ACIL ALLEN CONSULTING

REPORT TO
ENERGY QUEENSLAND

13 JUNE 2019

REVIEW OF SYSTEM PEAK DEMAND FORECASTS

A REVIEW OF FORECASTING METHODOLOGIES USED BY ENERGY QUEENSLAND IN RESPONSE TO THE 2018 RECOMMENDATIONS

FIGURES

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1 INTRODUCTION

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 to evaluate the extent to which compliance has been achieved with the recommendations made as part of the review dated 15 May 2018.

As part of this assignment ACIL Allen has reviewed Energy Queensland's peak demand forecasting models for both regional and South East Queensland:

— With reference to the recommendations for improvement made in the ACIL Allen review of forecasting methodologies dated 15 May 2018
— Addressing the validity, veracity and model/forecast accuracy consistent with the recommendations

The review has also:

— Reviewed the existing processes against best practice principles such as:
  – Transparency and repeatability
  – Accuracy and unbiasedness
  – Incorporation of key drivers
  – Use of consistent and most recent input information
  – Model validation and testing
— Reviewed the appropriateness of the key inputs and drivers including:
  – Dependent variable
  – Explanatory variables: Demographic, economic, weather and calendar variables
  – Post model adjustments: Electric vehicles, PV and battery storage post model adjustments
— Evaluated and assessed the model logic and structure and whether the resulting forecasts are reasonable
— Evaluated the models and resulting forecasts in response to the recommendations made previously
— Provided further recommendations for improvement to reflect best practice

1.1 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 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 maximum demand models.

1.2 Structure of this report

This report as structured as follows:

— Section 2 describes the AERs principles of best practice forecasting
— Section 3 outlines how Energex and Ergon have responded to the recommendations made in the previous review
— Section 4 reviews Energex's approach to system maximum demand
— Section 5 reviews Ergon's approach to system maximum demand

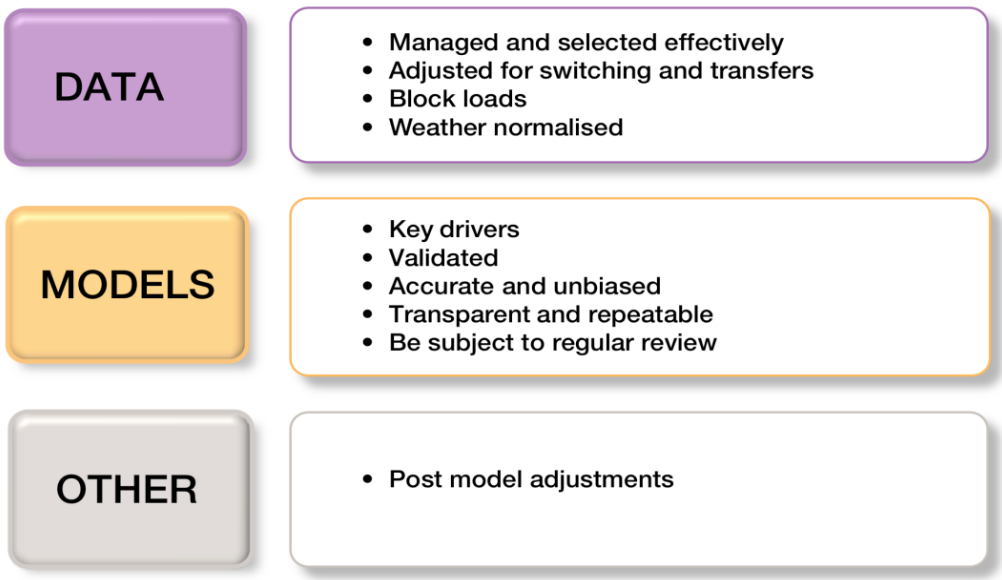
2 BEST PRACTICE FORECASTING

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"[1]

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

[1] 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, either directly or indirectly. These may include[2]:

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 within the system maximum demand forecasting models.

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] 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.

2.5 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 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.

CURRENT RESPONSE TO RECOMMENDATIONS OF THE PREVIOUS 2018 REVIEW

3

3.1 Introduction

In early 2018 ACIL Allen was commissioned by Energy Queensland to conduct a review of Energex's and Ergon Energy's forecasting approach to system maximum demand and energy delivered in each of their respective networks.

This review culminated in a report[3] which provided a set of recommendations for improvement. In developing their most recent system maximum demand forecasts, both Energex and Ergon Energy have sought to incorporate these recommendations into their current methodologies.

In this section we briefly describe the main recommendations made as part of last year's review and assess the degree or extent to which the recommendations have been implemented with respect to system maximum demand.

3.2 Previous recommendations made to Energex on its system maximum demand methodology

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

— Energex applied the NIEIR low case GSP forecast to produce its medium or base case system maximum demand forecast. ACIL Allen considered that the NIEIR low case was too pessimistic based on recent history and the forecasts of other independent experts. Our recommendation was for Energex to use the NIEIR medium case as the basis for its base or medium case forecasts. In ACIL Allen's view 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.

[3] Review of System Maximum Demand and Energy, ACIL Allen Consulting, 15 May 2018.

3.3 Energex's current response to the recommendations

Energex have responded to the recommendations made in the ACIL Allen review of 2018 as follows:

— Energex have adopted the NIEIR base case economic growth forecasts in the calculation of their base or medium case summer maximum demand forecasts. Similarly, the NIEIR high case is applied in the calculation of the high case demand forecasts, while the low economic growth case is applied to generate the low case maximum demand forecasts.

— Energex have moved away from extrapolation along a curve to forecast the uptake of rooftop PV systems. In their revised methodology, the PV forecast is based on projections of major underlying drivers. The newer PV uptake forecast is based off a model developed by Energeia for Energy Queensland (EQL) which is driven by factors such as electricity supply tariffs and cost of PV installation.

  The Energeia model is an Agent-Based Model (ABM), which is configured with inputs around EQL's planned tariffs, customer usage profiles, expected technology prices and uptake curves. The ABM simulates customers making decisions around tariff and technology adoption, based on their financial incentives. One of the key outputs is Solar PV adoption, broken down by Zone Substation and customer class (business or residential).

  These forecasts from the Energeia ABM are taken and adjusted slightly, (especially in the early years) to match the observed short-term level and trend in PV uptake. The Zone Substation forecasts are aggregated into system total forecasts for Ergon regional, and Energex total forecasts.

— The assumptions and methodology underlying the rooftop PV, battery storage and electric vehicle forecasts are documented in a technical report produced by Energeia. The report outlines the key methodologies, assumptions and inputs, including details of the model structure and the flow of calculations through the model. It is our view that the documentation describes the model in sufficient detail to be suitable for submission to the regulator and satisfies the recommendation made for improved documentation as part of the May 2018 review

— While Energex have not added an interactive term into its regression model, it has included the maximum temperature as a quadratic term, which gives an additional boost to the predicted maximum demand as maximum temperatures get high. While amendment to the model doesn't strictly address the increasing sensitivity of the temperature coeffcients over time, ACIL Allen notes that the use of interactive terms in the model specification introduces difficulties of interpretation and multicollinearity into the specification which may be counterproductive when trying the satisfy the regulator of the suitability of its model. For this reason, we believe that it is reasonable for Energex to not introduce interactive weather variables into its econometric model of system maximum demand.

3.4 Previous recommendations made to Ergon Energy on its system maximum demand methodology

After reviewing Ergon Energy's system maximum demand methodology we recommended 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

3.1 Ergon Energy's current response to the recommendations

Ergon Energy have responded to the recommendations made in the ACIL Allen review of 2018 as follows:

- Ergon Energy have developed a set of regional system maximum demand models for each of its six regions for both summer and winter maximum demand. This allows for models to be constructed that more accurately reflect local demographic and climatic conditions, rather than a one size fits all model for the entire Ergon Energy network which covers a huge geographical area with very different economic, demographic and weather characteristics. A system wide demand forecast for Ergon Energy is then derived from each of the six separate regions using a set of coincidence factors. This developed is in accordance with the recommendation made by ACIL Allen in its May 2018 review.
- Ergon Energy have simplified the number of variables used in their econometric specifications, and have limited the number of variables to those which are available from credible and reliable sources such as the ABS and Queensland Treasury. Unreliable measures from private sources whose reliability cannot be established have been excluded from the modelling process. In doing so, the Ergon Energy econometric models no longer use the number of air conditioning systems as a variable in their models. This is in line with the recommendations made in the review of May 2018.
- Ergon Energy have significantly reduced the length of the weather time series used in their weather normalisation process. Up until last year, the approach adopted by Ergon used 50 years of weather data in their weather normalisation process. ACIL Allen suggested that possible structural changes in the nature of the weather attributed to climate change may mean that weather behaviour in more recent years is more likely to persist in the future compared to years observed further in the past.
- The review of May 2018 recommended that Ergon consider and test a larger suite of candidate variables in their econometric models, such as electricity prices. It is our understanding, based on in-depth interviews with the personnel responsible for the development of these models that this process has occurred, with theoretical coherence and statistical significance being key concepts in determining inclusion or otherwise of potential explanatory variables.
- In accordance with the previous recommendations, Ergon Energy have now introduced post model adjustments for battery storage and electric vehicles. These are obtained from Energeia and are produced using an identical modelling methodology to that used to produce post model adjustments for Energex's network. In our view this is a desirable development, not only because it incorporates the impact of what are likely to become significantly growing methodologies, but also because it is an additional step towards the integration of the forecasting methodologies of Ergon Energy and Energex.

4 ENERGEX

4.1 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 2004 through to the end of March 2019.

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 the 2011-12 summer 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 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 rooftop PV, additional post model adjustments are made for the contribution of battery storage, electric vehicles (EVs) and block loads. One difference from the previous year's estimation process, is that there is no adjustment made for network demand management and efficiency in Energex's most recent forecasting process.

Energex have developed a single weather index based on data from three weather stations. More specifically, it is 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 4.1 PREFERRED ENERGEX SYSTEM MAXIMUM DEMAND MODEL

Variable	Coefficient	Standard Error	T statistic	Prob.
Constant	-1387.40	211.83	-6.55	0.00
Weighted Daily Maximum Temp (squared)	2.27	0.04	58.99	0.00
Weighted Daily Minimum Temp	33.28	2.50	13.34	0.00
Total Electricity Price	-26.85	6.60	-4.07	0.00
GSP	0.12	0.01	9.36	0.00
3 Continuous Hot Days dummy	71.84	16.27	4.42	0.00
Weekend or Public Holiday dummy	-560.70	11.59	-48.38	0.00
Friday dummy	-41.13	12.46	-3.30	0.00
Sunday dummy	-29.61	12.43	-2.38	0.02
Average relative humidity	0.75	0.36	2.08	0.04
Structural Break Started 11/12 dummy	-334.21	39.70	-8.42	0.00
Christmas Season dummy	-196.07	20.96	-9.36	0.00
Christmas Day dummy	-304.55	67.95	-4.48	0.00
AR(1)	0.51	0.02	23.76	0.00
SIGMASQ	25961.52	786.71	33.00	0.00
Constant				

SOURCE: ENERGEX

The main difference from the specification used in last year's review is that the weighted daily maximum temperature has now been included as a quadratic (squared) term. The addition of the daily maximum temperature term as a quadratic provides an added impetus to the daily peak demand on very hot days. This variable was found to be statistically significant and is in our view a reasonable inclusion into the model specification.

In addition, average relative humidity was included as an additional weather variable in the most recent model specification. The variable provides a small increase in explanatory power and was found to be statistically significant at the 5% level of statistical significance. In our view this is a reasonable change to the model specification.

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.

It is also understood that Energy Queensland are migrating their models from an excel environment to R or similar code to automate and reduce the otherwise manual overheads of the new and current models. Automating the forecast does however increase the risk of not capturing structural changes in the models that could occur over time, and which would be detected in a less automated process with adequate diagnostic testing and model validation procedures. Further it is recommended that for regulatory audits, that the excel structure or equivalent, is retained for audit transparency purposes.

4.2 Assessment of Energex approach to System maximum demand

4.2.1 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.

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.

4.2.2 Inclusion of main drivers

The main drivers used in the econometric model are:

- Squared weighted daily maximum and daily minimum temperatures
- A dummy for when there are three consecutive hot days
- Average relative humidity
- 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.

4.2.3 Key inputs

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

Gross State Product

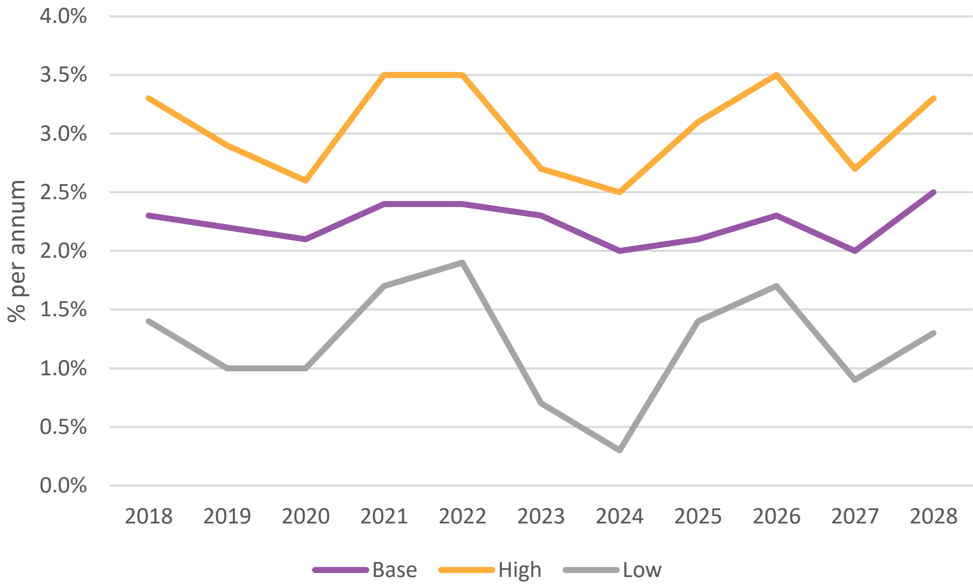
Energex have opted to use GSP forecasts from NIEIR to develop their system maximum demand forecasts. Specifically, Energex have chosen to apply NIEIRs low, base and high scenarios to each of its own respective low, medium and high scenarios. This differs from the approach taken last year where Energex applied NIEIRs low GSP growth case to its medium or base case forecasts. In the May 2018 review we argued 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 and recommended that Energex switch to using the NIEIR base case for its base case peak demand forecasts. The change in the most recent approach is consistent with the recommendations made in the May 2018 review.

Figure 4.1 below shows NIEIRs forecast GSP growth rates under all three of its scenarios.

Under the low scenario, NIEIR predicts an average rate of GSP growth of 1.2% per annum from 2018 to 2028. Under the medium scenario, NIEIR projects an average rate of GSP growth of 2.2% over the same period, while under the high case average GSP growth is projected to be 3.1%.

The NIEIR base case average growth rate of 2.2% per annum is consistent with Queensland's historical rate of GSP growth over the last five years which averaged 2.2% also.

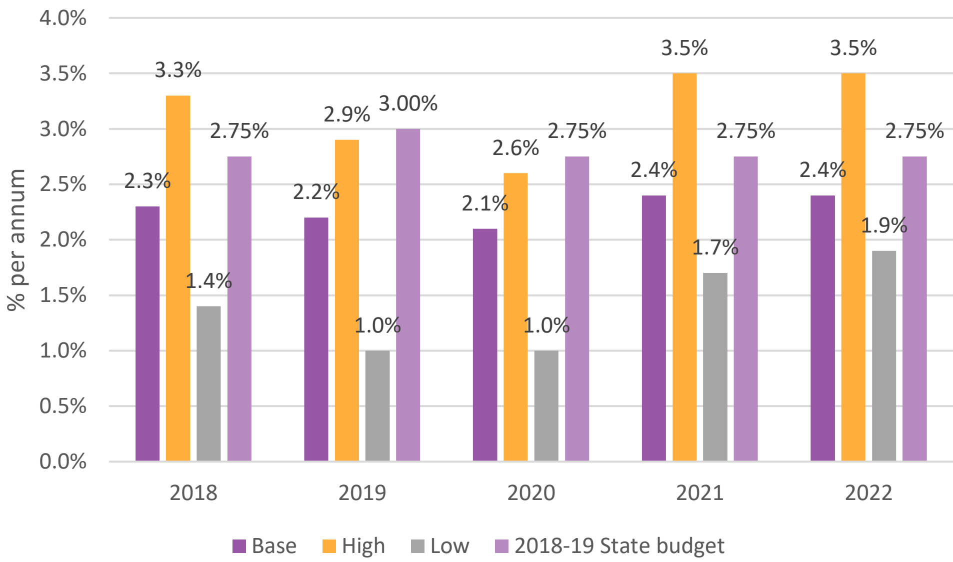
FIGURE 4.1 NIEIR GSP GROWTH FORECASTS, LOW, MEDIUM AND HIGH



SOURCE: NIEIR

Figure 4.2 shows NIEIRs GSP forecasts to the year 2022 against the most recent State budget forecasts of the Queensland Government. It is evident that NIEIRs base case forecasts lie below those of the Queensland Government in every year. In our view, the Queensland Government's forecasts have a long track record of overestimating the rate of economic growth in Queensland and it is of some comfort that NIEIRs base case forecasts lie consistently below those of the State Government.

FIGURE 4.2 NIEIR GSP GROWTH FORECASTS VERSUS 2018-19 STATE BUDGET



SOURCE: NIEIR AND QUEENSLAND GOVERNMENT

ACIL Allen considers that the NIEIR forecasts used by Energex as part of its forecasting process are consistent with the short to medium term historical behaviour of the Queensland economy and are reasonable.

Weather variables

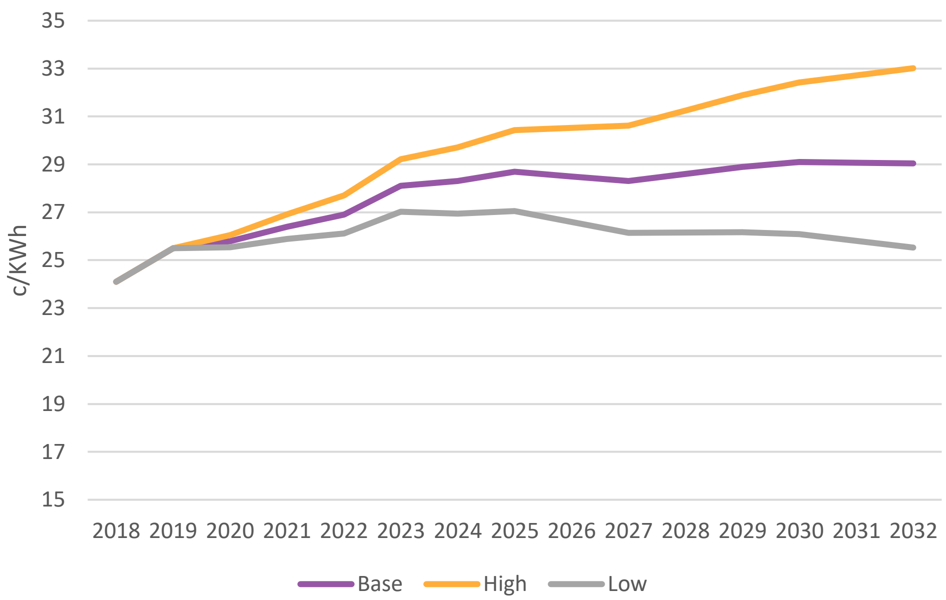
Energex employ weather data from three separate weather stations, Amberley, Archerfield Aero and Brisbane Aero. Data from each of the weather stations is weighted by population to create a single weighted daily maximum and daily minimum temperature series. ACIL Allen considers that this is a reasonable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

Electricity price

Energex use electricity price forecasts from NIEIR in generating their maximum demand forecasts.

Figure 4.3 shows NIEIRs electricity price forecasts under its three separate scenarios. Under the base case, electricity prices are projected to rise moderately over the next seven years to 2025 before stabilising.

FIGURE 4.3 FORECAST ELECTRICITY PRICES 2018 TO 2032



SOURCE: NIEIR

It is difficult to know how reasonable NIEIRs electricity price forecasts are in isolation. In December 2018, the Australian Energy Market Commission (AEMC) released the report '2018 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 2018-19 to 2020-21.

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

— Decreased by 6.8% from 2017-18 to 2018-19
— Are expected to decrease by 5.8% in 2019-20
— Are expected to increase by 0.3% in 2020-21

By contrast, NIEIR under the base case predicts a total increase of 1.2% between 2018-19 and 2019-20. The AEMC predicts a total decline of 5.8% over the same period. Between 2019-20 and 2020-21, NIEIR forecasts an increase of 2.3% while the AEMC predicts an increase of 0.3%.

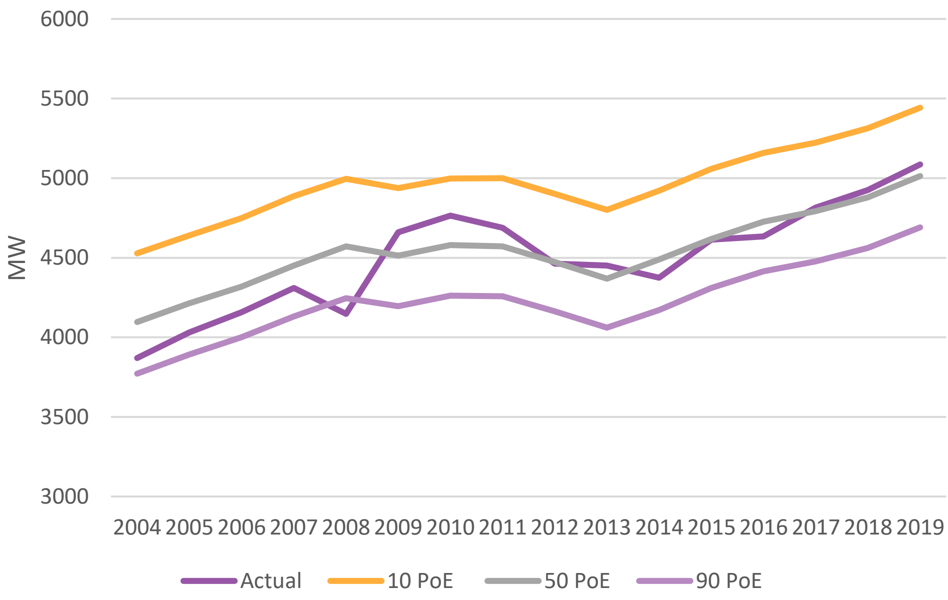
While NIEIRs electricity price forecasts lie above those of the AEMC over the next two years, ACIL Allen considers that NIEIRs electricity price forecasts do not deviate sufficiently from those of the AEMC to warrant any serious concern. In our view, the electricity price inputs are not unreasonable.

4.2.4 Weather normalisation

Energex apply a Monte Carlo simulation approach to weather normalisation. 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 4.4 shows Energex's historical weather normalised maximum demands and actual peaks for the period from 2004 to 2019. 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 4.4 HISTORICAL ACTUAL AND WEATHER NORMALISED SYSTEM MAXIMUM DEMANDS



SOURCE: ENERGEX

4.2.5 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 4.5** 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 4.1**, were found to be statistically significant at the 5% significance level.

FIGURE 4.5 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
	PTotalAEMO	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 89.3%, which means that close to 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.

4.2.6 Reasonableness of the forecasts

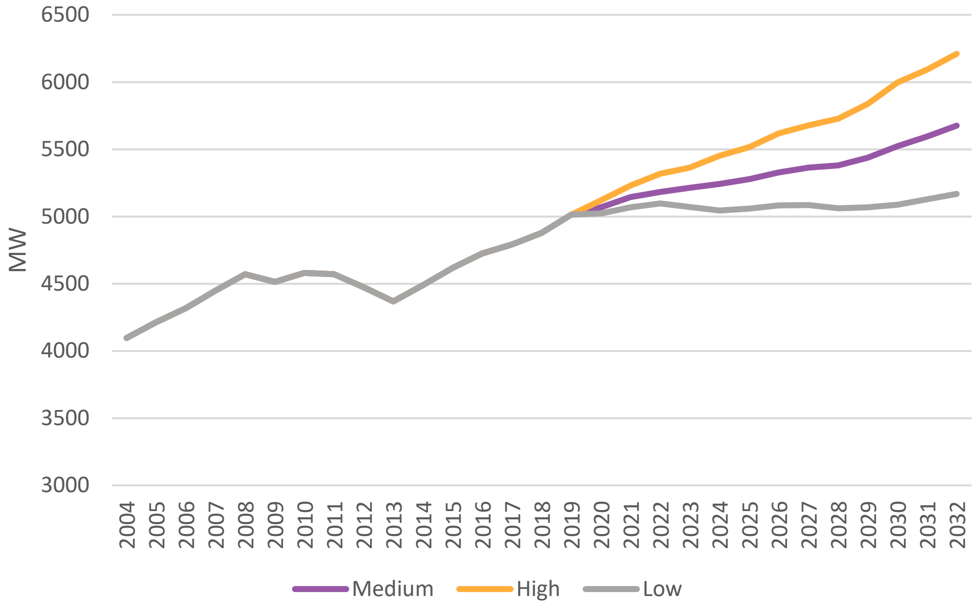
Figure 4.6 shows Energex's 50 POE system maximum demand forecasts under all three scenarios.

Energex's 50 POE medium forecasts behave in a way that is not inconsistent with the historical trend.

Over the ten-year period from 2009 to 2019, Energex's weather normalised 50 POE maximum demand grew at an average rate of 1.1% per annum. This compares to a forecast rate of growth of

0.8% per annum over the ten-year period from 2019 to 2029. The slower forecast rate of growth is largely due to the influence of rooftop PV and the rise of battery storage, while offset to some degree by the take up of electric vehicles.

FIGURE 4.6 ENERGEX 50 POE SYSTEM MAXIMUM DEMAND FORECASTS



SOURCE: ENERGEX

While the forecast growth rate lies slightly below the historical one over the forecast period, there is nothing that appears unreasonable or questionable in the forecasts based on the underlying assumptions of the key drivers.

4.2.7 Post model adjustments

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

— Battery storage
— Rooftop PV
— Electric Vehicles
— Block Loads

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

The Energeia model is an Agent-Based Model (ABM), which is configured with inputs around Energy Queensland's planned tariffs, customer usage profiles, expected technology prices and uptake curves. The ABM simulates customers making decisions around tariff and technology adoption, based on their financial incentives. One of the key outputs is solar PV adoption, broken down by zone substation and customer class (business or residential).

Energex take the forecasts from the Energeia ABM are taken and adjust them in the early years, to match the observed short-term level and trend in rooftop PV uptake. The zone substation forecasts are aggregated into system total forecasts for Energex.

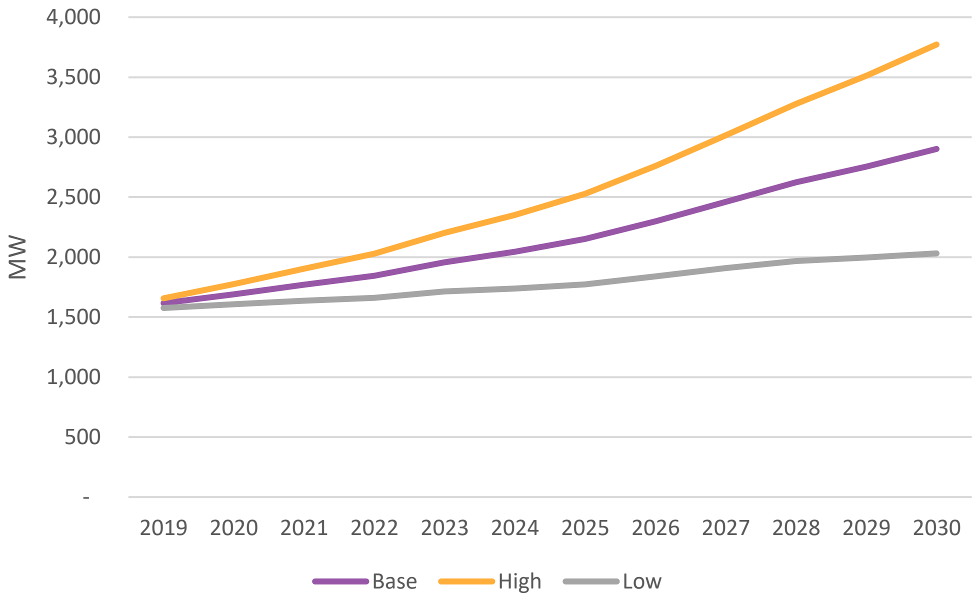
Energex no longer uses an extrapolation for forecast PV uptake. Instead, Energex (and Ergon) now have a single, combined PV forecast which is based on forecast of major underlying drivers. The newer PV uptake forecast is based off a model developed by Energeia for Energy Queensland which is driven by factors such as electricity supply tariffs and cost of PV installation.

This represents a significant improvement on the previous methodology employed by Energex, which relied on extrapolation along an S curve, rather than adopting a methodology based on changes to the fundamental drivers.

Figure 4.7 shows the projected uptake of rooftop PV within the Energex network for each of the three scenarios. Under the base or medium case, rooftop PV is projected to increase from 1,616 MW in 2019 to 2,902 MW in 2030. This is equivalent to an average annual compound rate of growth of 5.5% per annum. Based on the observed historical uptake this rate of growth is reasonable and not outside the bounds of plausibility. In fact, recent uptake of rooftop PV continues to be very strong and shows few signs of abating. This is true for all of the major Australian jurisdictions.

Under the high scenario, projected rooftop PV is expected to reach 3,772 MW, equivalent to an annual growth rate of 7.8%. Under the low scenario, rooftop PV is projected to grow at just 2.3% per annum, reaching 2,031 MW in 2030. In our view, the risk to the forecasts lie towards the upside, with an outcome skewed towards the high scenario being more likely than the low scenario trajectory.

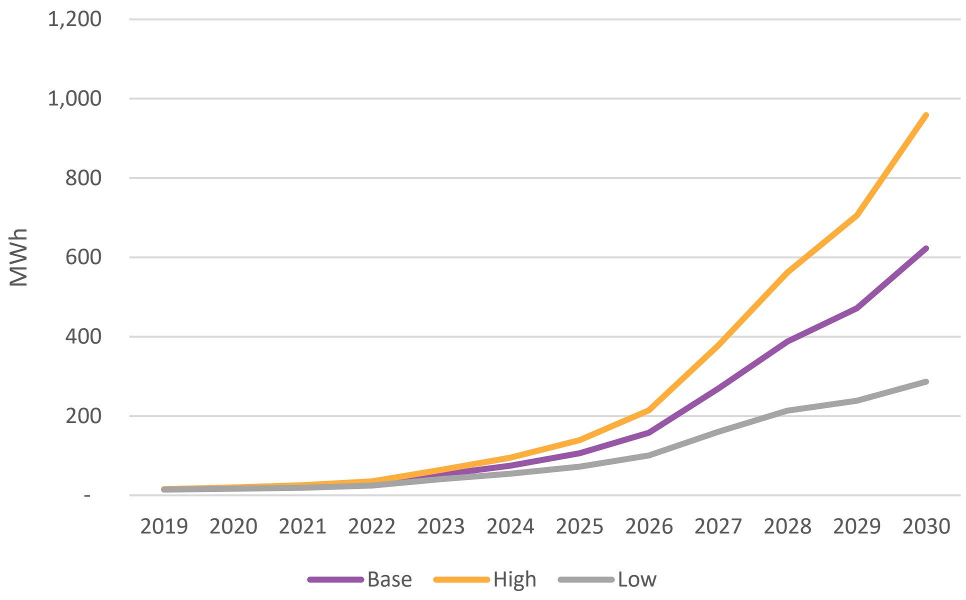
FIGURE 4.7 PROJECTED UPTAKE OF ROOFTOP PV IN THE ENERGEX NETWORK, LOW, MEDIUM AND HIGH SCENARIOS



SOURCE: ENERGEIA

Figure 4.8 shows the projected uptake of battery storage within the Energex network under the three growth scenarios. The uptake of battery storage is expected to remain very low right up to 2026, before accelerating under all three scenarios. In our view this is reasonable and consistent with the current economic fundamentals of battery storage systems. At present, the upfront cost of new battery storage systems is high, and while we expect the price of new systems to decline significantly over time, it will take quite a few years before they start to approach economic viability.

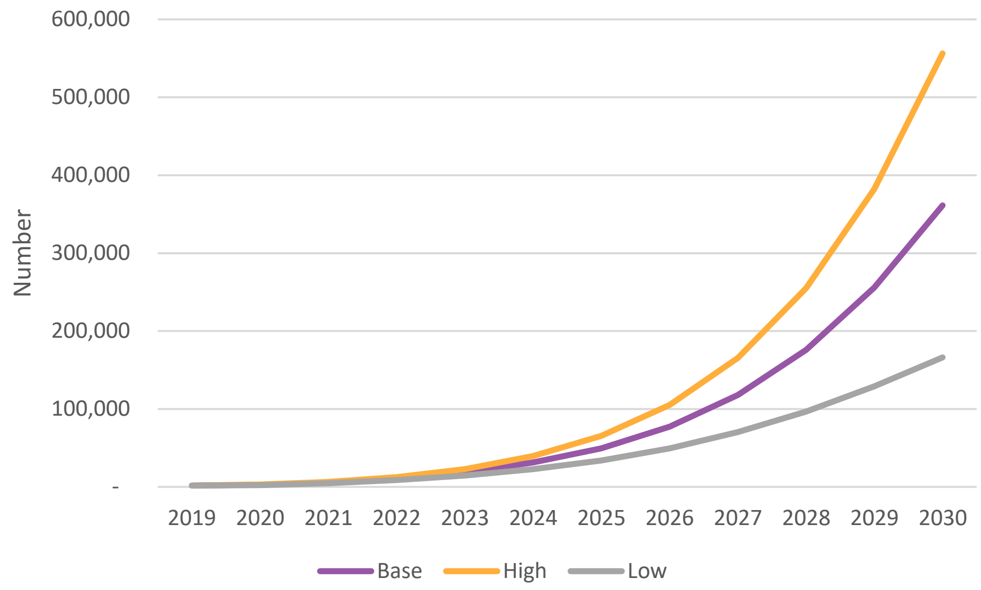
FIGURE 4.8 PROJECTED UPTAKE OF BATTERY STORAGE IN THE ENERGEX NETWORK, LOW, MEDIUM AND HIGH SCENARIOS



SOURCE: ENERGEIA

Figure 4.9 below shows the uptake of electric vehicles within the Energex network. Electric vehicles are projected to follow a similar trajectory to battery storage systems. Just like batteries, electric vehicles require a significant upfront cost to purchase relative to conventional internal combustion engine vehicles. Moreover, Australia has been slow in creating the necessary charging infrastructure for electric vehicles. While the cost and convenience of owning an electric vehicle are declining quickly, we expect there to be a significant lag before the uptake accelerates. This view is consistent with Energex's electric vehicle forecasts which are projected to remain very low up to 2027, before commencing a more rapid ascent.

FIGURE 4.9 PROJECTED UPTAKE OF ELECTRIC VEHICLES IN THE ENERGEX NETWORK, LOW, MEDIUM AND HIGH SCENARIOS



SOURCE: ENERGEIA

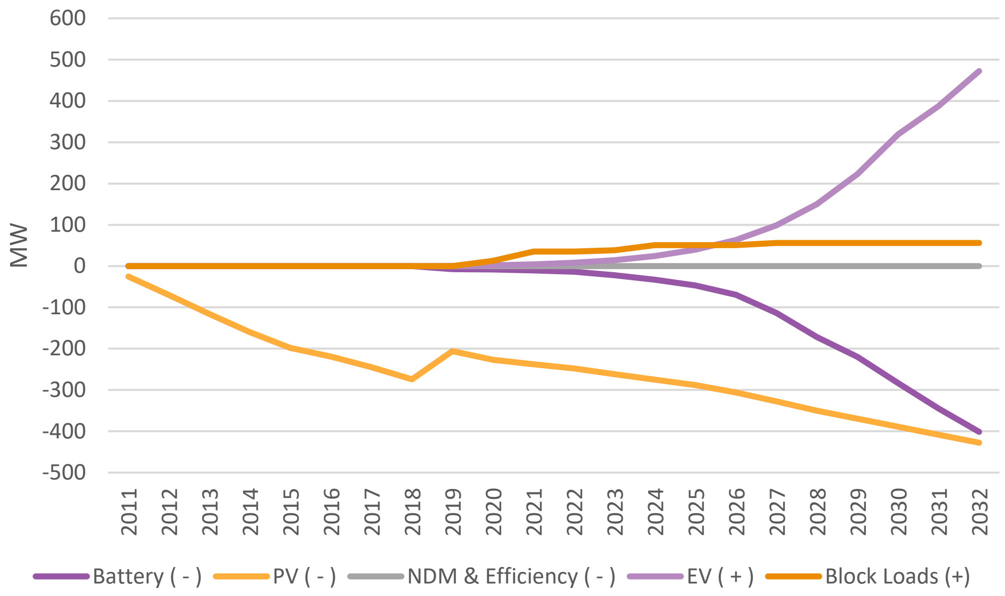
In order to convert the capacity of rooftop PV, into an impact on system maximum demand, Energex use a solar index over half hourly intervals which is applied to the total capacity installed to calculate the impact of rooftop PV on peak demand over each half hourly interval. Similar charging and discharging profiles are applied to generate half hourly impacts on peak demand of battery storage and electric vehicles. ACIL Allen considers this to be a sound approach and is consistent with best practice.

Figure 4.10 shows the estimated impact of each of Energex's post model adjustments on forecast system maximum demand.

The calculated impacts are very much in line with the forecasts of capacity shown previously. The impact of rooftop PV is expected to continue along the trajectory observed historically, while battery storage and electric vehicles are expected to have an impact only in the latter part of the forecast period. There is also a small positive contribution of 56 MW from 2027 onwards from the addition of new block loads.

These post model adjustments look reasonable. While we do not know exact detail of the methodologies applied by Energeia due to the proprietary nature of their models, the post model adjustments are not outside the bounds of what we might expect given our previous experience and professional judgement.

FIGURE 4.10 ENERGEX POST MODEL ADJUSTMENTS FOR THE BASE CASE



SOURCE: ENERGEX

4.2.8 Transparency and repeatability

As part of our review of May 2018, we assessed Energex's document, 'Network Forecasting: Constructing the summer peak system demand forecast' which outlined its approach to forecasting system maximum demand, including a description of the models estimated as well as the process involved in reaching the best model.

In our view, this 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. Moreover, this document is still highly relevant as the underlying methodology has not changed materially this year compared to the previous year.

While we have not been provided with an updated document for this year's review, ACIL Allen recommends that the document can be easily updated to reflect the minor changes in methodology that have been implemented this year.

4.3 Key recommendations summary

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

— Energex should update its existing documentation of its system peak demand methodology to reflect the most recent changes that have been made to its methodology

5 ERGON ENERGY

5.1 Ergon approach to system maximum demand

Ergon uses a multiple regression approach to forecasting maximum demand within its network. The multiple regression approach estimates the historical relationship between peak demand and its economic, demographic and weather drivers. Forecasts of the individual drivers are used in conjunction with the estimated models to generate the forecasts.

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

The regions are:

- Far North
- North
- Mackay
- Capricornia
- Wide Bay
- South West

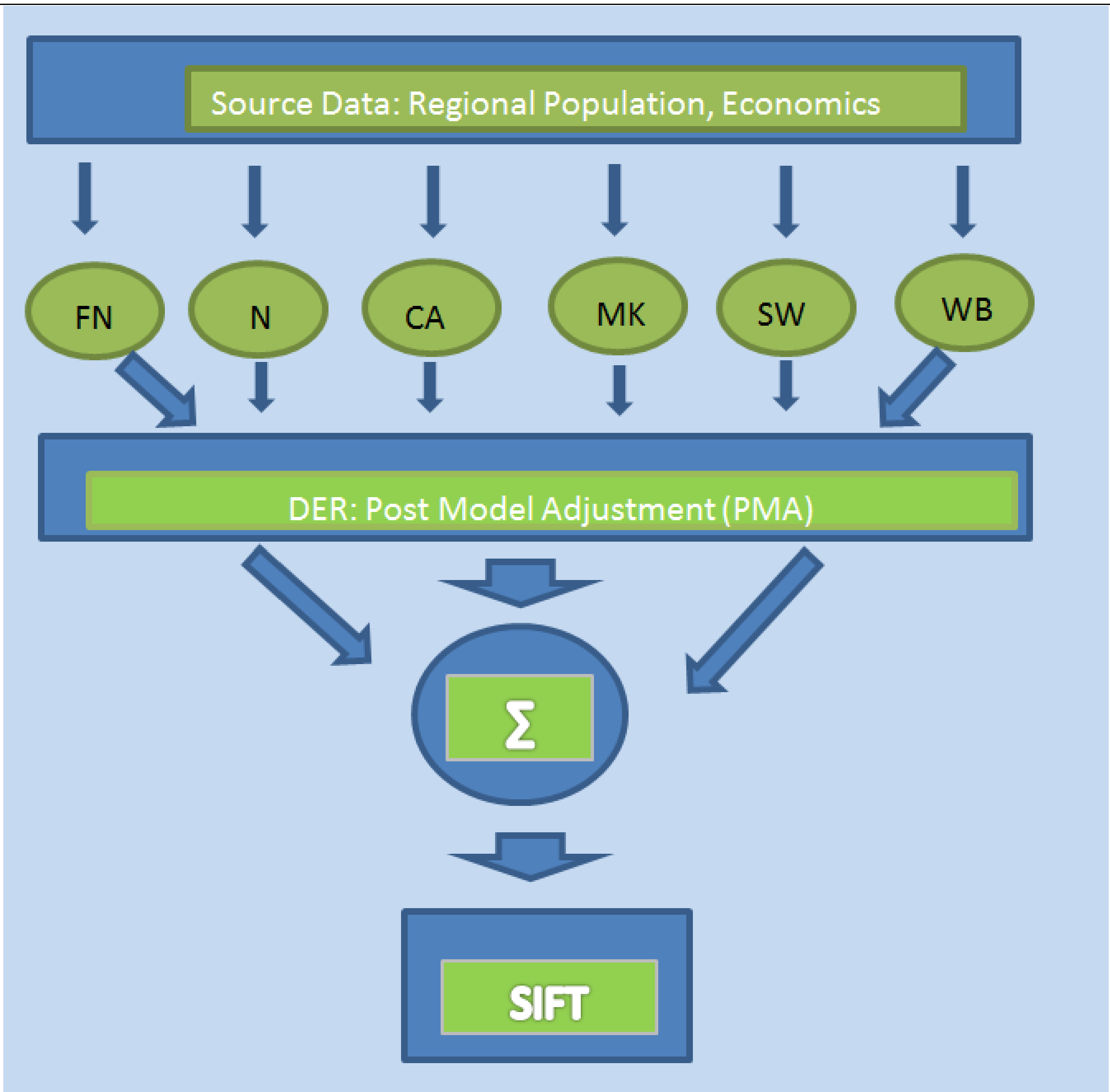
This is a significant departure from previous years where a single model was estimated for the entire Ergon network and a response to a recommendation made in ACIL Allen's review dated May 2018.

The main advantage of the regional approach is that the regional approach allows analysis at a more local level rather than 'a one size fits all' as was previously used by Energy Queensland in modelling the whole Ergon network within a single multivariate model.

The new approach uses multiple regional models and therefore a higher forecast precision for each region indicative of the response of the regional customers to future load demand. This will enable more accurate forecast growth commensurate with regional customer behaviour and therefore anticipated future load expectations across the connection points and downstream to the substations attached for each particular region.

It is our understanding that the Energy Queensland forecasting tool SIFT does have restrictive constraints on any regional model sets, but Energy Queensland has approached the solution by appropriately adding the regional model and forecast outputs at coincidence producing a total network forecast that can be used within the constraints of SIFT application. This approach is different to that used in prior years from that of a single network model in the past, and it now does offer a single output from SIFT to be deconstructed into regional and more meaningful forecasts. **Figure 5.1** on the following page presents a flow chart of each of the regional components of the Ergon methodology.

FIGURE 5.1 FLOW CHART OF ERGON REGIONAL MAXIMUM DEMAND MODELS



SOURCE: ENERGY QUEENSLAND

Ergon estimates separate regression models for both the summer and winter seasons for each of its six regions. Summer is defined as December through to February inclusive, while winter is defined as June, July and August. The months falling outside of summer and winter are excluded from the data set used in the regression analysis.

The summer models are calibrated using a time series from January 2008 through to the end of February 2019. The winter models are calibrated using data from the beginning of June 2008 to the end of August 2018. Both sets of models are using in excess of ten years of time series data which, in our view is adequate for the required modelling exercise.

Ergon have chosen to estimate their regression models on a per customer basis. By doing this, they ensure that both the dependent and explanatory variables in the regression are stationary and the risk of a spurious regression problem is reduced.

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 assume that the historical relationships between peak demand 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.

It is also understood that Energy Queensland are migrating their models from an excel environment to R or similar code to automate and reduce the otherwise manual overheads of the new and current models. Automating the forecast does however increase the risk of not capturing structural changes in the models that could occur over time, and which would be detected in a less automated process with adequate diagnostic testing and model validation procedures. Further it is recommended that for regulatory audits, that the excel structure or equivalent, is retained for audit transparency purposes.

5.1.1 Data requirements

The first step in the methodology is data collection. Ergon collects data from a number of sources. The main data requirements are:

- Daily summer and winter maximum demand from Ergon's internal systems
- Historical and forecast GSP data
  - Historical GSP data is sourced from the Australian Bureau of Statistics (ABS) while forecasts are purchased from the independent economic consultancy NIEIR.
- Historical and forecast regional population
  - These are obtained from the Queensland Government Statistician's office
- Historical daily maximum and minimum temperature data from the Bureau of Meteorology
  - Key weather stations include: Cairns Aero, Townsville Aero, Mackay, Amberley, Rockhampton Aero, Maryborough

5.1.2 Weather normalization

Ergon Energy applies a simulation approach to weather normalization.

The impact of weather is incorporated probabilistically by running the last 10 years of daily weather data from each regional weather station associated with each of Ergon's six regions, through the calibrated models. 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 simulation is run and a distribution of over 1,200 annual peaks for each of the historical and forecast years from 2008 to 2032 is generated. 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.

In previous year's Ergon has used a longer time series of weather data of 50 years to apply in its weather normalization procedure. In its review of May 2018, ACIL Allen recommended that Ergon should reduce the number of years it used as part of this process to reflect the fact that summer average temperatures have increased over the long term. Ergon responded to the ACIL Allen recommendation by reducing the total number of historical weather years used in the weather normalization to the most recent 10 years.

5.1.3 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

The main determinants of whether a variable is included in the model specification is statistical significance and theoretical coherence. All of the variables included in the models were found to be statistically significant.

5.1.4 Post model adjustments

Ergon Energy have now introduced post model adjustments for rooftop PV, battery storage and electric vehicles. This was done in response to the recommendations made by ACIL Allen in last year's review. Forecasts of rooftop PV, battery storage and electric vehicles are obtained from the external consulting firm, Energeia, using their own internal proprietary model. The model is an agent-based model which is driven by fundamental factors.

Rooftop PV capacity forecasts for the entire Ergon network are then combined with a set of half hourly charging/discharging profiles for each of the three technologies to calculate their impact on maximum demand. Incremental changes in the impacts of each technology are then added or subtracted to the base forecasts to obtain the post model adjusted forecast.

5.2 Assessment of Ergon approach to system maximum demand

5.2.1 Econometric modelling approach

Ergon applies multiple regression techniques to estimate a daily time series model of system maximum demand on a per customer basis. 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.

Ergon chooses are larger subset of candidate variables for inclusion into the models, which are then narrowed down using standard diagnostic techniques such as R^2, 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.

5.2.2 Inclusion of key drivers

Ergon's regional econometric specification modelled daily summer maximum demand per customer as a function of:

- A constant term
- GSP per capita
- Daily maximum temperature
- Daily Minimum temperature
- A dummy variable for weekends
- A dummy variable to capture break points in the data arising from system errors
- A dummy variable for Christmas day

The presence of the GSP per capital variable captures the impact of increasing economic activity both due to increasing population and productivity within each of the regions in the Ergon network

The presence of maximum and minimum temperatures captures the vast majority of weather-related variation in daily maximum demand across each of the regions in the Ergon network.

We note that the model specification does not allow for higher demand resulting from several hot days in a row. This is easily incorporated by including lags of the temperature variables. In our discussions with Ergon, it was explained that lags of temperature were tried within the model specification but these were found to be statistically insignificant.

Moreover, that real electricity prices were excluded from the preferred model specification for the same reason. At the time the model was estimated, real electricity prices were found to not exert a statistically significant influence on demand. As a result, price was not included in the model.

It is our view that the model adequately captures the economic and weather-related movement in maximum demand.

Although the model includes dummy variables for weekends and Christmas Day, it does not contain any additional dummies to account for other public holidays, such as Australia Day and Boxing Day. By not accounting for all public holidays, the goodness of fit of the models is reduced. ACIL Allen therefore considers that the model specifications can be improved by adding additional dummy variables for other public holidays not currently accounted for.

5.2.3 Assessment of key inputs

GSP

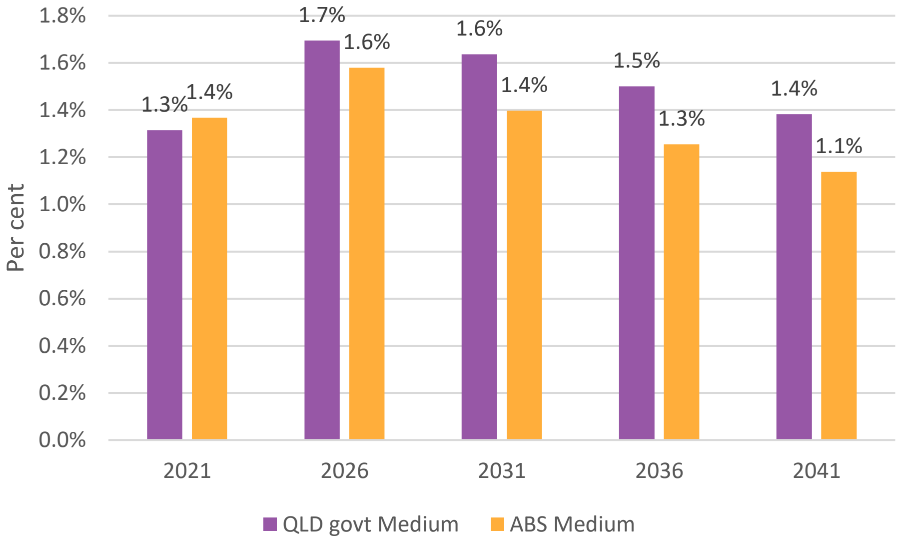
Ergon Energy have used forecasts of GSP that were obtained from the economic consultancy NIEIR. These same forecasts were also employed by Energex within its maximum demand forecasting methodology. A detailed assessment of the NIEIR forecasts are provided in the previous chapter in section 4.2.3. In this section ACIL Allen concluded that NIEIRs GSP forecasts are consistent with the sort to medium term historical behaviour of the Queensland economy and are therefore reasonable.

Regional population

Ergon Energy utilises estimated resident population data by LGA obtained from Queensland Government Statistician's Office to construct its regional population series. The Office also provides forecasts of regional Queensland population growth. To assess these forecasts, ACIL Allen has obtained an alternative set of population projections from the well respected and highly reputed Australian Bureau of Statistics and compared the two.

Figure 5.2 compares the latest forecasts of Queensland population growth rate medium cases from the Queensland Government and the ABS.

FIGURE 5.2 FORECAST POPULATION GROWTH, QUEENSLAND GOVERNMENT VERSUS ABS, MEDIUM CASE, AVERAGE BY FIVE YEAR INTERVALS



SOURCE: QUEENSLAND GOVERNMENT STATISTICIAN'S OFFICE AND AUSTRALIAN BUREAU OF STATISTICS

As expected, the Queensland Government numbers are above those of the ABS. However, the differences are relatively small and not significant enough to cause any major concerns.

Figure 5.3 and **Figure 5.4** show the same comparison for the high and low cases respectively. Again, as in the medium case, the Queensland Government projected growth rates are above those of the ABS, however, the differences are not large enough to warrant any major concerns.

FIGURE 5.3 FORECAST POPULATION GROWTH, QUEENSLAND GOVERNMENT VERSUS ABS, HIGH CASE, AVERAGE BY FIVE YEAR INTERVALS

SOURCE: QUEENSLAND GOVERNMENT STATISTICIAN'S OFFICE AND AUSTRALIAN BUREAU OF STATISTICS

FIGURE 5.4 FORECAST POPULATION GROWTH, QUEENSLAND GOVERNMENT VERSUS ABS, LOW CASE, AVERAGE BY FIVE YEAR INTERVALS

SOURCE: QUEENSLAND GOVERNMENT STATISTICIAN'S OFFICE AND AUSTRALIAN BUREAU OF STATISTICS

ACIL Allen considers that the Queensland Government Statistician's forecasts are fit for purpose to be applied within Ergon Energy's forecasting models.

Weather

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

Table 5.1 below lists the weather stations that are assigned to each of the six Ergon regions.

TABLE 5.1 WEATHER STATIONS ASSIGNED TO EACH REGION WITHIN ERGON NETWORK

Region	Station
Capricornia	Rockhampton Aero (39083)
Far North Queensland	Cairns Aero (31011)
Mackay	Mackay MO (33119)
North Queensland	Townsville Aero (32040)
South West	Amberley AMO (40004)
Wide Bay	Maryborough (40126)

ACIL Allen has analysed the time series from each of the listed weather stations and concluded that they are of sufficient quality to use in the modelling process. Each of them are located in significant population centres within each of the regions, and they all have sufficiently long time series with relatively few missing observations.

5.2.4 Weather normalisation

As described in 5.1.2 Ergon Energy employ a Monte Carlo simulation approach to weather normalization. Their methodology uses 10 years of historical weather data as well as sampling from a normal distribution with mean zero and a standard deviation equal to the standard error of the estimated model multiple times to generate over 1,200 simulated annual peaks for each forecast year. The 10, 50 and 90 POE forecasts are then obtained from this large distribution.

Figure 5.5 shows Ergon's historical weather normalised 50 POE maximum demands and actual peaks for the period from 2008 to 2019 for each of its six regions.

Based on this figure, the actual historical maximum demands are close to the adjusted 50 POE weather corrected demands, roughly spending half the time above the 50 POE curve as they spend below the 50 POE curve. This is what we would expect from a weather normalisation process that is unbiased.

However, the choice of only 10 years of historical weather data to use in the process raises concerns about whether this is sufficiently long to adequately capture and measure the 10 POE level of demand. Because a 10 POE peak demand is expected to occur only once every 10 years, the 10 years of historical data used in the weather normalisation process will only produce one 10 POE peak demand on average. Of course, using very long time series of weather data then raises issues of the relevance of very old data, given that temperatures have been rising over the long term. ACIL Allen considers that 20 years of weather data is likely to offer greater comfort to regulators, rather than using only 10 years. This recommendation is in line with the recommendation made in the review of May 2018, where we advised that Ergon Energy should reduce the number of years of weather data that are utilised in its weather normalisation process.

FIGURE 5.5 HISTORICAL ACTUAL AND WEATHER NORMALISED 50 POE SYSTEM MAXIMUM DEMANDS BY REGION

SOURCE: ENERGY QUEENSLAND

5.2.5 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 variation in daily peak demand per customer. As a consequence, some sense of the likely size and direction of model coefficients is possible.

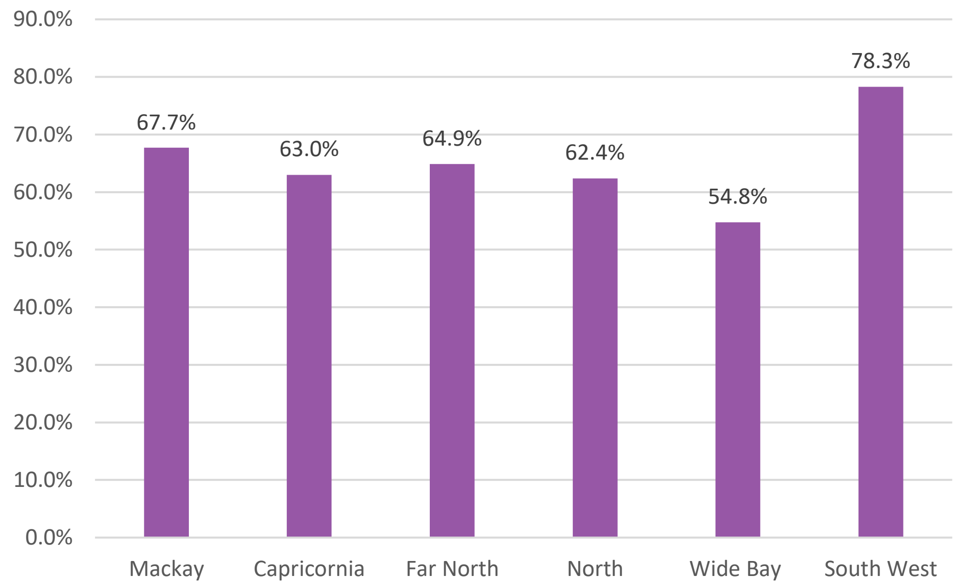
Goodness of fit

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.

Figure 5.6 shows the model R^2's of each of the separate ss the various models. The R^2 of the summer models are generally between 60% and 70%, with South West showing the highest R^2 of 78%, while Wide Bay had the lowest R^2 of the six regions of only 55%. The goodness of fit of these models while below that that would be obtained by estimating a single system level model, are lower because of higher levels of randomness in the regional data compared to the system level data, that cannot be easily captured by the higher level variables used in the model specifications. In our view, this is not necessarily problematic, although we would expect that the model R^2s can be improved once additional dummy variables for missing public holidays are added to the model specifications.

FIGURE 5.6 MODEL R^2 FOR EACH OF ERGON'S SIX REGIONAL SUMMER MODELS



SOURCE: ENERGY QUEENSLAND

Statistical significance

Ergon Energy tests 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.

In our view Ergon Energy's approach to model validation is sound and reasonable.

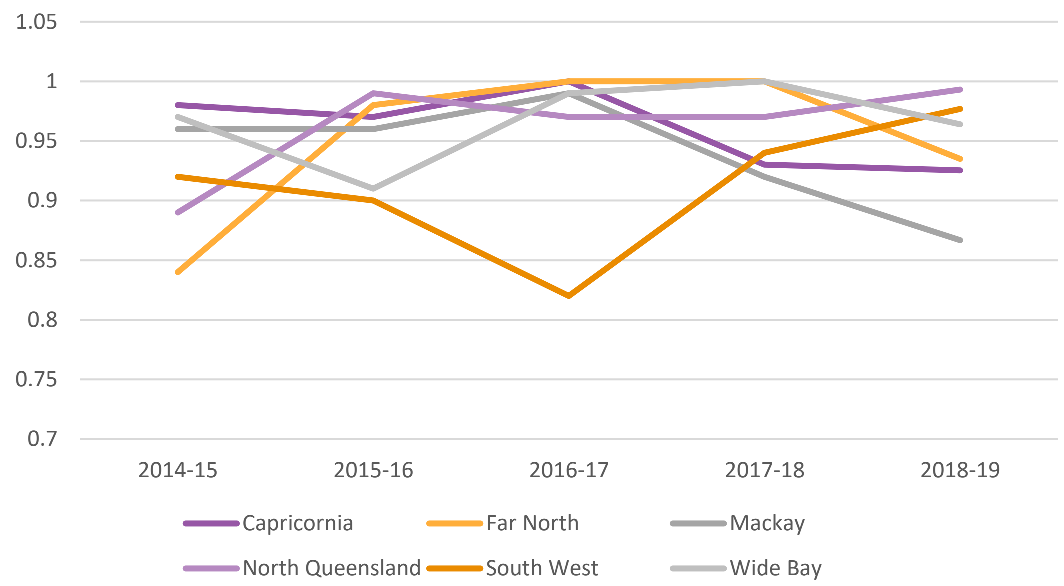
5.2.6 Coincidence factors

In building up from the regional to the system level, Ergon apply a set of coincidence factors to each of the regional forecasts which are then summed to obtain the peak demand forecast at the system level. Ergon uses the most recent year's coincidence factor in the calculations. This is a reasonable thing to do if the latest coincidence factor can be considered representative of the coincidence factor in the future. However, if there is significant volatility in the historical coincidence factors, it may be better to use an average coincidence factor over some period rather than the most recently observed value.

Figure 5.7 shows the summer coincidence factors for each of Ergon's six regions. The figure shows that using the most recent value for the coincidence factors is reasonable for most of the regions. The one exception is Mackay, where the latest value has fallen well below the other regions, as well as relative to its own past. Further investigation may reveal that the recent fall can be explained and be considered permanent. If not, ACIL Allen recommends that the Ergon system level forecast can be improved by using a 5 year average of historical coincidence factors for the Mackay region rather than the most recent value.

It is understood however, that the choice of the most recent year for the Regional model's coincidence factor, was to keep the methodology between the system forecast and the SIFT application consistent across both networks.

FIGURE 5.7 SUMMER COINCIDENCE FACTORS FOR EACH OF ERGON'S SIX REGIONS



SOURCE: ENERGY QUEENSLAND

5.2.7 Reasonableness of forecasts

Figure 5.8 shows the 50 POE system maximum demand forecasts for each of Ergon's six regions under the medium scenario. The figure shows that the 50POE medium forecasts behave in a way that is not inconsistent with the historical trend and are reasonable in our view.

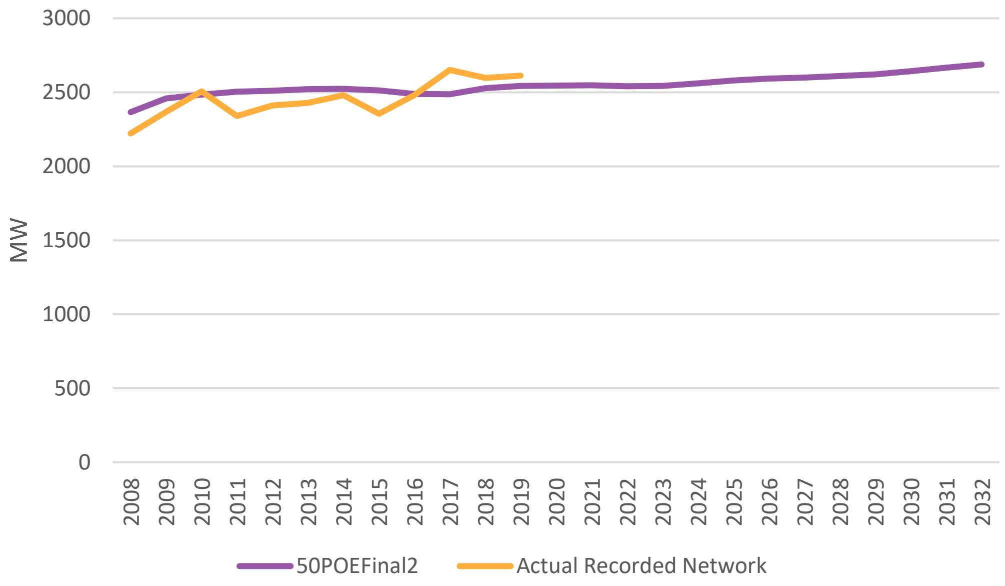
FIGURE 5.8 FORECASTS OF ERGON'S SIX REGIONS, 50 POE, MEDIUM CASE, NON-COINCIDENT

SOURCE: ENERGY QUEENSLAND

Figure 5.9 shows the aggregated coincident forecasts at the Ergon system level and after post model adjustments have been applied.

Over the ten-year period from 2008 to 2019, Ergon's weather normalised 50 POE maximum demand grew at an average rate of 0.66% per annum. Over the forecast period, Ergon's 50 POE system maximum demand is forecast to grow at a slightly slower rate of 0.43% per annum, reaching 2,688 MW by 2032. The slowdown in the rate of growth seems reasonable and is driven by the continued rapid uptake of rooftop PV as well as the emergence of significant growth in battery storage systems.

FIGURE 5.9 ERGON SUMMER FORECASTS, 50 POE, MEDIUM CASE



SOURCE: ENERGY QUEENSLAND

5.2.8 Post model adjustments

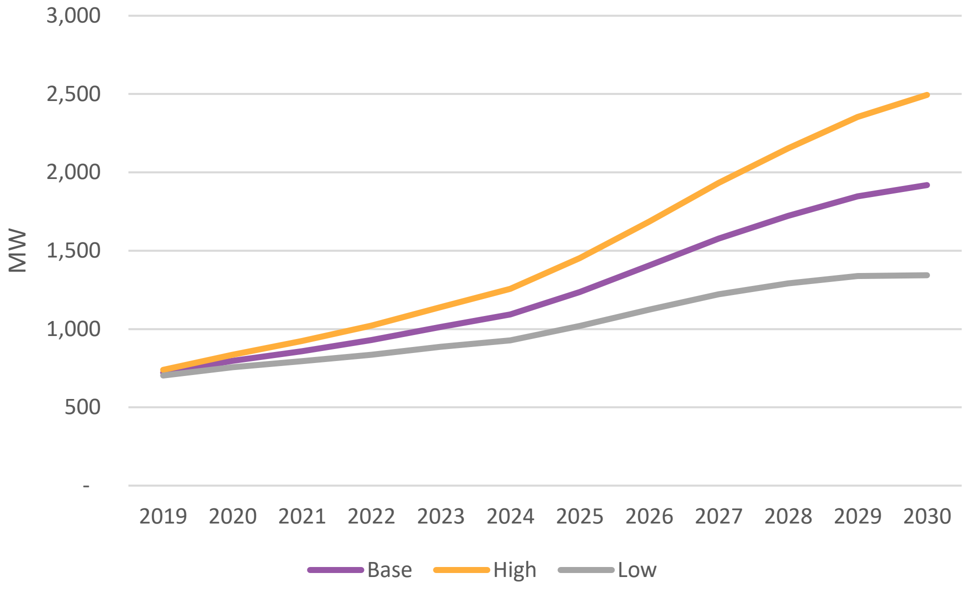
As mentioned earlier in this section, Ergon has introduced three post model adjustments into tis methodology, where previously no adjustments were made. Post model adjustments are made for rooftop PV, battery storage and electric vehicles.

Rooftop PV

Figure 5.10 shows the projected uptake of rooftop PV within the Ergon network for each of the three scenarios. Under the base or medium case, rooftop PV is projected to increase from 721 MW in 2019 to 1,919 MW in 2030. This is equivalent to an average annual compound rate of growth of 9.3% per annum. While this rate of growth is strong, it is consistent with recent trends and is reasonable on this basis.

Under the high scenario, projected rooftop PV is expected to reach 2,495 MW, equivalent to an annual growth rate of 11.7%. Under the low scenario, rooftop PV is projected to grow at 6.1% per annum, reaching 1,343 MW in 2030.

FIGURE 5.10 PROJECTED UPTAKE OF ROOFTOP PV IN THE ERGON NETWORK, LOW, MEDIUM AND HIGH

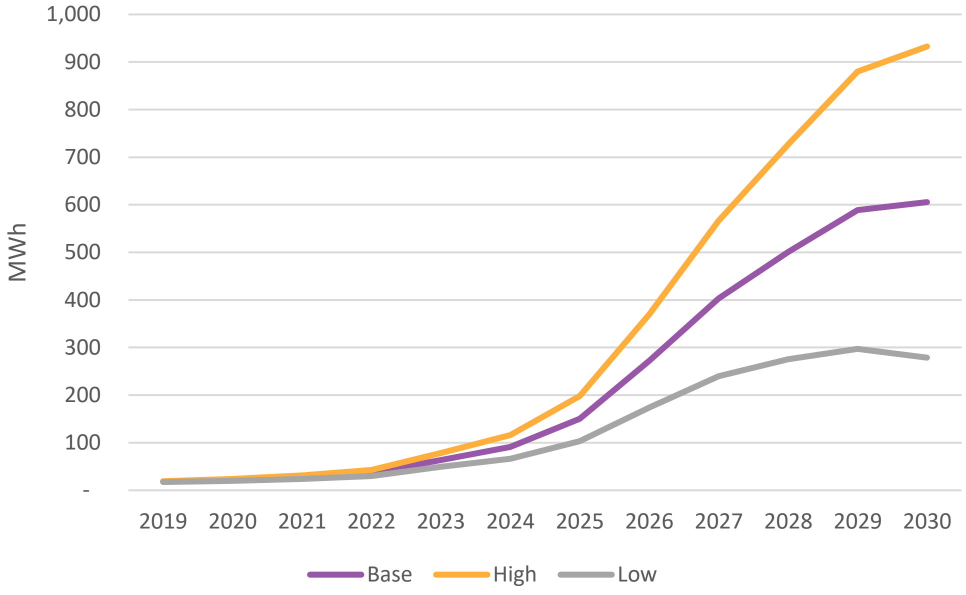


SOURCE: ENERGEIA

Figure 5.11 shows the projected uptake of battery storage within the Ergon network under the three growth scenarios. The uptake of battery storage is expected to remain very low up until the second half of the forecast period, before accelerating under all three scenarios. In our view this is reasonable and consistent with the current economic fundamentals of battery storage systems.

While the current installation cost of new battery storage systems is high, and while we expect the price of new systems to decline significantly over time, it will take quite a few years before they start to approach economic viability.

FIGURE 5.11 PROJECTED UPTAKE OF BATTERY STORAGE IN THE ERGON NETWORK, LOW, MEDIUM AND HIGH

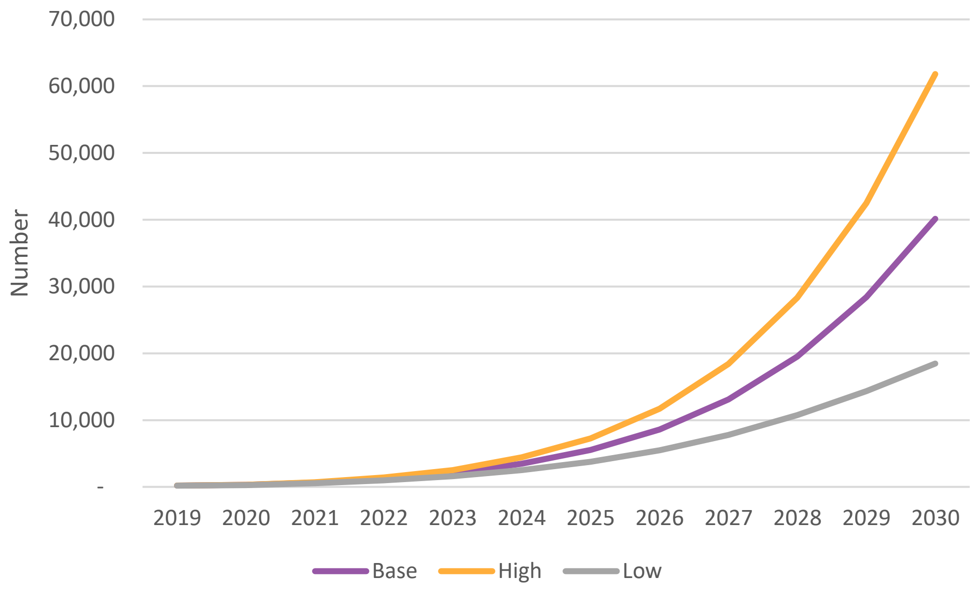


SOURCE: ENERGEIA

Figure 5.12 below shows the uptake of electric vehicles within the Ergon network. Electric vehicles are projected to follow a similar trajectory to battery storage systems. Electric vehicles remain prohibitively expensive relative to conventional internal combustion engine vehicles.

Moreover, the slow rollout of the necessary charging infrastructure for electric vehicles provides a further disincentive to consumers to switch to electric vehicles. While the cost and convenience of owning an electric vehicle are declining quickly, we expect there to be a significant lag before the uptake accelerates. This view is consistent with Ergon's electric vehicle forecasts which are projected to remain very low up until the mid-2020s, before commencing a rapid growth phase.

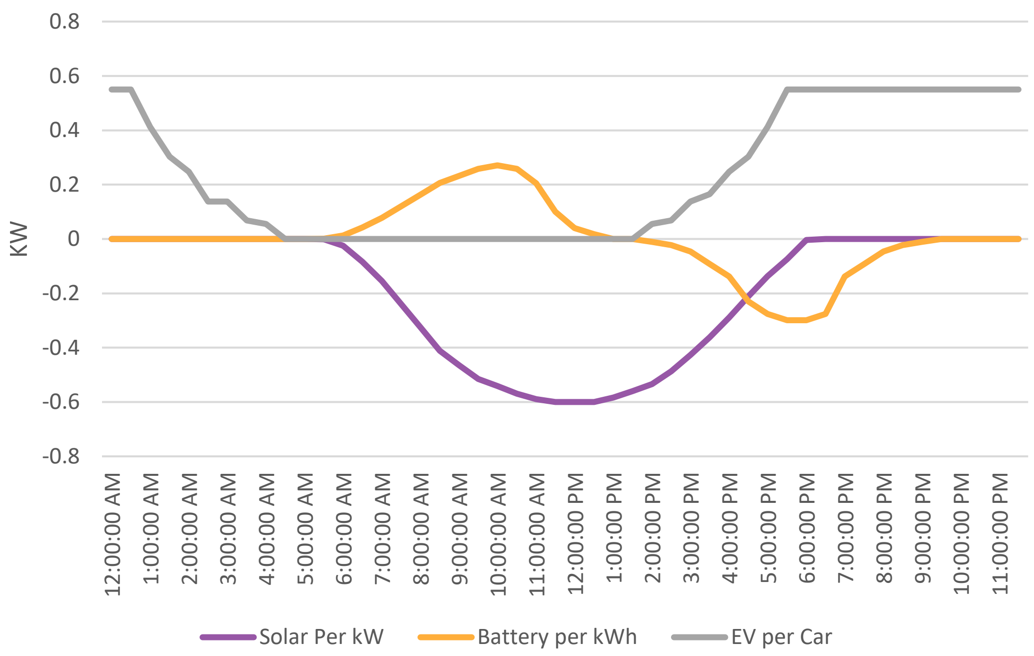
FIGURE 5.12 PROJECTED UPTAKE OF ELECTRIC VEHICLES IN THE ERGON NETWORK, LOW, MEDIUM AND HIGH



SOURCE: ENERGEIA

The capacity projections for rooftop PV, battery storage and electric vehicles are converted into impacts using a set of half hourly profiles which rate used to calculate the impact on maximum demand at each half hour. These are shown in **Figure 5.13** below.

FIGURE 5.13 DER PROFILES FOR ROOFTOP PV, BATTERY STORAGE AND ELECTRIC VEHICLES



SOURCE: ERGON

The profiles appear reasonable and are behave exactly as we would expect them to. Rooftoop PV has a major impact on maximum demand in the middle of the day when solar insolation is at its maximum. Battery storage systems add to maximum demand in the middle of the day when rooftop

PV is generating the most, and then reduce demand starting from the late afternoon as people get home from work and school and start to use the stored energy from their batteries. Electric vehicles are assumed to be charged from the early evening when people start to get home from work.

5.2.9 Transparency and repeatability

At this stage of the process, Energy Queensland has yet to develop a detailed set of documentation to describe its methodology in relation to forecasting maximum demand for the Ergon network. Although this is understandable at this early stage of development, we would expect that more detailed documentation would be developed over time to enhance the transparency and repeatability of the whole forecasting process. ACIL Allen recommends that priority be given to developing documentation which adequately explains each step in the forecasting process, from data collection, through to model estimation and post model adjustments.

5.3 Key recommendations summary

On the basis of the review of Ergon's maximum demand methodology, ACIL Allen recommends the following:

— Ergon should add additional dummy variables into its model specifications to account for public holidays that are not currently accounted for. In our view, this will improve model fit and reduce the risk of biased coefficients. Although statistical tests show only marginal improvements in the adjusted R squared by using additional holiday variables across a number of the regions, it is seen as standard best practice that can account for future changes in forecasting should these additional variables become larger in significance.

— That Ergon should consider using an average coincidence factor over a 3 or 5 year period rather than the most recent year's coincidence factor, especially for Mackay, whose most recent coincidence factor has deviated significantly from the degree of coincidence in years prior to the most recent season. It is understood that the choice of the most recent year for the Regional model's coincidence factor, was to keep the methodology between the system forecast and the SIFT application consistent across both networks.

— Ergon has amended its weather normalisation process from previous years by shortening the time series of weather data used in the simulation process to 10 years. ACIL considers that 10 years is not a sufficiently long enough time series to accurately estimate the 10 POE demand which is occurs on average only once every 10 years. We recommend extending the time series used in the weather normalisation process to 20 years. Although it is understood that if the current last ten years which showed a significant local deviation from the previous ten is continued then this shorter time frame may be a closer representation to the climate change expected over future years.

— Ergon should commence the process of developing more detailed documentation of its methodology. This would greatly increase the degree of transparency and repeatability of the forecasting process. ACIL Allen understands from discussions that Ergon are in the process of doing this as this will greatly increase the degree of transparency and repeatability of the forecasting process.