ACIL ALLEN

14 September 2022

Report to Energy Queensland

System peak demand forecasting methodology review

ACIL ALLEN

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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 13 June 2019.

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 13 June 2019
- 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 Approach to the review

In consultation with Energy Queensland, ACIL Allen has adopted a high level approach to reviewing the forecasting methodologies and procedures. Rather than focussing on the low 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 as well as associated documentation describing the methodology.

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

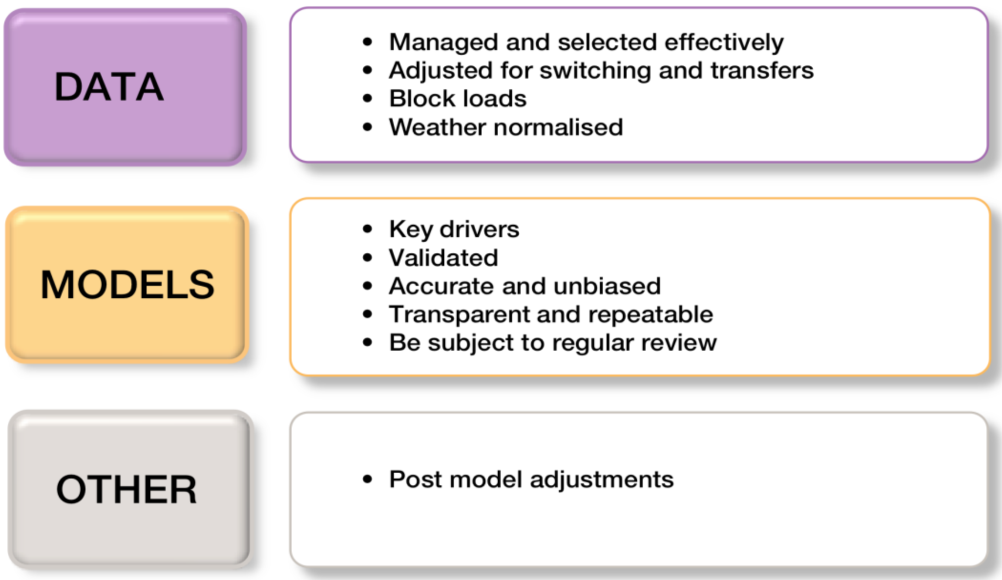
Best practice forecasting 2

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]:

- Economic growth
- Electricity price
- Population growth and/ or growth in the number of households
- Temperature, humidity and rainfall/wind data
- Any seasonal and calendar effects
- Growth in the number of air conditioning systems
- Growth in the number of heating systems
- Growth and change in usage of key appliances and other relevant technological changes
- Uptake and impact of Electric vehicles
- Uptake and impact of battery storage systems
- 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.)

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.

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 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 previous recommendations 3

3.1 Introduction

In June 2019 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 the 2019 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

In the June 2019 review of Energex's system maximum demand methodology, ACIL Allen recommended that:

— 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

3.3 Energex's current response to the recommendations

Energex have responded to the recommendations made in the ACIL Allen review of June 2019 as follows:

— Energex's documentation has been updated to reflect the most recent models, data and methodology

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

After reviewing Ergon Energy's system maximum demand methodology in June 2019 we recommended 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

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

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.

3.5 Ergon Energy's current response to the recommendations

Since the previous review Ergon Energy's system maximum demand methodology and approach has been overhauled and replaced with a completely new methodology. As a result, some of the previous recommendations are no longer relevant.

Ergon Energy have responded to the recommendations made in the ACIL Allen review of June 2019 as follows:

— The new methodology accounts for all public holidays and non-working days
— Coincidence factors are no longer relevant in the new methodology which models maximum demand on a half hourly basis.
— The new methodology still only uses 10 years of weather data for the weather normalisation process. However, it applies a bootstrapping technique that retains the internal correlation structure of the data to generate a much longer synthetic time series of weather data.
— The original documentation is no longer relevant. However, Ergon's current documentation describing the new methodology is still in its infancy and requires further development.

Energex 4

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 January 4 2001 through to the end of March 2022.

The model incorporates the main drivers of demand such as temperature and GSP. Also included as explanatory variables are a dummy variables for calendar related effects such as separate dummies for weekends and public holidays, Fridays, 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.

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 Final Energex System Maximum Demand Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-1678.834	110.319	-15.218	0.00
Weighted daily max temp (squared)	2.065	0.037	56.563	0.00
Weighted daily minimum temp	33.330	2.105	15.833	0.00
GSP	0.117	0.005	24.663	0.00
3 Continuous hot days dummy	62.525	14.087	4.438	0.00
Weekend or public holiday dummy	-538.330	9.319	-57.769	0.00
Friday dummy	-27.747	10.207	-2.718	0.01
Average relative humidity	0.739	0.312	2.368	0.02
Trend variable from 2011 to 2013	-211.794	16.435	-12.887	0.00
Christmas season dummy	-200.667	23.012	-8.720	0.00
Christmas day dummy	-301.853	39.912	-7.563	0.00
COVID 19 impact dummy	-98.432	28.158	-3.496	0.00
AR(1)	0.548	0.015	37.097	0.00
SIGMASQ	34371.028	787.049	43.671	0.00

Source: Energy Queensland

The main difference from the specification used in previous review is the removal of the Sunday dummy variable and the electricity price from the estimated model. These were found to be statistically insignificant during the estimation process. Moreover, a dummy variable for a structural break commencing in the 2011-12 summer was replaced with a trend variable from 2011 to 2013, picking up a decline in maximum demand over that period which could not be explained by other drivers. An additional new variable was a dummy to pick up the impact of the COVID 19.

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

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
— GSP
— A dummy variable to capture the negative impact of COVID 19
— Calendar effects such as:
  – Dummy variables for lower demand on Fridays
  – 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 trend to capture lower demand over the period from 2011 to 2013

It is our view that this model specification captures the main demographic and economic, 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 and temperature. These are discussed below.

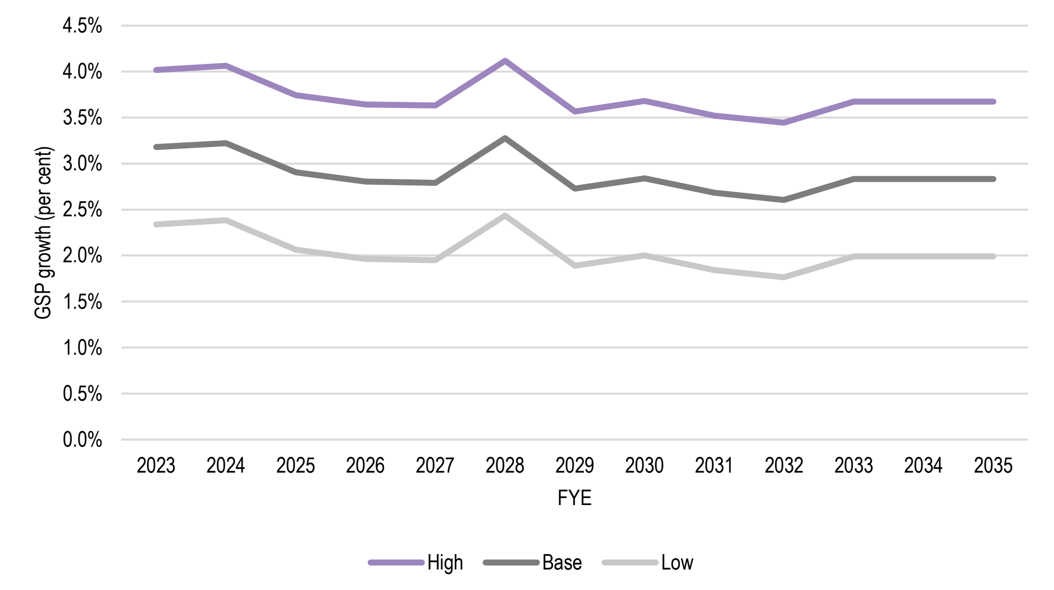
Gross State Product

Energex have opted to use GSP forecasts from Deloitte to develop their system maximum demand forecasts. Specifically, Energex have chosen to apply Deloitte's low, base and high scenarios to each of its own respective low, medium and high scenarios. This differs from the approach taken in previous years where Energex applied NIEIRs low GSP growth case to its medium or base case forecasts.

Figure 4.1 below shows Deloitte's forecast GSP growth rates under all three of its scenarios.

Under the low scenario, Deloitte predicts an average rate of GSP growth of 2.0% per annum from 2023 to 2035. Under the medium scenario, Deloitte projects an average rate of GSP growth of 2.9% over the same period, while under the high case average GSP growth is projected to be 3.7%.

Figure 4.1 Deloitte GSP Growth forecasts, low, medium and high



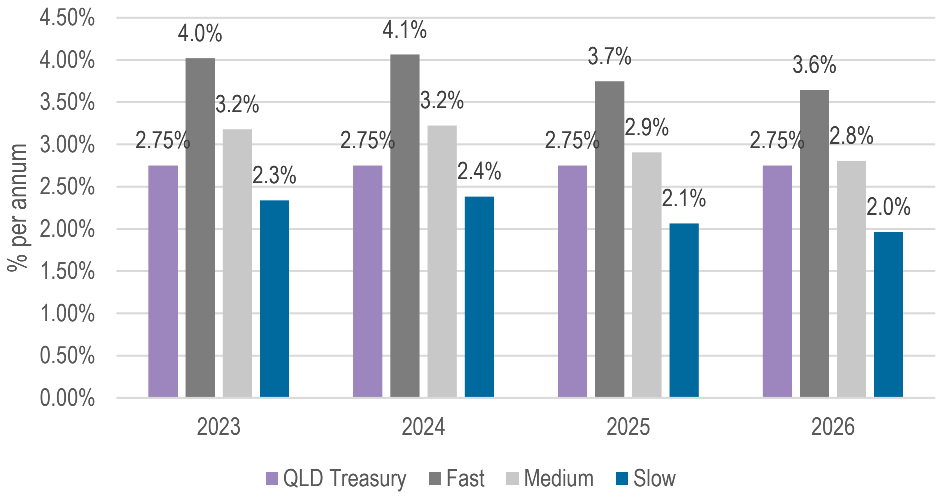
Source: Deloitte

Figure 4.2 shows Deloitte's GSP forecasts to the year 2026 against the most recent State budget forecasts of the Queensland Government.

It is evident that Queensland Government forecasts lie between Deloitte's medium and slow forecasts in each of the next four years. While Deloitte's medium forecasts are somewhat higher in 2023 and 2024, they are very close to the Queensland Government projections in 2025 and 2026.

We therefore consider Deloitte's GSP forecasts to be broadly consistent with those of the Queensland Treasury and are reasonable.

Figure 4.2 Deloitte GSP growth forecasts versus 2022-23 Queensland State budget



Source: Deloitte and Queensland Government

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

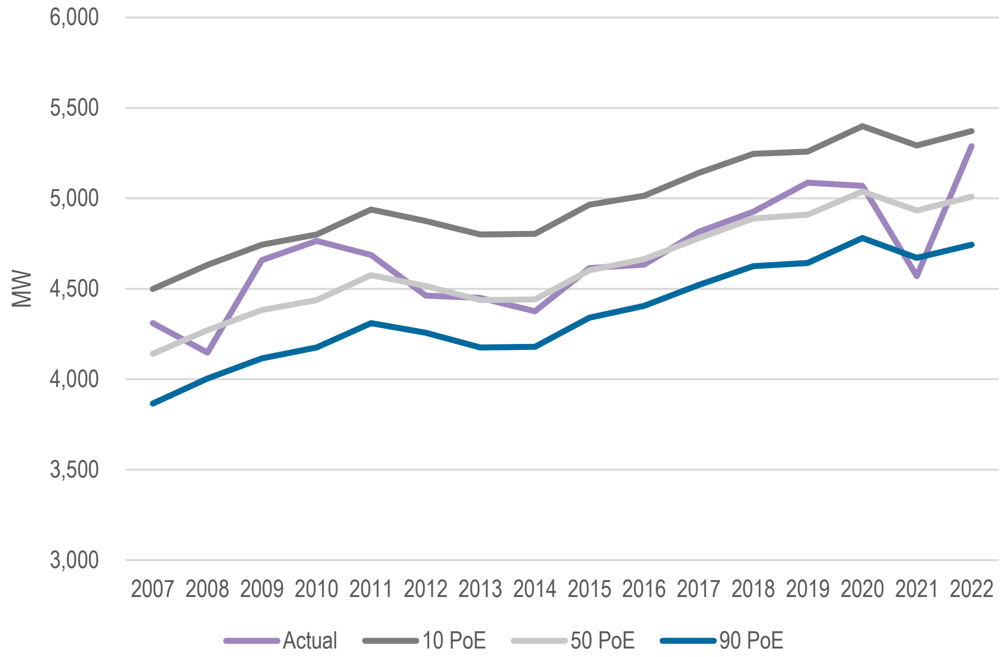
Energex have excluded electricity price from this year's model specification due to its statistical insignificance.

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 4.3 shows Energex's historical weather normalised maximum demands and actual peaks for the period from 2007 to 2022. 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 4.3 Historical actual and weather normalised system maximum demands



Source: Energy Queensland

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 4.4** 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 4.4 Potential variables for inclusion into the daily summer maximum demand model

Symbols, Definitions and Data Sources of Potential Variables						
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**	**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 & PEACE	No	
Economic Variables	PTotal	Total Electricity Price	c/kWh	ENEA and NIEIR	No	Annual electricity distribution (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	WgtTMaxSq	Weighted Daily Maximum T ^2	°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	Average relative humidity over the coincident half hou
	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	No	Dummy - structural break started from 11/12
	T11to13	Trend from 2011 to 2013	Integer	N/A	Yes	Trend variable from 2011 to 2013
	DmyGFC	2008 Global Financial Crisis	Integer	N/A	No	
	DmyFld	2011 QLD Flood	Integer	N/A	No	
	DmyCOV19	1 = COVID 19 Impacts	Integer	N/A	Yes	Dummy variable for capturing the COVID 19 impacts
Calendar Related Variables	CHtDy315	1 = 3 Continuous Hot Days	Integer	N/A	Yes	3 consecutive days with WgtTMax > = 31.5 °C
	WeMix	1 = WkEnd or Public Holiday	Integer	N/A	Yes	Treat public holiday as weekend
	FriNorm	1 = Friday	Integer	N/A	Yes	Friday dummy variable
	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	Dummy variable for Saturdays
	SunFlg	1 = Sunday	Integer	N/A	No	Dummy variable for Sundays

Source: Energy Queensland

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 considers 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 accounted for 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.

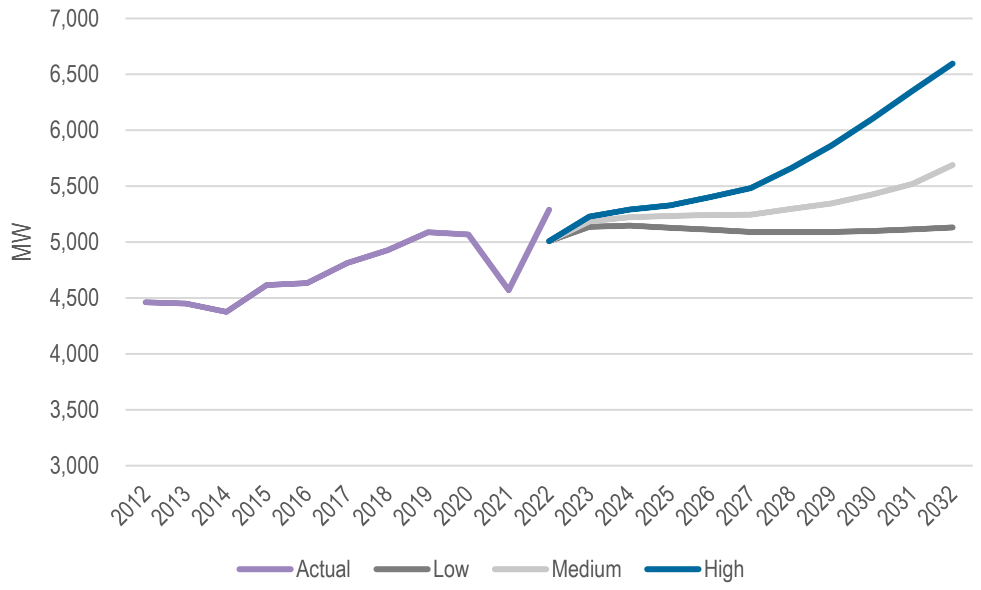
4.2.6 Reasonableness of the forecasts

Figure 4.5 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. There is an acceleration on the forecast peak demand from the late 2020's which is driven predominantly by a significant increase in the uptake of electric vehicles.

Over the ten-year period from 2012 to 2022, Energex's weather normalised 50 POE maximum demand grew at an average rate of 1.2% per annum. This compares to a forecast rate of growth of 1.3% per annum over the ten-year period from 2022 to 2032. This is very much in line with the historical rate of growth.

Figure 4.5 Energex 50 POE System maximum demand forecasts- Medium Case



Source: Energy Queensland

While the forecast growth rate lies slightly above 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 ENEA.

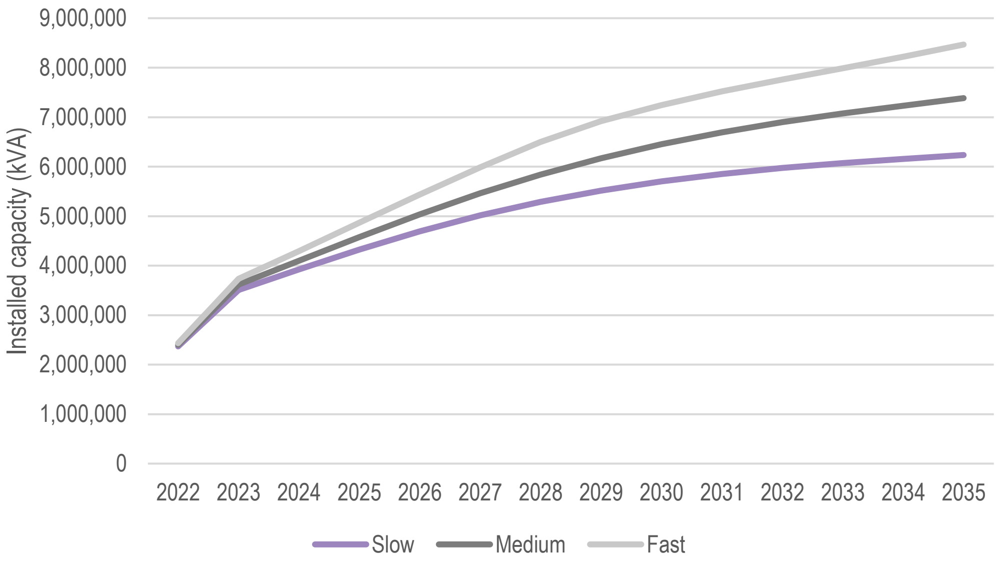
While we do not have a detailed knowledge of the methodology applied by ENEA, we understand that the PV, battery storage and EV forecasts are based on a set of fundamental models that are driven by a set of underlying drivers, such as electricity supply tariffs and cost of PV installation.

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 4.6 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 2.4 million kVA in 2022 to 6.90 million kVA in 2032. This is equivalent to an average annual compound rate of growth of 11.1% 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 7.76 million kVA, equivalent to an annual growth rate of 12.3%. Under the low scenario, rooftop PV is projected to grow at just 9.7% per annum, reaching 5.97 million kVA in 2032.

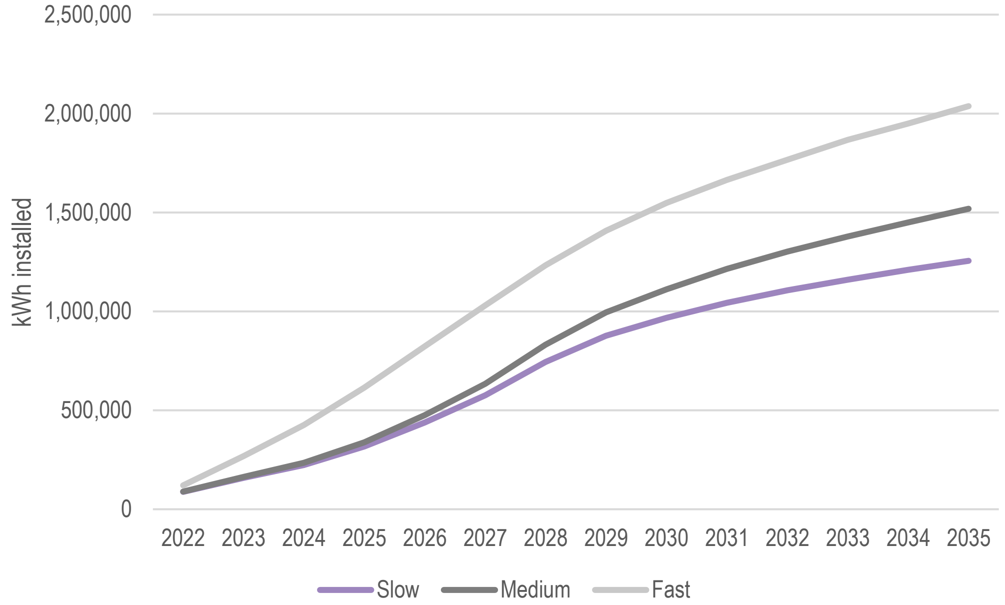
Figure 4.6 Projected uptake of rooftop PV in the Energex network, Slow, Medium and fast scenarios



Source: Energy Queensland

Figure 4.7 shows the projected uptake of battery storage within the Energex network under the three growth scenarios. The uptake of battery storage is expected to accelerate under all three scenarios, albeit off a very low base. 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, however the price of new systems to expected to decline significantly over time, leading to a significant increase in the uptake of the technology.

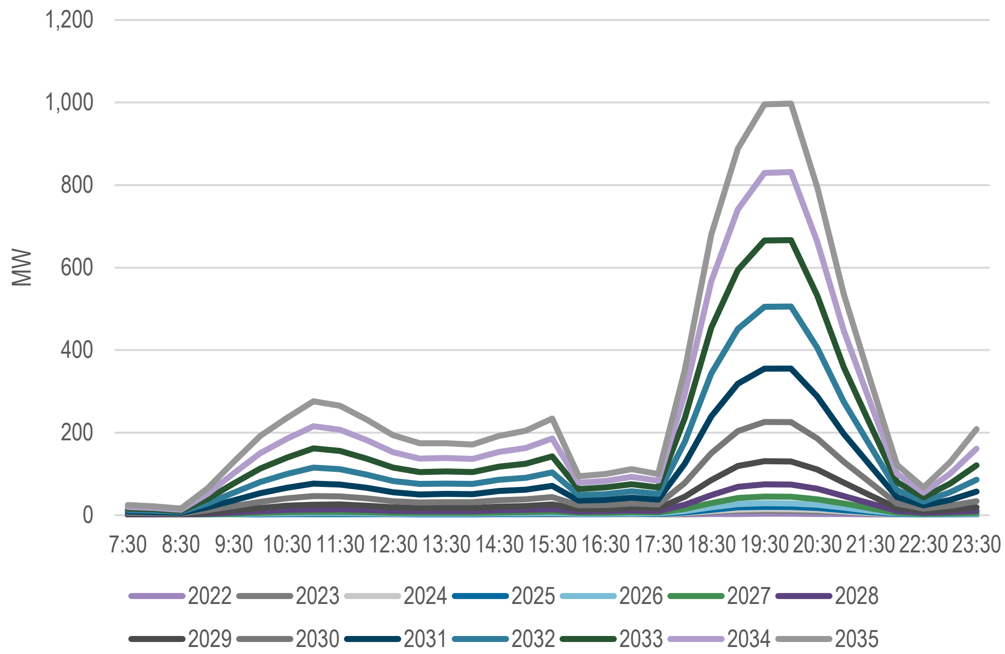
Figure 4.7 Projected uptake of battery storage in the Energex network, Low, Medium and high scenarios



Source: Energy Queensland

Figure 4.8 below shows the impact of electric vehicles on system peak demand 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 lag before the uptake accelerates. This view is consistent with Energex's electric vehicle forecasts which are projected to remain very low up to the mid 2020's, before commencing a rapid ascent.

Figure 4.8 Projected impact of Electric vehicles on the Energex network, Medium case



Source: Energy Queensland

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

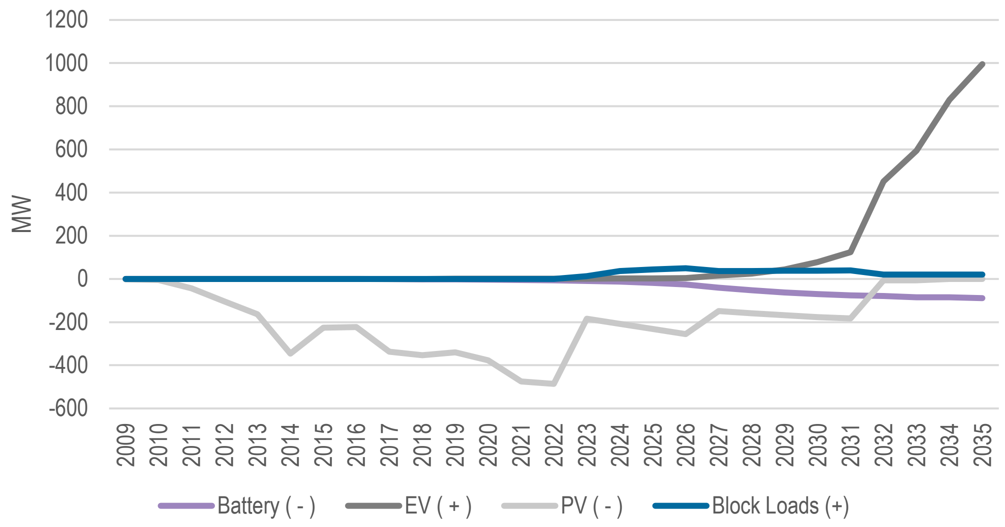
The calculated impacts are very much in line with the forecasts of capacity shown previously. The impact of rooftop PV is expected to continue along the trajectory observed historically, while battery storage and electric vehicles are expected to have a large impact only in the second half of the forecast period. The impact of PV systems starts to reduce in the latter part of the forecast period as a result of peak demand shifting to later in the day when PV systems are generating less energy.

There is also a small positive contribution 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 ENEA 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.

One potential change that Energex should consider is modelling the likely implementation of EV charging policies to prevent the massive increase in peak demand after 2032. It is our view that governments are likely to introduce either price incentives or load control measure to spread the burden of EV charging across the entire off-peak overnight period, rather than allowing all the vehicles to charge in the early evening, resulting in a large spike in peak demand. While this doesn't affect the forecasts for the next regulatory period, it will become an issue in the future if the uptake of EVs meets current expectations.

Figure 4.9 Energex post model adjustments for the base case



Source: Energy Queensland

4.2.8 Transparency and repeatability

As part of this review we assessed Energex's document, 'Network Forecasting: Constructing the summer peak system demand forecast' which outlines 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.

One area in which the document could be enhanced is in its description of the methodology used to generate the post model adjustment impacts. Currently the documentation does not include much detail on how the post model adjustment impacts for PV, battery storage and EVs are generated. For example, the documentation could include details of the various profiles that were used to calculate the post model adjustment impacts.

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 include greater detail of the methodology used to calculate the post model adjustment impacts of PV, battery storage and electric vehicles.

— Energex should consider modelling the likely implementation of EV charging policies such as price incentives and load control measures to prevent the massive spike in peak demand after 2032.

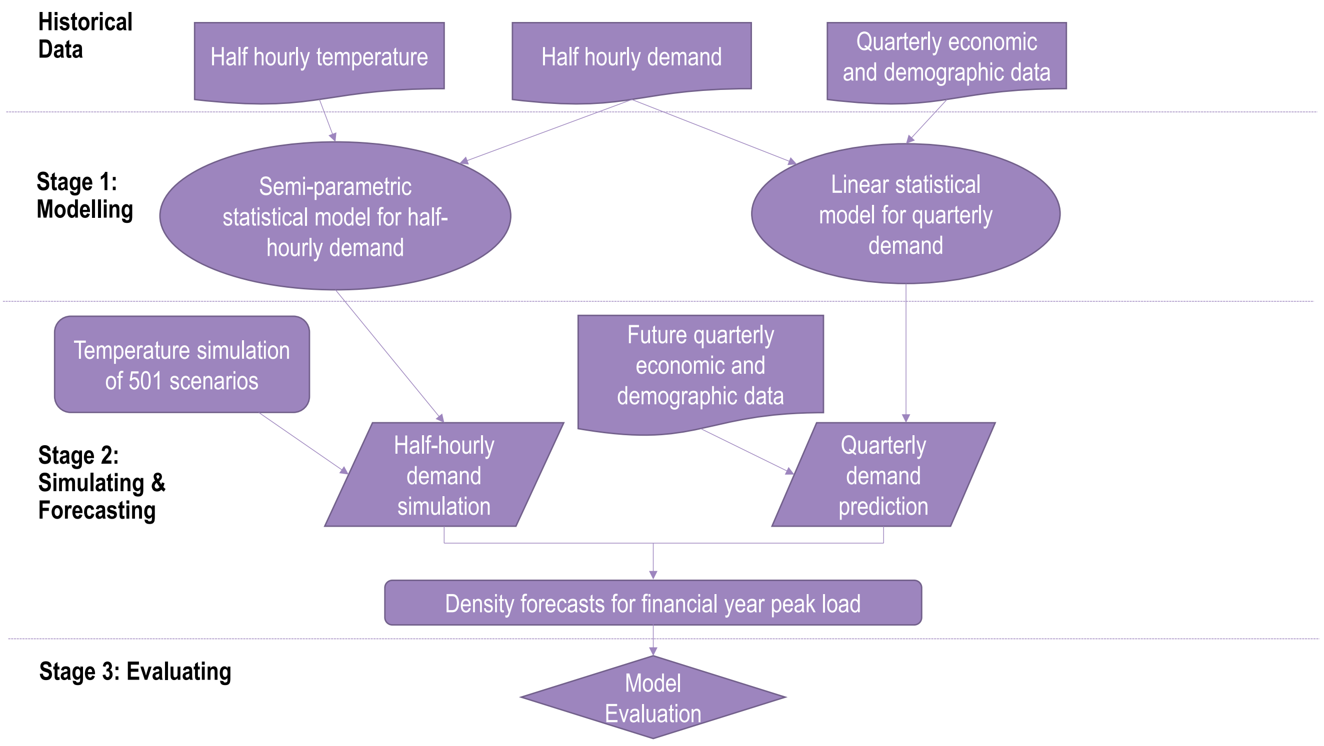
5 Ergon

5.1 Ergon approach to System maximum demand

Ergon has based their approach to forecasting system maximum ("peak") demand on a forecasting model developed by Hyndman, R J and S Fan (2010) described in "Density forecasting for long-term peak electricity demand"[4]. A block diagram of the approach is shown in Figure 5.1 below and can be summarised in the following three stages:

1. Collection of historical data to develop two separate models to create a combined output:
   a) A non-linear half hourly demand model fitted for each half hour demand period. The model captures the relationship between half hourly demand and key driver variables: temperature (during the period and previous periods) and calendar days.
   b) A linear quarterly demand model which captures the relationship between demand and seasonal demographic, economic variables, and the number of degree days (cooling and heating degree days in each season) which give a measure how hot or cold a season is.

Figure 5.1 Block diagram of Ergon methodology based on Hyndman and Fan demand forecasting model



[4] https://robjhyndman.com/papers/LTDF.pdf

2. Simulate 501 different scenarios for each half hour and financial year using simulated temperatures for each period. The number of simulations can be set to be any odd number (2n+1), where n is any natural number. Combine the outputs of the half hourly and quarterly models. For each financial year extract the POE50 and POE90 peak demand result.
3. Review and validate the results.

The above methodology is applied to each region. The regions are:

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

A key difference of this model over the previous model used by Ergon is the use of a non-linear half-hourly demand model. This removes the need for two separate linear regression models to model summer and winter. An additional benefit of is that it also captures energy, minimum demand and other outputs of interest to Ergon

5.1.1 Data requirements

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

— Half hourly maximum demand from Ergon's internal systems
— Historical and forecast GSP for Queensland
  – Historical GSP data is sourced from the Australian Bureau of Statistics (ABS) while forecasts are purchased from the independent economic consultancy Deloitte.
— Historical and forecast Queensland population
  – These are obtained from the economic consultancy Deloitte, and disaggregated using regional data from the Queensland Government Statistician's office
— Half hourly temperature data from the Bureau of Meteorology – Key weather stations include: Cairns Aero, Townsville Aero, Mackay, Amberley, Rockhampton Aero, Maryborough

5.1.2 Data normalisation

One of the key steps in the methodology is data normalisation to remove the impact of drivers not included in the model such as distributed energy resources (DER) and industrial loads. Ergon has relied on data from ENEA to forecast DER capacity and half hourly generation. Ergon has not developed their own forecasts for industrial loads, so they were not subtracted from the underlying half hourly demand profile. The main reasons for this were difficulty to predict block loads into the future and an assumption that GSP would capture the increase in block load, and a high GSP case scenario would incorporate the increased load from industry electrification.

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 half hourly and quarterly model as measured by R squared
— Scatter plots and duration curves of actual versus fitted values

— An elliptic envelope was applied of the data to ensure extreme events are not excluded

The main determinants of whether a variable is included in the model specification is statistical significance and theoretical coherence. For most regions all variables included in the half hourly model were found to be statistically significant. For the quarterly model only some of the variables were found to be statistically significant. This is likely due to less data being available as only data from 2010 was available to fit the model. ACIL Allen is satisfied that Energy Queensland has tested the key drivers for each model and narrowed them down to the best set of divers that provide the most explanatory power

5.2 Assessment of Ergon approach to peak demand

5.2.1 Modelling approach

Ergon applies a comprehensive approach to forecast peak demand. First, additive models are used to estimate the relationship between demand and driver variables, including temperatures, calendar effects and some demographic and economic variables. Then the demand distributions are forecasted by using a mixture of temperature simulation and assumed future economic scenarios. We consider that this approach if applied in conjunction with suitable model fitting and diagnostic checking techniques will produce a model with unbiased and consistent coefficient estimates of the main drivers of daily demand.

5.2.2 Inclusion of key drivers

Ergon has modelled regional half hourly demand as a function of:

— Half hourly temperature and recent temperatures

— Day of week by separating out workdays and non-workdays (including weekends and holidays)

Ergon has modelled regional quarterly demand per capita as a function of:

— GSP per capita

— Number of heating days

— Number of cooling days

— Rainfall

The presence of temperature and recent captures most of the weather-related variation in daily maximum demand across each of the regions in the Ergon network. Recent temperature captures higher demand from several hot days in a row.

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

Electricity prices were not included in the model due to the inability to predict accurately so would not be valuable to the model.

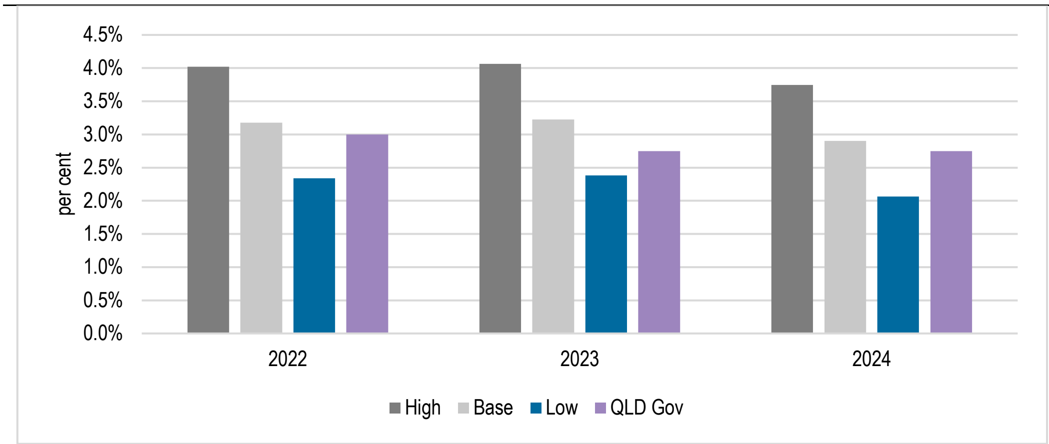
It is our view that the model adequately captures the economic and weather-related movement in maximum demand.

5.2.3 Assessment of key inputs

GSP

Ergon Energy have used forecasts of GSP that were obtained from the economic consultancy Deloitte. These same forecasts were also employed by Energex within its maximum demand forecasting methodology. Deloitte’s GSP forecasts are consistent with the sort to medium term historical behaviour of the Queensland economy and are therefore reasonable.

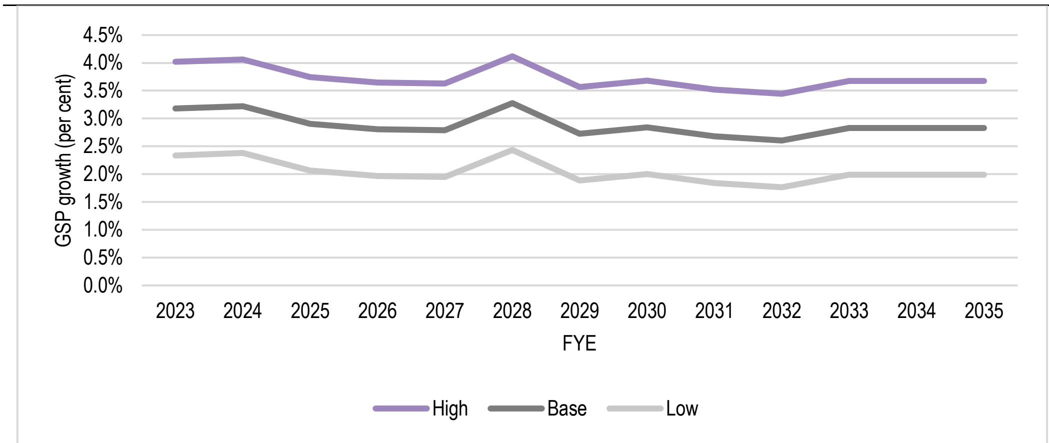
Figure 5.2 Comparison of Ergon GSP forecast with QLD government forecast



Source: Deloitte and Queensland Government

Ergon's GSP growth projections remain relatively stable from 2023 to 2035 which is reasonable.

Figure 5.3 Ergon GSP growth projections

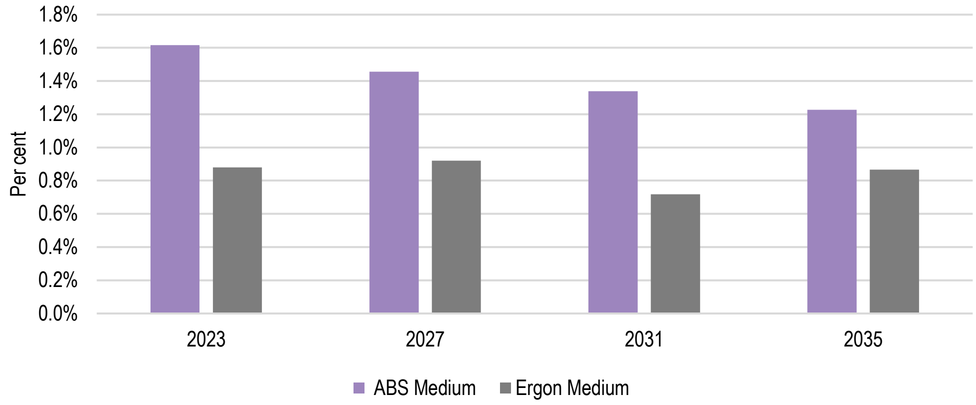


Source: Deloitte

Regional population

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

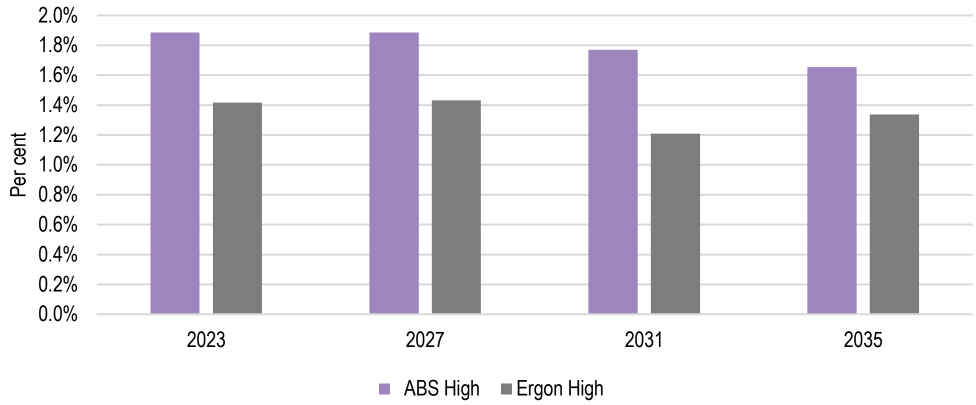
Figure 5.4 Forecast population growth, Ergon Medium case versus ABS, average by four year intervals



Source: Queensland government statistician's office and Australian bureau of statistics

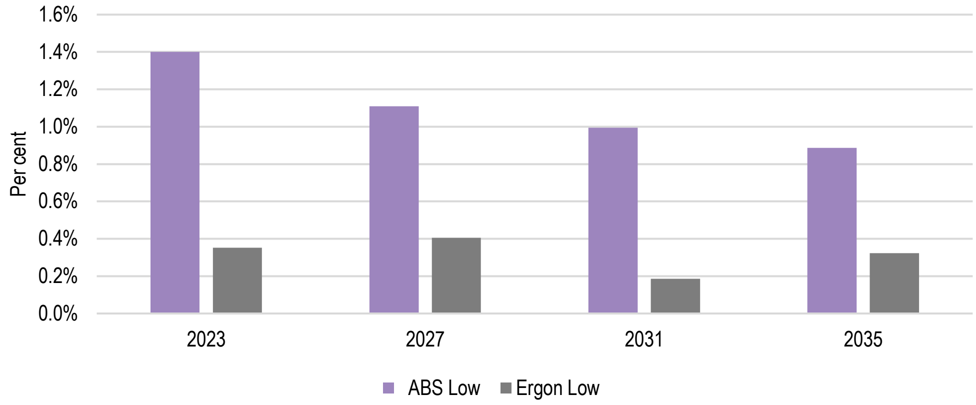
The Ergon low, medium and high projections are relatively consistent with however generally lower than the Queensland ABS projections which is expected because the Ergon data excludes South East Queensland which has a higher population growth rate than the Ergon regions.

Figure 5.5 Forecast population growth, Ergon High case versus ABS, average by four year intervals



Source: Ergon data and Australian bureau of statistics

Figure 5.6 Forecast population growth, Ergon Low case versus ABS, average by four year intervals



Source: Queensland government statistician's office and Australian bureau of statistics

5.2.4 Post model adjustments

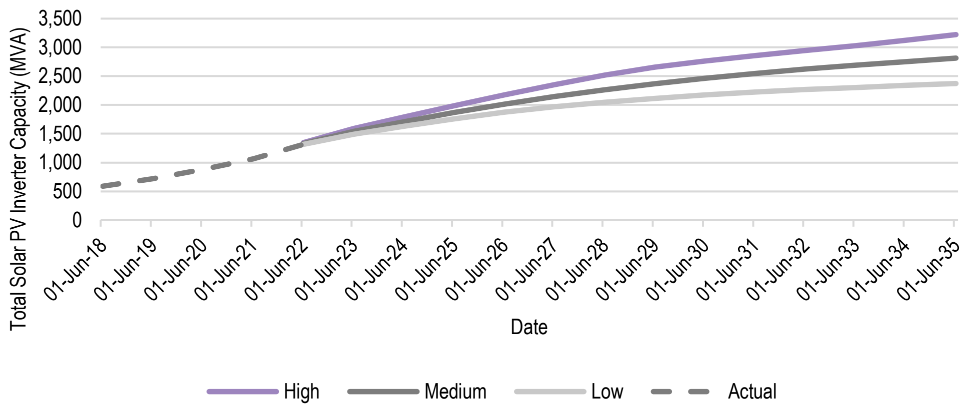
As mentioned earlier in this section, Ergon has introduced three post model adjustments into its methodology, where previously no adjustments were made. Post model adjustments are made for rooftop PV, battery storage and electric vehicles. PV battery storage and electric vehicle uptake projections were provided by an external consultant.

Rooftop PV

Figure 5.7 shows the historical and 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 1331 MW in 2023 to 2814 MW in 2035. This is equivalent to an average annual compound rate of growth of 5.9% per annum which is much lower than the average rate of growth from 2017 to of 22.3% per annum. It is our view that the growth projections are reasonable because PV growth is likely to decline due to several drivers: a lower government rebate, lower feed in tariffs due to high solar generation and market saturation in the next five to ten years.

Under the high scenario, projected rooftop PV is expected to reach 3222 MW, equivalent to an annual growth rate of 6.9%. Under the low scenario, rooftop PV is projected to grow at 4.6% per annum, reaching 2372 MW in 2035.

Figure 5.7 Projected uptake of Rooftop PV in the Ergon network, Low, Medium and High



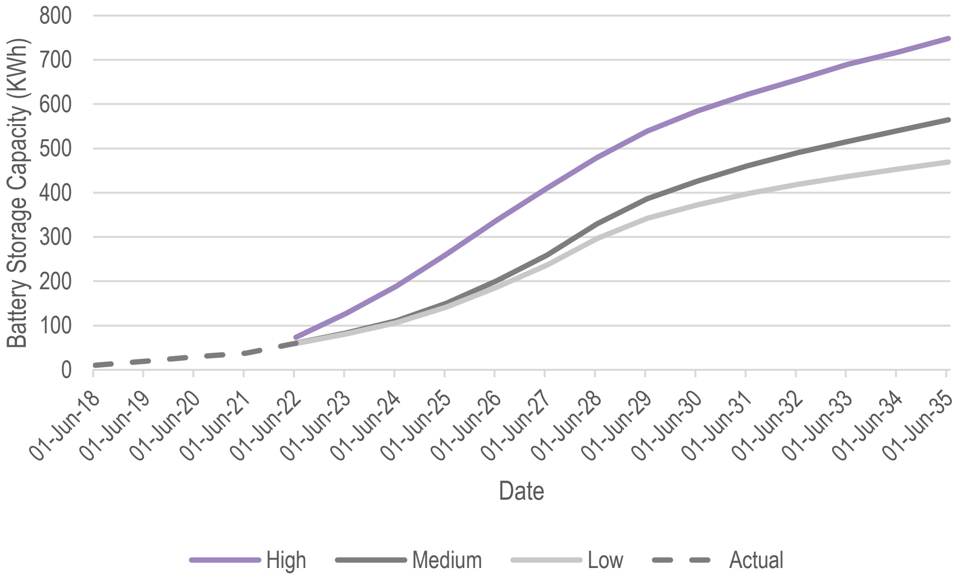
Source: Energy Queensland, DER_GSP_GSI_POP_SOI.parq file

The capacity projections for rooftop PV are converted into half hourly generation using a solar PV linear regression model developed by Ergon. The model has been fitted using recorded grid voltage data from of a sample set of around 3500 customers. One of the key issues of estimating PV output using a model is that it relies on instantaneous hourly GHI weather input readings to approximate output which may vary significantly within each hour due to cloud cover. The model could potentially be improved by incorporating algorithms to detect clouds or by using post processed weather data with cloud detection and other atmosphere related filters to improve accuracy.

Figure 5.8 shows the projected uptake of battery storage within the Ergon network under the three growth scenarios. The uptake of battery storage is expected to accelerate up until the second half of the forecast period, before mildly slowing down 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.

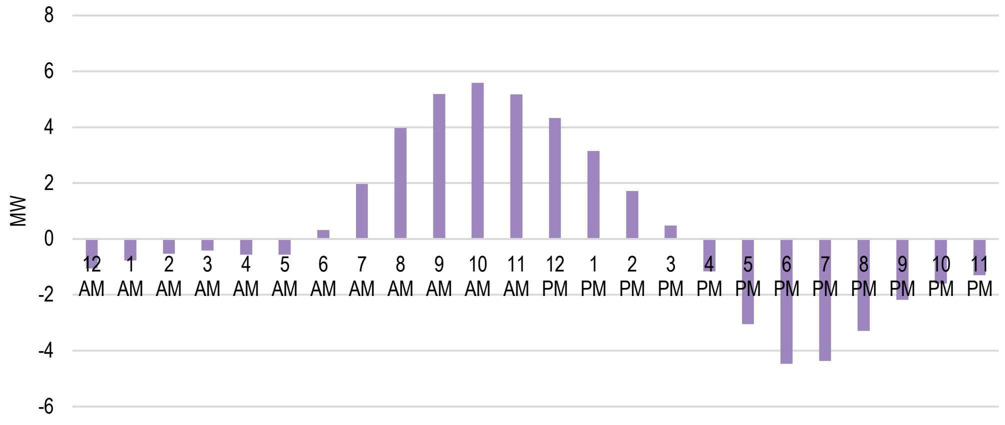
Figure 5.8 Projected uptake of battery storage in the Ergon network, Low, Medium, High



Source: Energy Queensland, DER_GSP_GSI_POP_SOI.parq file

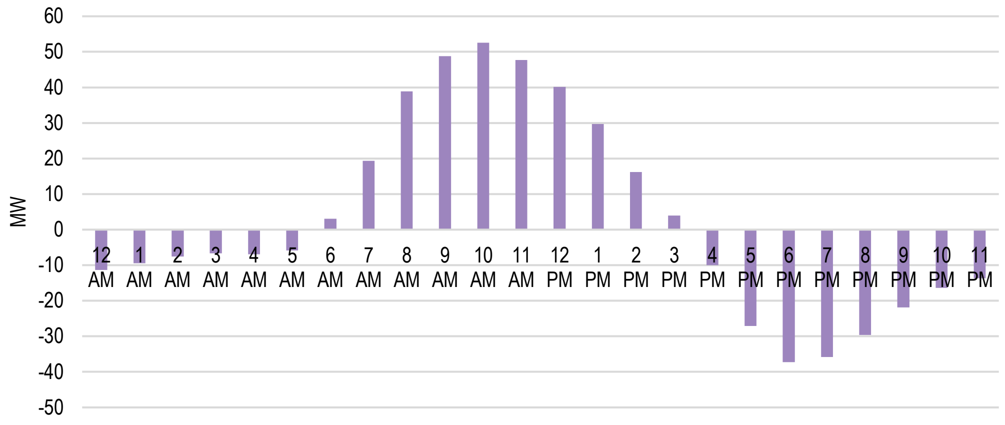
Battery storage and electric vehicles half hourly profiles were provided by an external consultant and were applied to the simulated demand profiles to calculate the impact on maximum demand. **Figure 5.9** and **Figure 5.10** show the average time of day profile for commercial and residential battery storage in 2023 and 2035. We find that the battery profiles are reasonable because it is expected that charge will occur mainly during the middle day when rooftop PV generates, and discharge is expected to occur during the evening peak hours when rooftop PV is unavailable.

Figure 5.9 Average time of day profile for commercial and residential battery storage in 2023



Source: Energy Queensland, Battery_EV.parq file

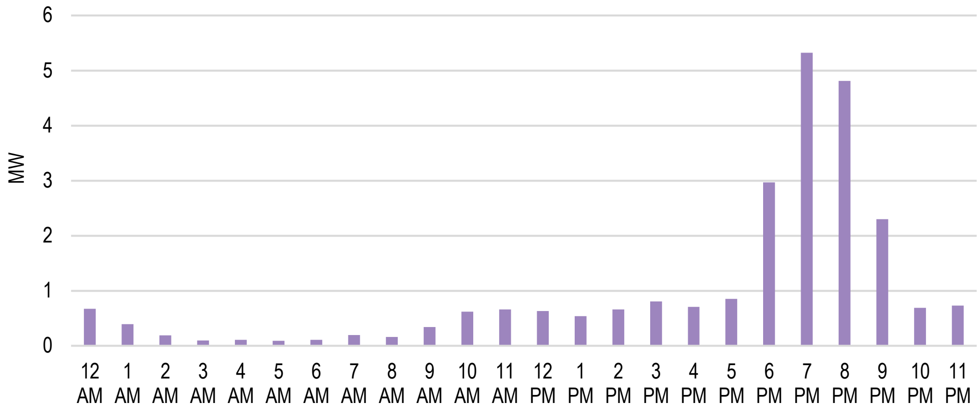
Figure 5.10 Average time of day profile for commercial and residential battery storage in 2035 – Medium case



Source: Energy Queensland, Battery_EV.parq file

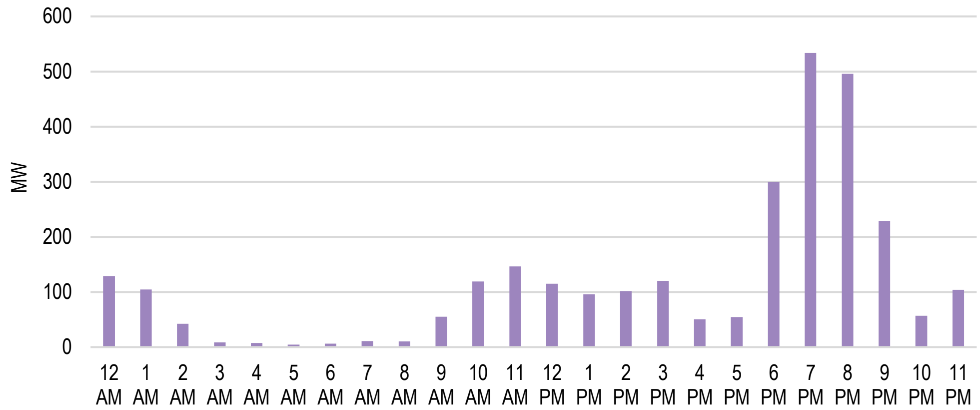
Figure 5.11 and **Figure 5.12** show the average time of day profile for EVs. The level of EV charge is significantly higher during the evening peak from 6pm to 9pm. This appears to be driven by the assumption that most people will charge their car based on convenience rather than solar aligned charging based on self-consumption, tariffs and other incentives. We find this assumption to be reasonable as it is plausible that people may prefer to charge their EVs in the evening after returning from work or other daytime activities.

Figure 5.11 Average time of day profile for EVs in 2023 – Medium case



Source: Energy Queensland, Battery_EV.parq file

Figure 5.12 Average time of day profile for EVs in 2035 – Medium case



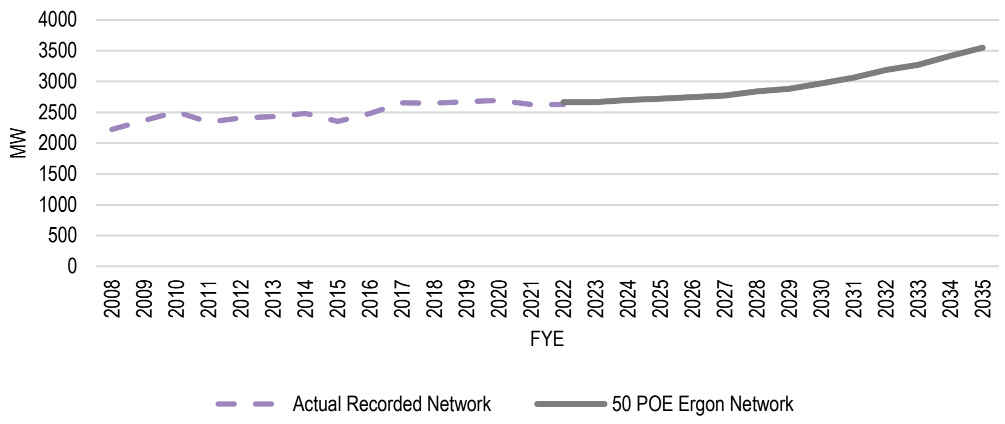
Source: Energy Queensland, Battery_EV.parq file

5.2.5 Reasonableness of forecast

Figure 5.13 shows the aggregated coincident forecasts at the Ergon system level and after post model adjustments have been applied.

Over the fifteen-year period from 2008 to 2022, Ergon's historical maximum demand grew at an average rate of around 1.4 percent per annum. Over the forecast period, Ergon's 50 POE system maximum demand is forecast to grow at a similar rate till 2030, reaching 2,970 MW by 2030. The increase in the rate of growth from 2030 onwards is driven by the significant growth in EVs and battery storage systems. The figure shows that the 50POE medium forecast over the medium term is not inconsistent with the historical trend and is reasonable in our view.

Figure 5.13 Ergon Summer Peak Demand Forecast, 50 POE, Medium Case



Source: Energy Queensland, result_review.parq file

5.2.6 Transparency and repeatability

At this stage of the process, Energy Queensland has developed draft documentation to describe the Ergon network peak demand approach. This documentation provides an overview of the methodology and summary of results but does not describe in detail the input data sources used and the exact steps to produce the forecast so a third party can reproduce them. 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.

We understand the model data preparation, simulation and analysis has been implemented using Python code and Databricks which means that a third party can reproduce the forecast if necessary. This assumes that the code and data preparation steps are documented adequately.

5.3 Key recommendations summary

Based on the review of Ergon's system maximum demand methodology, ACIL Allen recommends:

— Ergon should expand its documentation to include greater detail of the forecasting process including data inputs, model estimation and model selection

— Ergon should expand its documentation to include greater detail of the methodology used to calculate the post model adjustment impacts of PV, battery storage and electric vehicles.