most recent review of Energex's system maximum demand methodology, Frontier recommended that where Energex uses interactive variables, it should also include the main effect as well. In response, Energex added separate main effects for temperature and GSP, but removed the interactive effects. By doing this, Energex has imposed a fixed temperature sensitivity going forward. This runs counter to ACIL Allen's experience and is also counter-intuitive when you consider that the size of Energex's network is increasing over time.

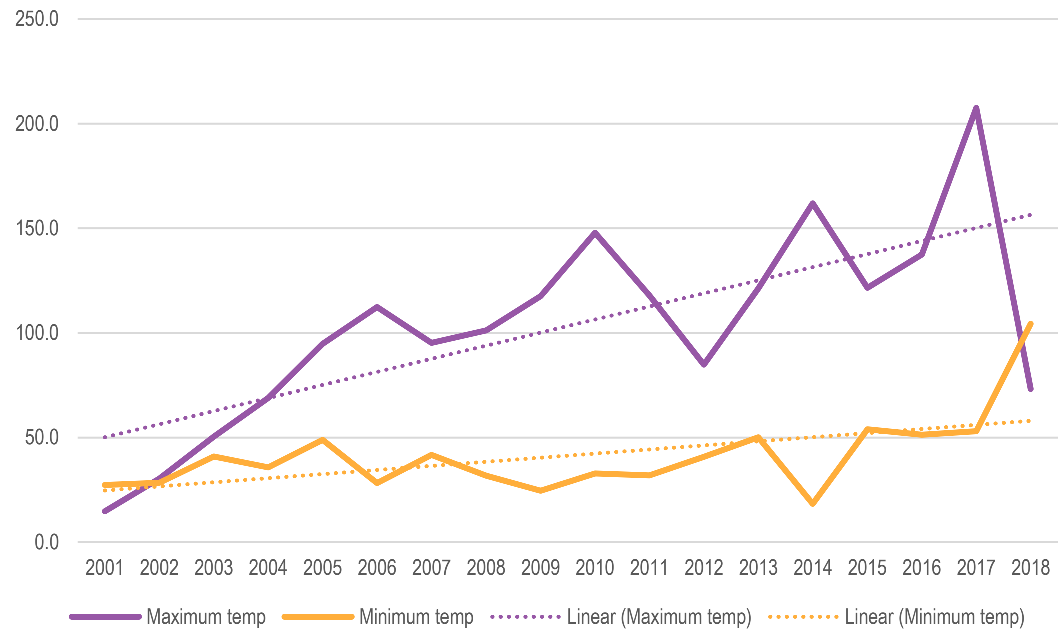
Consequently, one might expect that as the number of customers within Energex's network increases over time, the MW response to an increase in maximum and minimum temperature should also rise over time.

As a test, ACIL Allen split Energex's daily summer maximum demand time series into separate summer seasons and ran some simple regressions to determine the behaviour of the individual season maximum and minimum temperature coefficients.

These coefficient estimates are plotted in **Figure 6.2** below. It is evident that both the weighted daily maximum and minimum temperature coefficients display considerable movement, but around a rising trend.

ACIL Allen recommends that Energex re-consider the introduction of interactive terms on the temperature variables or some other innovative approach that allows the demand response to temperature to increase over time.

FIGURE 6.2 PLOT OF WEIGHTED MAXIMUM AND MINIMUM TEMPERATURE COEFFICIENTS FROM SEQUENTIAL SINGLE SEASON REGRESSIONS



SOURCE: ACIL ALLEN CONSULTING

6.3.5 Model validation

Energex has adopted a comprehensive approach to model validation in response to the previous review of its methodology.

Statistical significance

Energex tests a large number of possible explanatory variables using the general to specific method. Under this approach a large number of potential variables are included in early econometric specifications and then those variables that fail to achieve statistical significance or that provide lesser explanatory power compared to other similar variables are progressively removed from the estimated model. **Figure 6.3** shows the wide range of variables that were tested as possible inclusions into the final model specification. ACIL Allen is satisfied that Energex has tested a large number of possible drivers and narrowed them down to a best set of drivers that provide the most explanatory power. All of the explanatory variables used in the preferred model, shown in **Table 6.1**, were found to be statistically significant at the 5% significance level.

FIGURE 6.3 POTENTIAL VARIABLES FOR INCLUSION INTO THE DAILY SUMMER MAXIMUM DEMAND MODEL

Category	Symbol	Definition	Unit	Source	Selected?	Note
Dependent Variables	PkMW	Recorded System Peak MW	MW	Major Cust. DB (MCDB)	No	Recorded daily system maximum MW
	PkMWAll	PkMW Plus PV & NDM	MW	MCDB & Strat-Ct-Int. (SCI	Yes	Target Variable
	PkMWCt	PkMW per Customer	MW/Cust	MCDB, Pricing & PEACE	No	
	PkMWAllCt	PkMWAll per Customer	MW/Cust	MCDB, SCI, Pricing & PEAC	No	
Economic Variables	Ptotal	Total Electricity Price	c/kWh	NIEIR	Yes	Annual distrib. (not retail) charge
	PTotalAEMC	Total Electricity Price	c/kWh	AEMO	No	AEMO does not provide data
	GSP	Gross State Product	$M	ABS	Yes	Annual Queensland Real GDP
	GSI	Gross State Income	$M	ABS	No	
	GSPpc	GSP Per Capita	$/person	ABS	No	
	GSIpc	GSI Per Capita	$/person	ABS	No	
	CustNo	Total Customer Numbers	Integer	Pricing Group & PEACE	No	Unique NMI Counts
Weather Variables	WgtTMax	Weighted Daily Maximum T	°C	BOM & ABS	Yes	Amberly, Archerfield & Brisbane Airport
	WgtTMin	Weighted Daily Minimum T	°C	BOM & ABS	Yes	Amberly, Archerfield & Brisbane Airport
	WgtTmean	Weighted Daily Mean T	°C	BOM & ABS	No	
	RHAvg	Average Relative Humidity	Number	BOM	No	
	Rainfall	Daily Rainfall	mm	BOM	No	
	DCHI	Daily Cooling/Heating Index	Number	BOM	No	
External Shocks	DmySBK12	Structural Break Started 11/12	Integer	N/A	Yes	Dummy - structural break started from 11/12
	T11to17	Trend from 2011 onwards	Integer	N/A	No	Trend variable from 2011 onwards
	DmyGFC	2008 Global Financial Crisis	Integer	N/A	No	
	DmyFld	2011 QLD Flood	Integer	N/A	No	
Calendar Related Variables	CHtTDy310	1 = 3 Continuous Hot Days	Integer	N/A	Yes	WgtTMax > = 31.0 °C
	WeMix	1 = WkEnd or Public Holiday	Integer	N/A	Yes	Treat public holiday as weekend
	FriCtrl	1 = Friday	Integer	N/A	Yes	Friday dummy variable if peak time >= 3pm
	DmyXmas	1 = Christmas Season	Integer	N/A	Yes	Normally 3 weeks around Christmas period
	DmyXmaxDy	1 = Public Holidays	Integer	N/A	Yes	Dummy variable for Christmas day
	SatFlg	1 = Saturday	Integer	N/A	No	
	SunFlg	1 = Sunday	Integer	N/A	Yes	Dummy variable for Sundays

SOURCE: ENERGEX

Goodness of fit

Energex's preferred daily summer maximum demand model was able to achieve an adjusted R^2 of 90.9%, which means that over 90% of the variation in the historical daily maximum demand can be explained or accounted for by the variation in the key inputs. ACIL Allen consider this to be a good result with the model demonstrating a high degree of explanatory power.

Analysis of the model residuals and other diagnostic checking

Energex employ a battery of diagnostic tests to validate their econometric models. Apart from statistical significance, they employ tests of serial correlation, heteroscedasticity, multicollinearity, formal tests of stationarity, and tests for structural breaks.

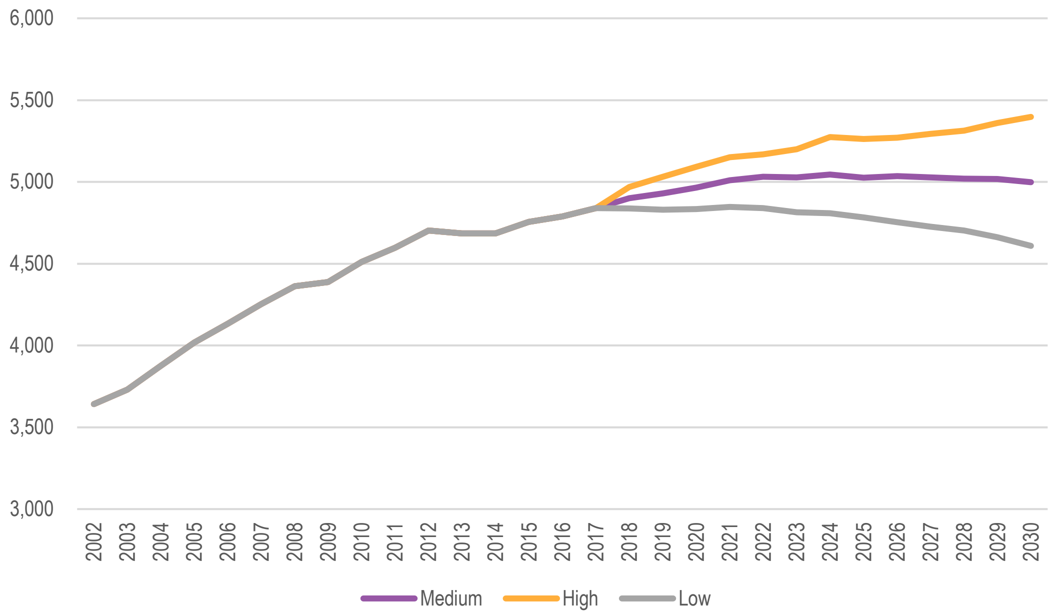
In fact, in its preferred model specification, Energex has identified a structural break which commences in the 2011-12 summer, as well as serial autocorrelation in the residuals which is captured by the inclusion of an autoregressive term in the model.

ACIL Allen considers that Energex's approach to model validation and testing lends a strong degree of credibility to Energex's methodology in the eyes of the regulator. We consider it to good practice and very much in accordance with the AERs best practice forecasting principles.

6.3.6 Reasonableness of the forecasts

Energex's 50 POE medium forecasts behave in a way that is consistent with the historical trend up to 2021 before levelling off. As the forecast period progresses, the influence of rooftop PV and the rise of battery storage increase significantly, leading to a levelling off in system maximum demand (see **Figure 6.4**).

FIGURE 6.4 ENERGEX 50 POE SYSTEM MAXIMUM DEMAND FORECASTS



SOURCE: ENERGEX

Over the seven year period from 2010 to 2017, Energex's weather normalised 50 POE maximum demand grew at an average rate of 1% per annum. This compares to a forecast rate of growth of 1.2% per annum over the seven year period from 2017 to 2024. While the forecast growth rate lies slightly above the historical one for the first seven years, there is nothing that appears unreasonable or questionable in the forecasts based on the underlying assumptions of the key drivers.

6.3.7 Post model adjustments

Energex apply five separate post-model adjustments to their base econometric forecasts. These are for:

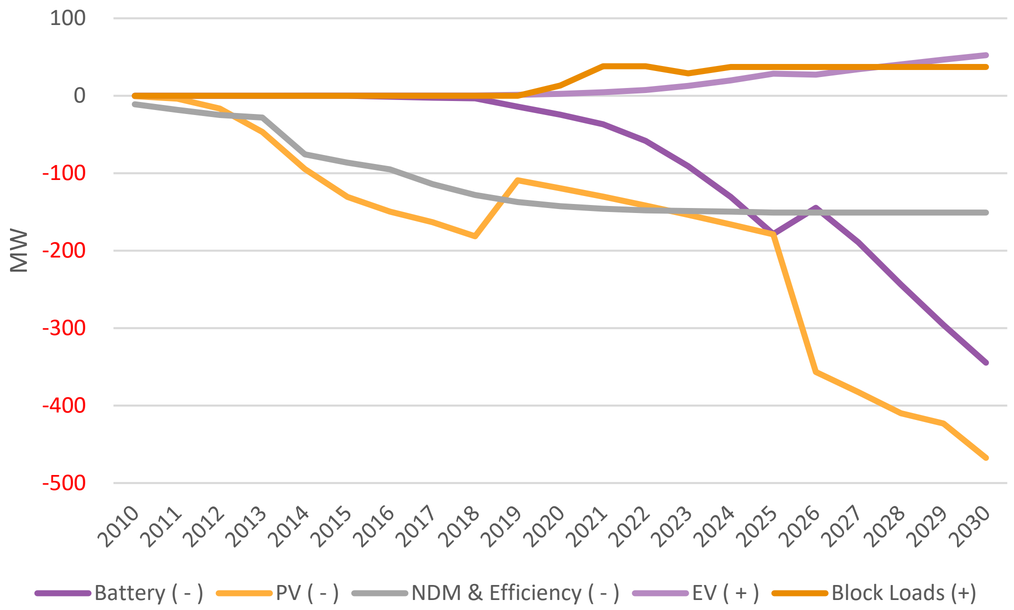
— Battery storage
— Rooftop PV
— Network demand management
— Electric Vehicles
— Block Loads

Energex's rooftop PV, battery storage and Electric Vehicle forecasts are obtained externally from the consultancy Energeia. ACIL Allen were not provided with any documentation detailing the approach taken to generate these forecasts, apart from some description for rooftop PV which we reviewed in section 4.3.5.

In this section we recommended Energex move away from a rooftop PV model which relies on extrapolation along an S curve and adopt a modelling approach which relies on changes to the fundamental drivers. This recommendation also applies to system maximum demand.

Figure 6.5 shows the estimated impact of each of Energex's post model adjustments on forecast system maximum demand. While we cannot comment in any great detail on the methodology used, we are able to apply a sense check on the projections themselves.

FIGURE 6.5 ENERGEX POST MODEL ADJUSTMENTS FOR THE BASE CASE



SOURCE: ENERGEX

As expected, the influence of EVs and block loads is very small as a share of the total system maximum demand. Network demand management and efficiency gains represent a modest increase over the adjustment made historically. These post model adjustments look reasonable. We are not prepared, however, to offer a view on the impact of battery storage and rooftop PV on system maximum demand due to limited information.

6.3.8 Transparency and repeatability

Energex's document, 'Network Forecasting: Constructing the summer peak system demand forecast' outlining its approach to forecasting system maximum demand describes the models estimated as well as the process involved in reaching the best model.

The document provides a detailed coverage of the process of data collection, model estimation and diagnostic checking and model validation. The documentation is comprehensive in outlining the process that Energex has used to select the best base econometric model. The documentation lists all the possible variables and describes the methodology used to move from a general to a specific model. The documentation also adequately describes Energex's comprehensive diagnostic testing and model validation procedures. The process by which the models are selected is well described.

However, just like its documentation of the energy delivered methodology, while the model selection and validation phase is explained in depth, there is little coverage of the methodology used to produce the post model adjustments, namely rooftop PV, battery storage and EVs.

Also, there is no discussion or coverage of how the forecasts of PV, battery storage and EV capacity numbers translate into an impact on system maximum demand.

ACIL Allen understands that the lack of detail regarding the post model adjustments is largely a result of the forecasts being outsourced to an external consultant. Despite this, the absence of this detail in a regulatory submission would be interpreted as a lack of transparency. ACIL Allen recommends that Energex address this by either adding further detail to the Network Forecasting document, or providing supplementary material from the independent consultant as part of its regulatory submission.

6.4 Key recommendations summary

On the basis of the review of Energex's system maximum demand methodology, ACIL Allen recommends:

— Energex have applied the NIEIR low case GSP forecast to produce its medium or base case system maximum demand forecast. ACIL Allen considers that the NIEIR low case is too pessimistic based on recent history and the forecasts of other independent experts. Our recommendation is for Energex to use the NIEIR medium case as the basis for its base or medium case forecasts. These are more consistent with historical economic activity after the GFC

— Energex should consider shifting to a fundamentally driven model of rooftop PV uptake that is based on forecasts of the major drivers such as the cost if installation, changes in feeds in tariffs and other subsidies, and electricity prices, rather than relying on a method of extrapolation along an S curve

— Energex could improve the transparency and repeatability of its forecasts by adding detail to its documentation on the methodology used to forecast the uptake of PV, battery storage and electric vehicles

— Energex should re-consider the introduction of interactive terms on the temperature variables or some other innovative approach that allows the demand response to temperature to increase over time. Currently Energex's model only allows for a fixed temperature sensitivity of demand over time, while intuitively, one might expect the MW response to get bigger in response to say a 1 degree movement in temperature, as the number of customers in its network increase

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ABN 68 102 652 148

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