ACIL ALLEN

22 February 2023

Report to Energy Queensland

Review of energy forecasting methodology

ACIL ALLEN

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1.1 Project scope

ACIL Allen has been appointed by Energy Queensland to review the forecasting methodologies of Ergon Energy and Energex with respect to energy consumption.

As part of this review ACIL Allen has:

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

1.2 ACIL Allen's approach to the review

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

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

ACIL Allen was provided with a number of Python files and Excel spreadsheets to be reviewed. Moreover, we were provided with several documents describing the methodology and process of model selection and validation.

1.3 Structure of this report

This report as structured as follows:

- Section 2 describes the AERs principles of best practice forecasting
- Section 3 reviews the Energex and Ergon residential energy forecasts
- Section 4 reviews the ICC and CAC tariff forecasts
- Section 5 reviews the controlled tariff forecasts
- Section 6 reviews the unmetered supply forecasts
- Section 7 reviews the SAC business tariff forecasts
- Section 8 concludes and summarises any recommendations

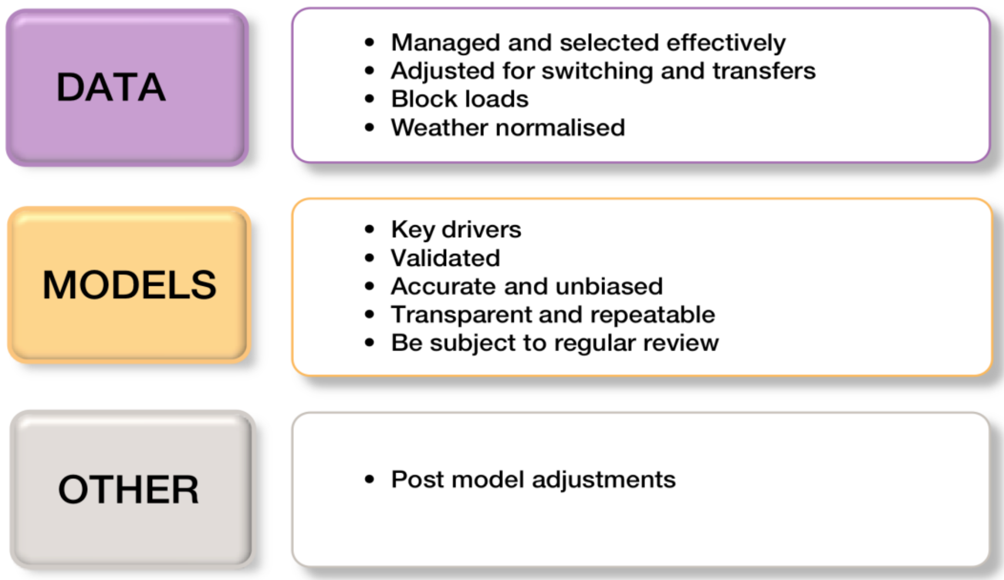
Best practice forecasting 2

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"

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

1.1 Incorporating key drivers

The forecasting methodology should incorporate the key drivers of energy consumption, either directly or indirectly. These may include[1]:

1. Economic growth
2. Electricity prices
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

1.2 Weather normalisation

Energy consumption is well known to be sensitive to weather. It is therefore necessary to control for variations in weather within the modelling process.

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

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

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

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

[1] 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.

1.3 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.

1.4 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 energy consumption 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.

1.5 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.

1.6 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

1.7 Use of the most recent information

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

1.8 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.

Review of residential energy forecasts 3

3.1 Approach to residential energy forecasting

Energy Queensland use an econometric approach to estimate residential energy sales for both the Energex and Ergon regions.

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

The main advantage of the econometric approach is that it allows the forecaster to incorporate their view about the future course of the drivers and their impact on the variable of interest. This is the main advantage of the econometric approach over less sophisticated methods like trend analysis which assumes that the historical relationship between energy delivered and its key drivers remains constant into the future.

The approach first estimates a base case model which excludes the impact of emerging technologies such as electric vehicles, battery storage systems and solar PV. These are estimated separately and then added to the forecast as a post model adjustment. The impacts of the post model adjustments impacts are provided by the external consultants ENEA.

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

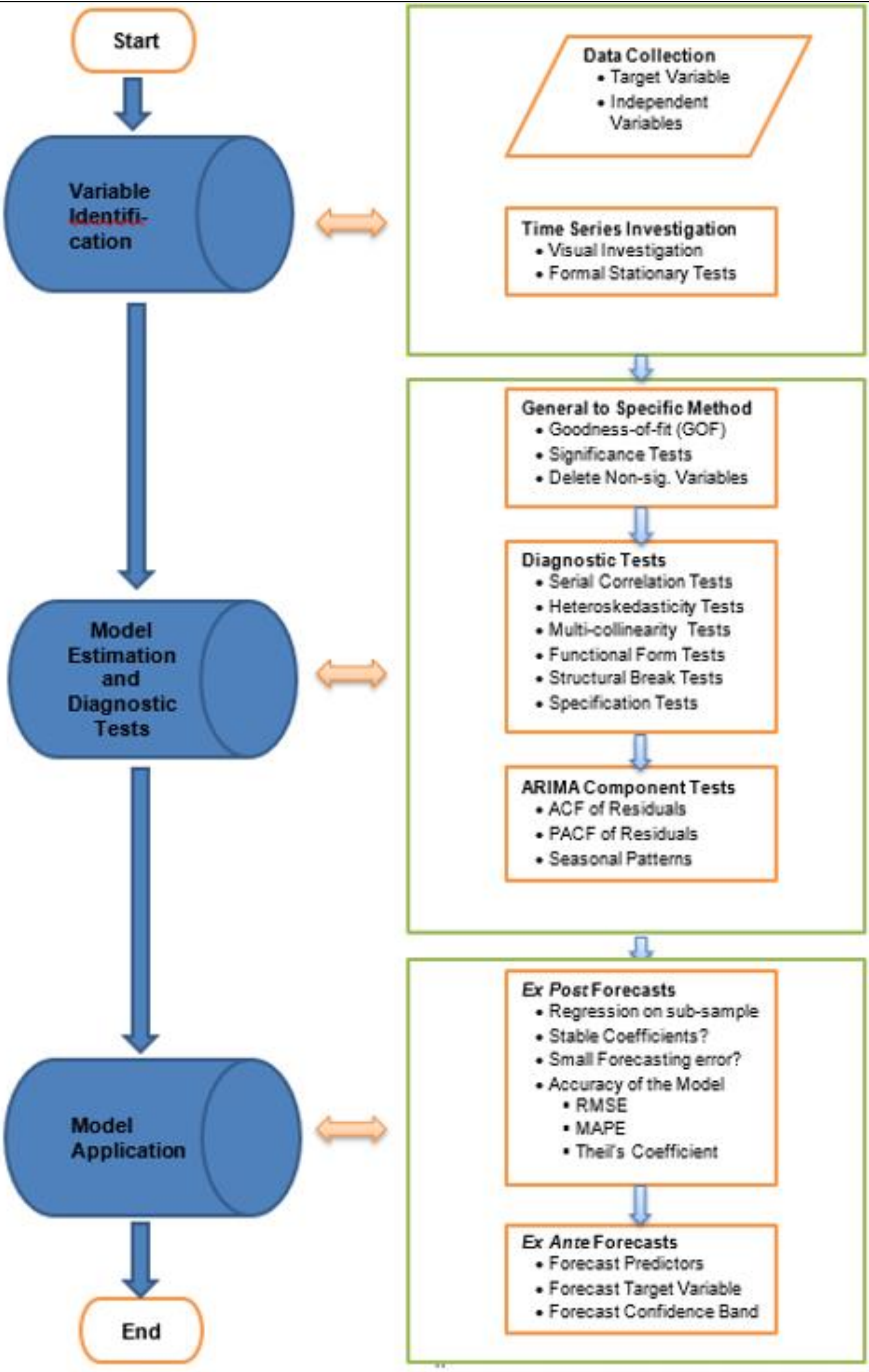
Figure 3.1 below shows a flow chart from Energy Queensland's documentation that presents the Energy Queensland forecasting methodology for residential energy sales.

The process commences with the collection of relevant data. This includes long term drives such as social and economic factors such as GSP and GSI, as well as shorter term drivers such as temperature, rainfall, and relative humidity. Additional variables are generated for external shocks such as COVID 19 and cyclical patterns such as calendar related factors.

Each of the selected variables are subjected to stationarity testing to ensure that the estimated model is free of spurious relationships.

A general to specific method is adopted, with tests of statistical significance being used to eliminate models that fails to achieve statistical significance. Potential candidate models are then subjected to a battery of diagnostic tests such as tests of serial correlation in the model residuals, tests for heteroscedasticity and tests for multicollinearity. Remedial action is then taken such as the inclusion of an autoregressive term in the model to eliminate any serial correlation in the error term.

Figure 3.1 Process of model development, estimation and validation



Source: Energy Queensland

In the case of residential customers, average daily consumption per customer regressions were estimated covering the historical periods from March 2008 to June 2022 (for the Energex region) and March 2016 to June 2022 (for the Ergon region). The regressions included the main drivers of domestic energy consumption per customer. The main variables included in the Energex model were:

— Accumulated cooling and heating degree days for summer

— Accumulated cooling and heating degree days for winter

— Accumulated cooling and heating degree days for the rest of the year
— Average daily rainfall in winter
— Average daily rainfall in the rest of the year
— Average cumulative relative humidity
— Log of the residential electricity price
— Gross State Income per customer
— Dummy for the GFC
— A trend variable starting from 2011
— Dummy variable capturing the impact of COVID19
— Dummy variable capturing the impact of the 2020 and 2021 summer periods
— The model also includes an autoregressive term

Table 3.1 presents the estimated coefficients from the Energex final residential model.

Table 3.1 Model of Energex residential energy sales

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	15.9605	2.6384	6.0494	0.0000
Accumulated CDD and HDD summer	0.0480	0.0020	24.3093	0.0000
Accumulated CDD and HDD winter	0.0368	0.0022	16.8828	0.0000
Accumulated CDD and HDD rest of year	0.0395	0.0022	17.7945	0.0000
Rainfall winter	0.1136	0.0475	2.3900	0.0180
Rainfall rest of year	0.0464	0.0146	3.1856	0.0017
Average cumulative relative humidity	0.0147	0.0032	4.5497	0.0000
Log of residential price	-2.2099	0.7497	-2.9478	0.0037
Gross State Income per customer	0.0007	0.0003	2.4725	0.0145
GFC dummy	-0.5322	0.2269	-2.3457	0.0202
Trend from 2011	-0.0577	0.0236	-2.4468	0.0155
COVID 19 dummy	1.1788	0.2563	4.6004	0.0000
Dummy for 2020 and 2021 summer	1.0284	0.3581	2.8721	0.0046
AR(1) term	0.6923	0.0625	11.0717	0.0000
SIGMASQ	0.0981	0.0110	8.9126	0.0000

Source: Energy Queensland

The final model had an estimated R^2 of 94.5% and all selected variables were statistically significant at the 5% significance level.

For the Ergon region, three separate models were estimated for the East and West regions of the network as well as Mt Isa.

The main variables included in the Ergon East region model were:

— Accumulated cooling and heating degree days for summer
— Accumulated cooling and heating degree days for winter
— Average cumulative relative humidity
— Log of the residential electricity price
— Gross State Income per customer
— Dummy variable capturing the impact of COVID19
— Dummy variable capturing the impact of the 2020 and 2021 summer periods
— The model also includes an autoregressive term

Table 3.2 presents the estimated coefficients from the Ergon (East) residential model.

Table 3.2 Model of Ergon (East) residential energy sales

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	24.2440	4.3904	5.5221	0.0000
Accumulated CDD and HDD summer	0.0311	0.0011	27.7443	0.0000
Accumulated CDD and HDD winter	0.0271	0.0016	16.5716	0.0000
Average cumulative relative humidity	0.0136	0.0034	4.0211	0.0001
Log of residential price	-4.9319	1.0664	-4.6247	0.0000
Gross State Income per customer	0.0006	0.0004	1.7208	0.0898
COVID 19 dummy	0.5744	0.2646	2.1711	0.0334
Dummy for 2020 and 2021 summer	0.7608	0.2755	2.7612	0.0074

Source: Energy Queensland

The estimated R^2 for the final Ergon (East) model was 94.5%. All variables except the GSI and COVID19 variables were significant at the 1% level, with the COVID19 and GSI variables found to be significant at the 5% and 10% levels of significance respectively.

The main variables included in the final Ergon West region model were:

— Accumulated cooling and heating degree days for summer
— Accumulated cooling and heating degree days for winter
— Accumulated cooling and heating degree days for the rest of the year
— Average cumulative relative humidity
— Log of the residential electricity price
— Gross State Income per customer
— The model also includes an autoregressive term

Table 3.3 presents the estimated coefficients from the Ergon (West) residential model.

Table 3.3 Model of Ergon (West) residential energy sales

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	33.7159	8.0006	4.2142	0.0001
Accumulated CDD and HDD summer	0.0299	0.0023	13.1139	0.0000
Accumulated CDD and HDD winter	0.0125	0.0047	2.6759	0.0094
Accumulated CDD and HDD for rest of year	0.0240	0.0038	6.2828	0.0000
Average cumulative relative humidity	0.0192	0.0070	2.7589	0.0075
Log of residential price	-7.4070	1.5212	-4.8694	0.0000
Gross State Income per customer	0.0010	0.0013	0.7607	0.4495
AR(1)	0.4463	0.1125	3.9661	0.0002
SIGMASQ	0.5286	0.0969	5.4548	0.0000

Source: Energy Queensland

The estimated R^2 for the final Ergon (West) model was 93.3%.

All variables in the Ergon (West) model were found to be statistically significant except for the GSI per customer variable, which was retained for its economic significance.

Energy Queensland projected customer numbers for the Energex and Ergon regions by estimating an econometric relationship between customer numbers and population and then applying the estimated coefficients to project into the forecast period using a set of population projections.

3.1.1 Inclusion of key drivers

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

Temperature drivers are captured through cooling and heating degree day variables. Separate rainfall variables are included for the summer, winter and rest of the year periods. Also included in the model specification is relative humidity, which adds to energy delivered in the residential models.

Economic activity is captured through the inclusion of Gross State Income per customer. Also included are real residential electricity prices.

The residential energy models also include dummy variables for the global financial crisis (GFC) and the impact of the COVID19 pandemic. An additional autoregressive term is included to capture any remaining autocorrelation in the model residuals. In addition to the autoregressive component, the residential models include a seasonal adjustment term.

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

3.1.2 Approach to model validation

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

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

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

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

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

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

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

Goodness of fit

On the basis of model fit, Energy Queensland's residential energy per customer models display exceptional explanatory power.

In the case of the Energex customers' average daily usage, Energex's estimated model was able to achieve an adjusted R^2 of 94.5%. Moreover, both the Ergon region residential models achieved an estimated R^2 of well over 90%.

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

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

Statistical significance

Energy Queensland applies the standard of statistical significance in the process of selecting between potential explanatory variables. The majority of the variables included in the residential energy use models were found to be significant at the 1% or 5% significance levels. There are several exceptions, however. In the Ergon East model, the Gross State Income variable was found to be statistically significant only at the 10% significance level. Moreover, statistical significance for the GSI variable was not achieved at all for the Ergon West model.

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

Energy Queensland's final residential models also mops up any remaining patterns in the model residuals through the inclusion of a first order autoregressive term and a seasonal adjustment term. It is ACIL Allen's view that any remaining pattern in the residuals is more than adequately soaked up by the autoregressive and seasonal terms.

3.1.3 Assessment of key inputs

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

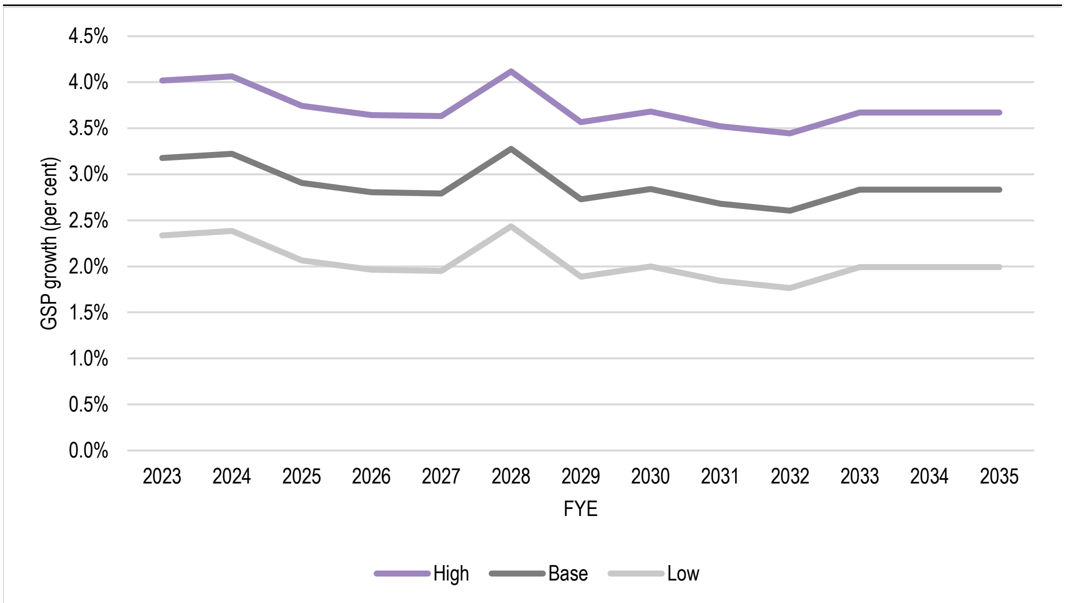
Gross State Product

Energy Queensland have opted to use GSP forecasts from Deloitte as a proxy for GSI to develop their energy forecasts. Specifically, Energy Queensland have chosen to apply Deloitte's low, base and high scenarios to each of its own respective low, medium and high scenarios.

Figure 3.2 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%.

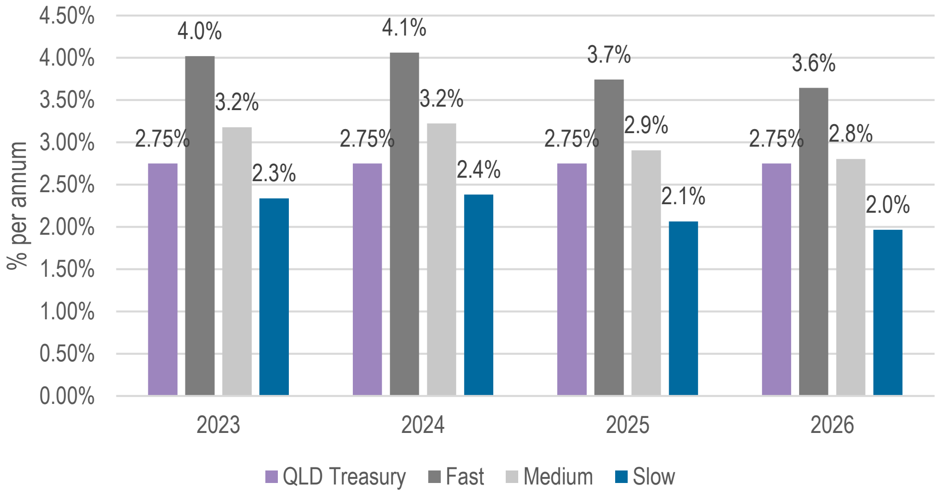
Figure 3.2 Deloitte GSP Growth forecasts, low, medium and high



Source: Deloitte

Figure 3.3 shows Deloitte's GSP forecasts to the year 2026 against the most recent State budget forecasts of the Queensland Government.

Figure 3.3 Deloitte GSP growth forecasts versus 2022-23 Queensland State budget



Source: Deloitte and 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.

Weather inputs

The main weather inputs used by Energy Queensland within its Energex region residential energy forecasting model are heating and cooling degree days calculated using data from three separate weather stations, Amberley, Archerfield and Brisbane Aero.

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

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

In the case of the Ergon (East) region, a similar approach was taken, but instead using data from 6 separate weather stations namely, Cairns, Townsville, Mackay, Rockhampton, Hervey Bay and Toowoomba. These were also weighted by population size to construct a single temperature index.

For Ergon (West), the weather stations used were Cooktown, Emerald, Longreach, Normanton, Roma and Townsville. Just as in the other models, these were weighted by population size to create a single temperature variable.

3.1.4 Reasonableness of the forecasts

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

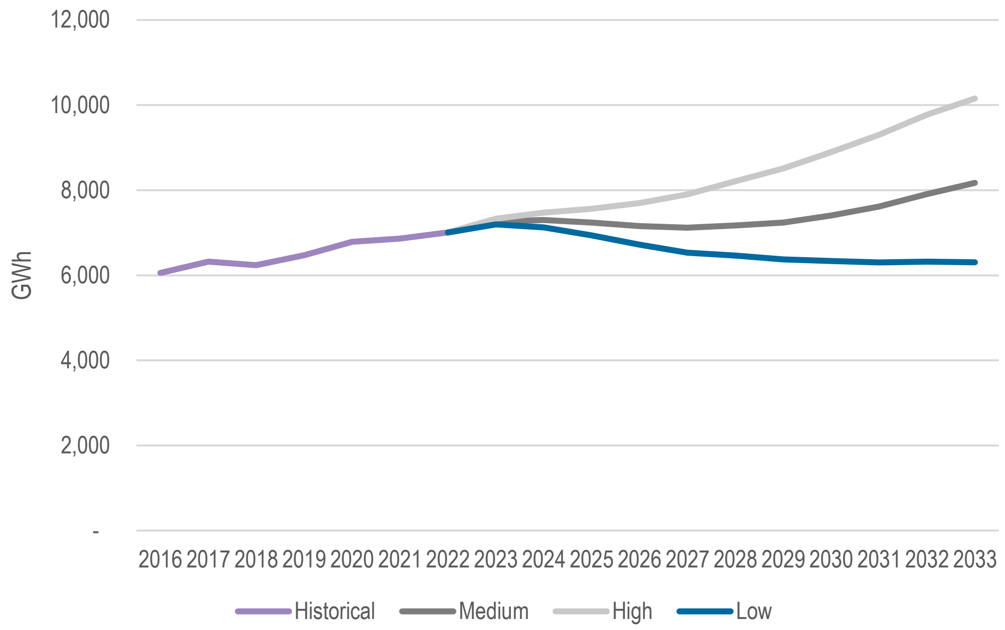
Figure 3.4 shows total energy sales under the low, medium and high scenarios for the Energex region.

Under the medium case, total energy sales in the Energex network is projected to grow at a rate of 1.4% per annum over the period from 2022 to 2033.

Under the high case, total energy sales in the Energex network is projected to grow at a rate of 3.4% per annum over the period from 2022 to 2033, while under the low scenario energy sales are projected to fall by 0.95% per annum.

The bands between the low and high expand significantly over the forecast period reflecting the rapidly increasing uncertainty as the forecasting horizon expands.

Figure 3.4 Residential energy sales, Energex region, Forecast and Historical



Source: Energy Queensland

Growth is more subdued over the first half of the forecast horizon, but then starts to move higher after 2030 as the uptake of electric vehicles accelerates after 2029.

In our view, the Energex region residential forecasts are reasonable.

Figure 3.5 shows total residential energy sales under the low, medium and high scenarios for the Ergon (East) region.

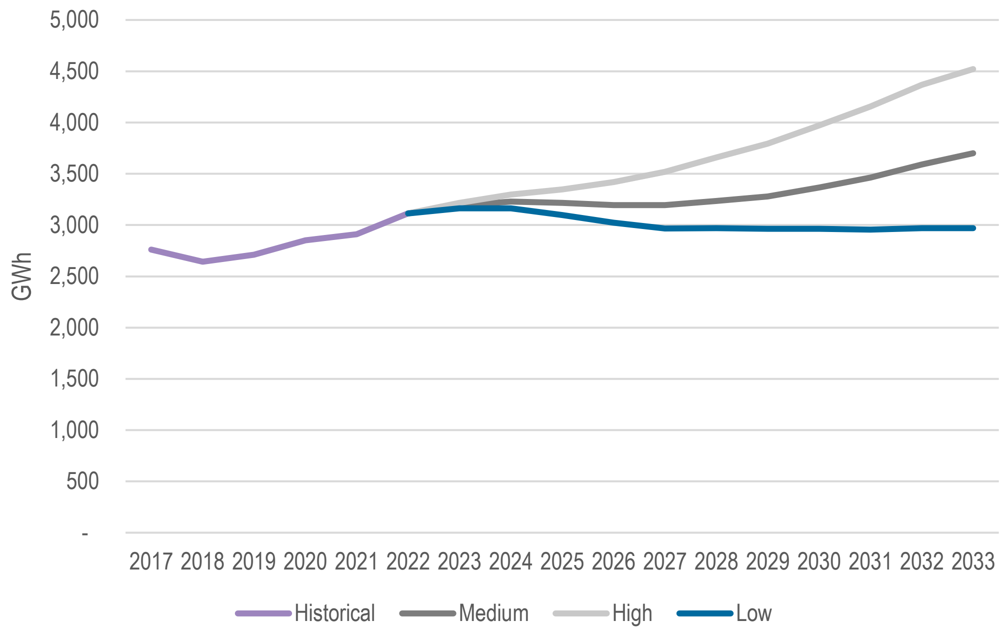
Under the medium case, total energy sales in Ergon (East) are projected to grow at a rate of 1.58% per annum over the period from 2022 to 2033.

Under the high case, total energy sales in Ergon (East) are projected to grow at a rate of 3.4% per annum over the period from 2022 to 2033, while under the low scenario energy sales are projected to fall by 0.43% per annum.

The forecasts follow a similar trajectory to the Energex region forecasts, with subdued growth in the first half of the forecast period, before the rapid increase in the uptake of electric vehicles drives total residential energy consumption higher.

The forecast trajectory for Ergon (East) follows a reasonable path in our view, with possible outcomes likely to lie within the low and high scenarios over time.

Figure 3.5 Residential energy sales, Ergon (East), Forecast and Historical



Source: Energy Queensland

Figure 3.6 shows total residential energy sales under the low, medium and high scenarios for the Ergon (West) region.

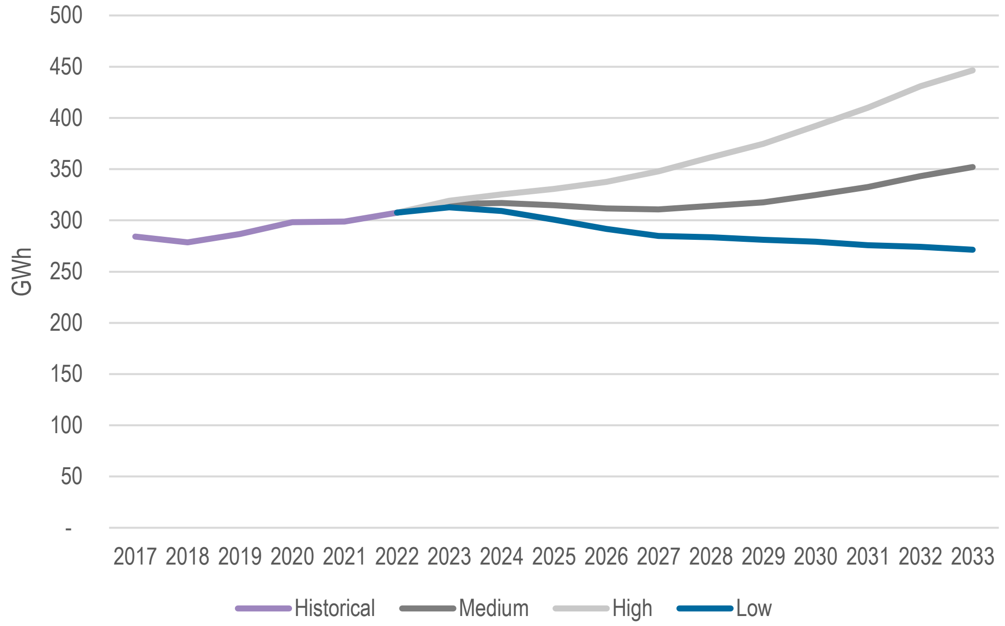
Under the medium case, total energy sales in Ergon (West) are projected to grow at a rate of 1.24% per annum over the period from 2022 to 2033.

Under the high case, total energy sales in Ergon (West) are projected to grow at a rate of 3.45% per annum over the period from 2022 to 2033, while under the low scenario energy sales are projected to fall by 1.13% per annum.

The forecasts follow a similar trajectory to the Energex and Ergon (East) forecasts, with electric vehicles playing a similar role as in the other two regions.

The forecast trajectory for Ergon (West) follows a reasonable path in our view, with possible outcomes likely to lie within the low and high scenarios over time.

Figure 3.6 Residential energy sales, Ergon (West), Forecast and Historical



Source: Energy Queensland

3.1.5 Transparency and repeatability

Energy Queensland's document, 'Energy Forecast: Part 2, 2022-23 -2031-32', dated October 2022, describing its approach to forecasting residential energy sales and customer numbers within the Energex and Ergon regions is of a very high standard. The document describes the models estimated as well as the process involved in reaching the best model in some detail.

The document describes the process of data collection, model estimation and diagnostic checking and model validation very well. It is our view that the document is fit for purpose and adequately describes the forecasting methodology.

Review of ICC and CAC forecasts 4

4.1 Assessment of Energy Queensland approach to ICC & CAC forecast

ICC and CAC forecasts are calculated for each NMI and then aggregated to produce a total forecast. The large number of NMIs to be forecast results in a high degree of computational load and complexity.

Energy Queensland uses a time series approach to estimate a suitable model for each NMI. Separate time series models are estimated such as exponential smoothing, naïve, simple mean, and ARIMA models and the out of sample performance of each model is evaluated. The best performing model is then selected for each NMI. The forecasts for each NMI are then produced using this model and aggregated to get a network level forecast. The only data required in this approach is the underlying energy and demand data for each NMI. There are no other external inputs such as economic or demographic drivers. This is reasonable given the models are estimated at the level of the NMI. Macro level economic drivers are unlikely to correlate well individual businesses.

Energy Queensland has adopted a new method based on time-series cross-validation which is well suited to time series forecasts and is supported by many experts in the field. A key feature of this approach is the use of multiple samples to train and test different forecasting models to assess the predictive ability and select the model with the best performance.

The approach has two main improvements over the existing one:

— The process is fully automated using Python code which increases transparency and repeatability, reduces manual errors and improves the speed to produce and update results. The previous process used Excel macros and required manual intervention.

— Out of sample testing is performed to validate the model and reduce the risk of overfitting. The previous model performed only in sample testing which is not best practice.

4.2 Reasonableness of ICC Energy and Demand Forecasts

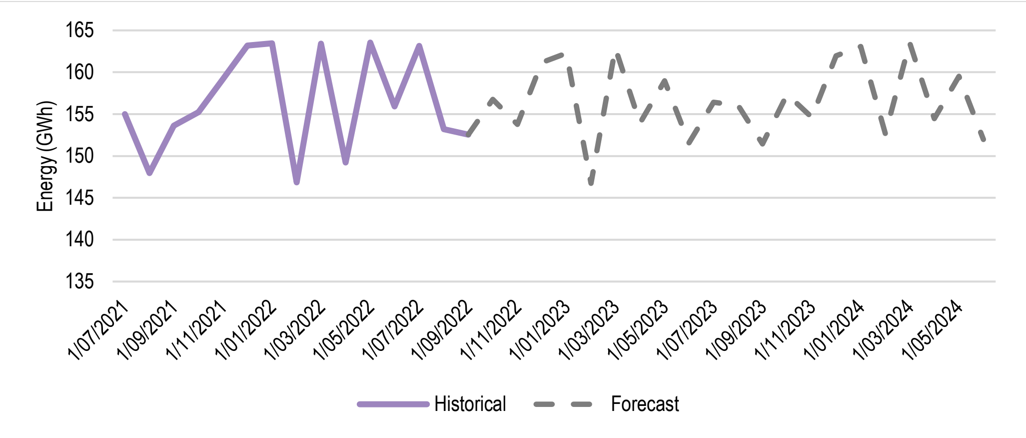
Because the forecasts are produced using time series techniques with stationary coefficients, any patterns seen in forecasts should resemble patterns observed in the historical data. In this section we assess the reasonableness of the forecasts against the historical behaviour of the series.

The figures below show a comparison of SEQ, East and West ICC energy and demand forecasts with historical data from the previous 15 months to check whether there are any material changes which cannot be explained. We found that all the forecasts follow the recent trends of energy and demand growth which is an acceptable outcome. Forecast energy and demand growth in SEQ and the West remains relatively stagnant. Forecast demand and energy increases mildly in the East which is plausible as this is where most of the industrial load and historical growth exists currently.

4.2.1 SEQ

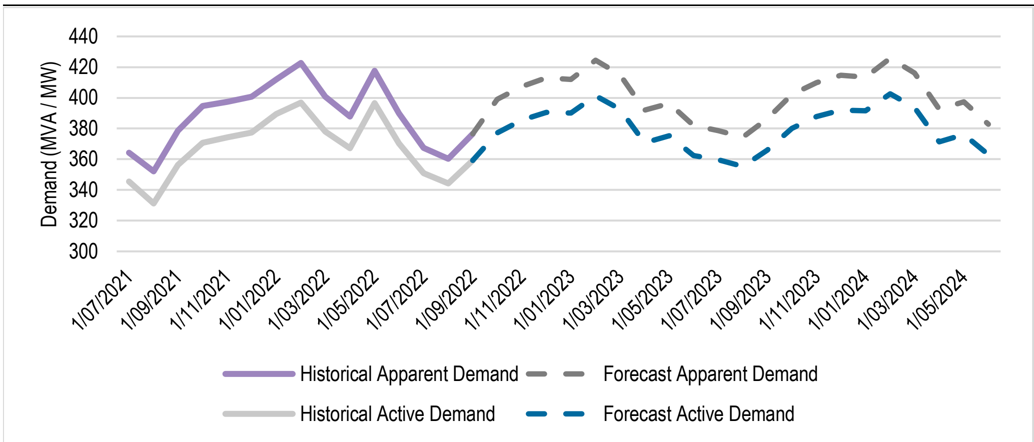
The ICC energy and demand forecasts for the South East Queensland region are shown in the following two figures.

Figure 4.1 Aggregate SEQ ICC Energy Forecast



Source: Energy Queensland

Figure 4.2 Aggregate SEQ ICC Demand Forecast

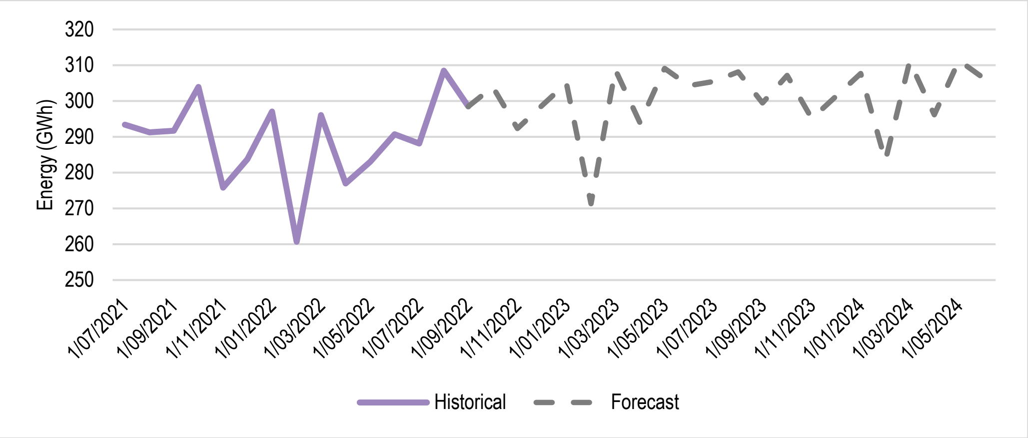


Source: Energy Queensland

4.2.2 East

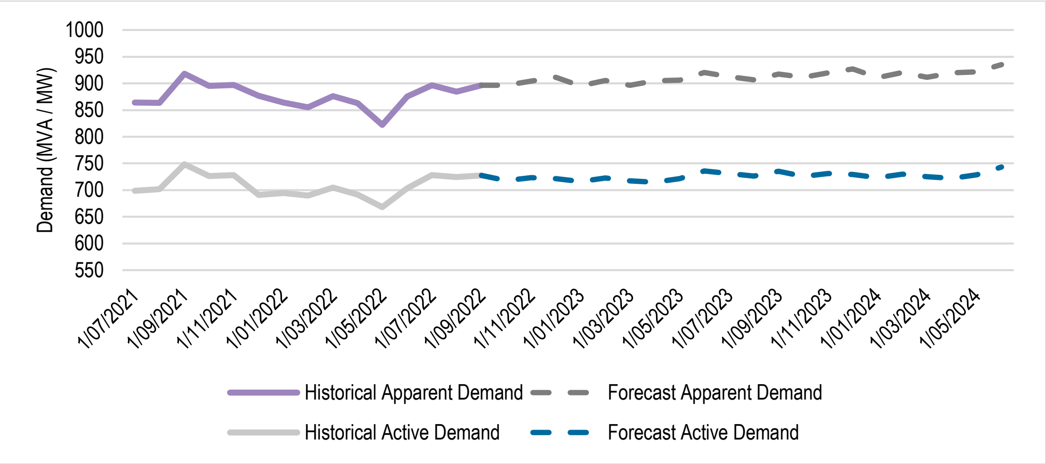
The ICC energy and demand forecasts for the Ergon (East) region are shown in the following two figures.

Figure 4.3 Aggregate East ICC Energy Forecast



Source: Energy Queensland

Figure 4.4 Aggregate East ICC Demand Forecast

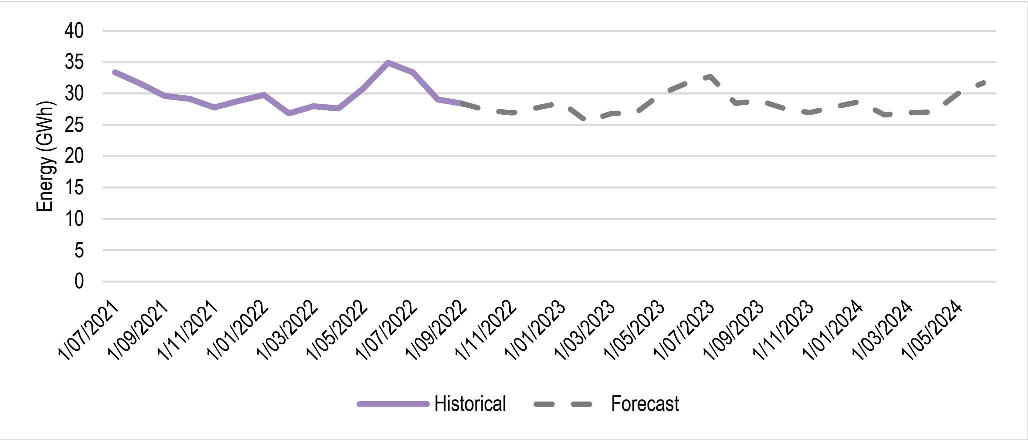


Source: Energy Queensland

4.2.3 West

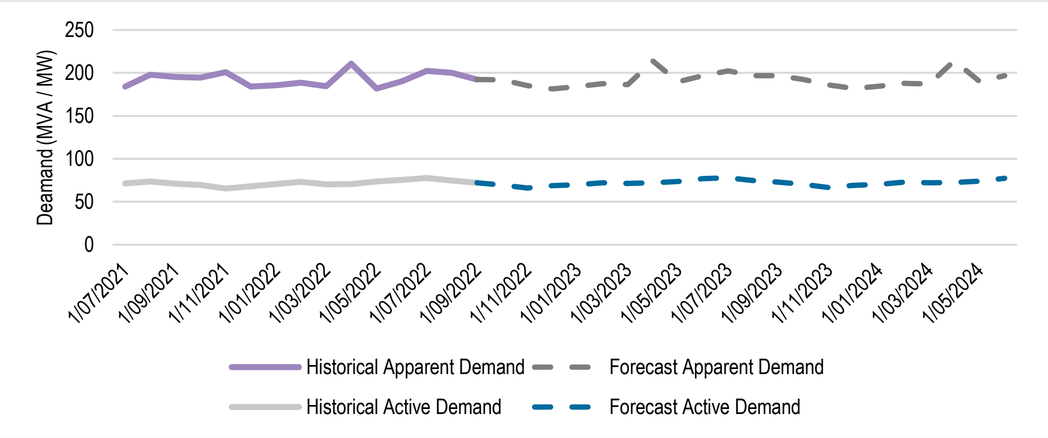
The ICC energy and demand forecasts for the Ergon (West) region are shown in the following two figures.

Figure 4.5 Aggregate West ICC Energy Forecast



Source: Energy Queensland

Figure 4.6 Aggregate West ICC Demand Forecast



Source: Energy Queensland

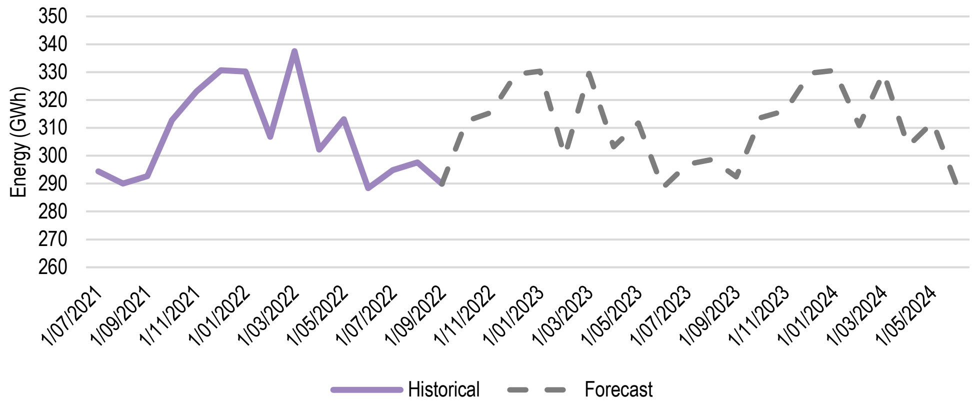
4.3 CAC Forecasts

The figures below show a comparison of SEQ, East and West CAC energy and demand forecasts with historical data from the previous 15 months to check whether there are any unexplainable changes. The forecasts appear to be reasonable as there are no material changes and are consistent with historical seasonal variation.

4.3.1 SEQ

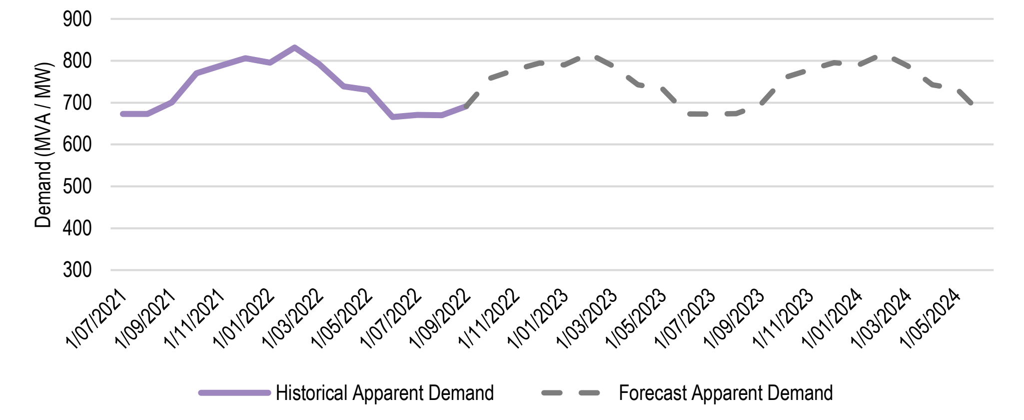
The CAC energy and demand forecasts for the South East Queensland region are shown in the following figures.

Figure 4.7 Aggregate SEQ CAC Energy Forecast



Source: Energy Queensland

Figure 4.8 Aggregate SEQ CAC Demand Forecast

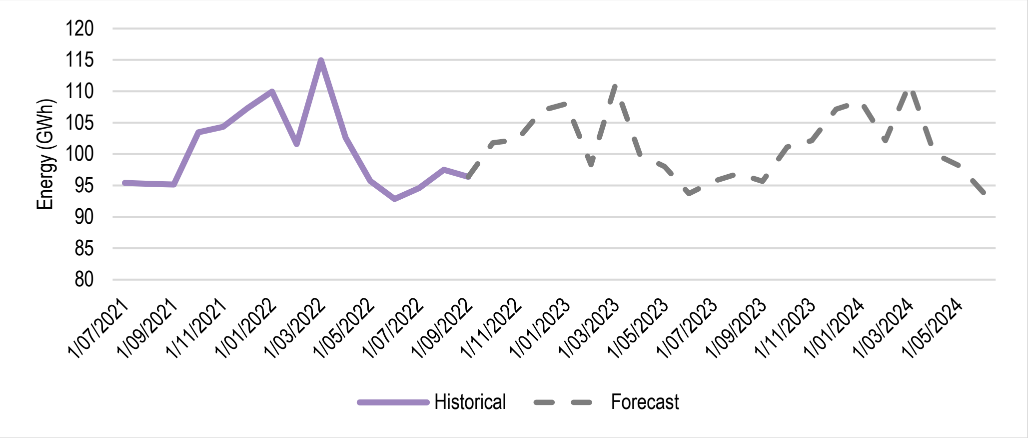


Source: Energy Queensland

4.3.2 East

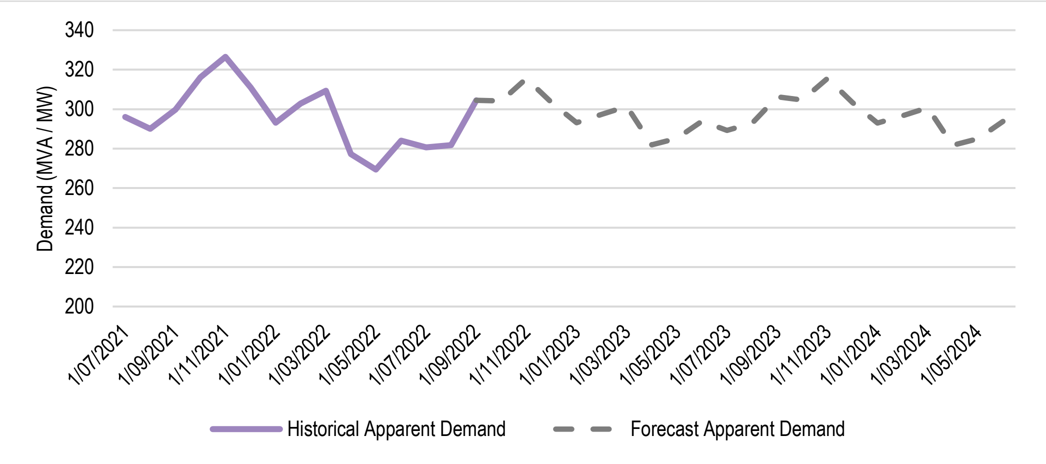
The CAC energy and demand forecasts for the Ergon (East) region are shown in the following figures.

Figure 4.9 Aggregate East CAC Energy Forecast



Source: Energy Queensland

Figure 4.10 Aggregate East CAC Demand Forecast

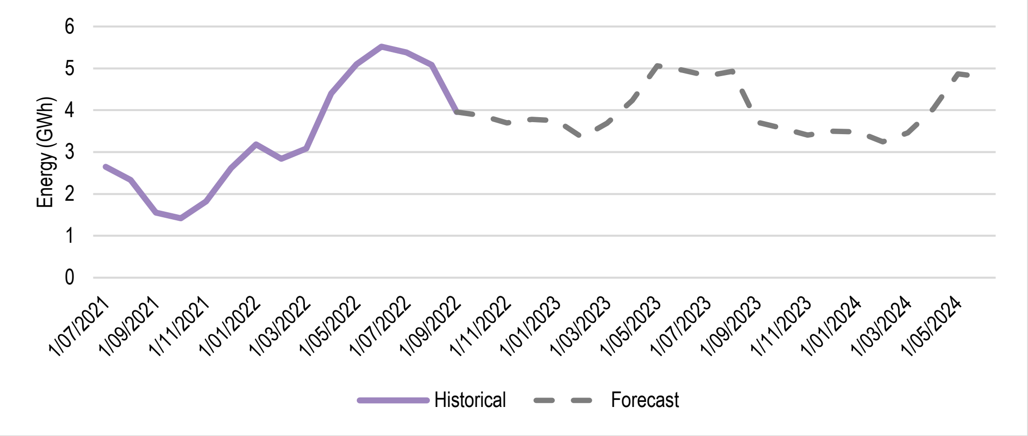


Source: Energy Queensland

4.3.3 West

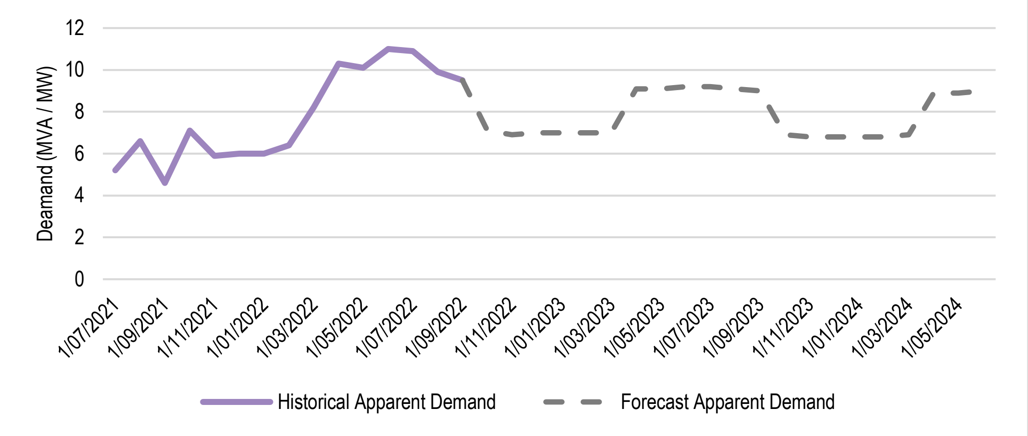
The CAC energy and demand forecasts for the Ergon (West) region are shown in the following figures.

Figure 4.11 Aggregate West CAC Energy Forecast



Source: Energy Queensland

Figure 4.12 Aggregate West CAC Demand Forecast



Source: Energy Queensland

Review of controlled tariff forecasts 5

5.1 Assessment of Energy Queensland approach to controlled tariff forecasts

Energy Queensland has used a new methodology for controlled tariff forecasts with the following key features to improve the predictive ability of the model:

1. Use of multiple weather station temperature data over of a single weather station as input to the regression model. This captured more accurately temperature variation over a large geographical area and produced an improved fit with the actuals without autocorrelation.
2. In zones with significant numbers of air conditioners on controlled load tariffs, maximum daily apparent temperature was used as input to a nonlinear regression model due to the non-linear relationship.
3. A breakdown of TUOS zones in the East Pricing Zone to achieve a better fit as TUOS zone 2 has a different seasonality to zones 1 and 3. Zone 2 also has a significantly higher incidence of air-conditioners being connected.

There are three residential customer number forecasts (NMIs) for each region which are inputs into the controlled tariff forecasts. These forecasts were created using a linear regression model and using as input forecasted population growth numbers from ABS annual LGA data and Deloitte's quarterly QLD data.

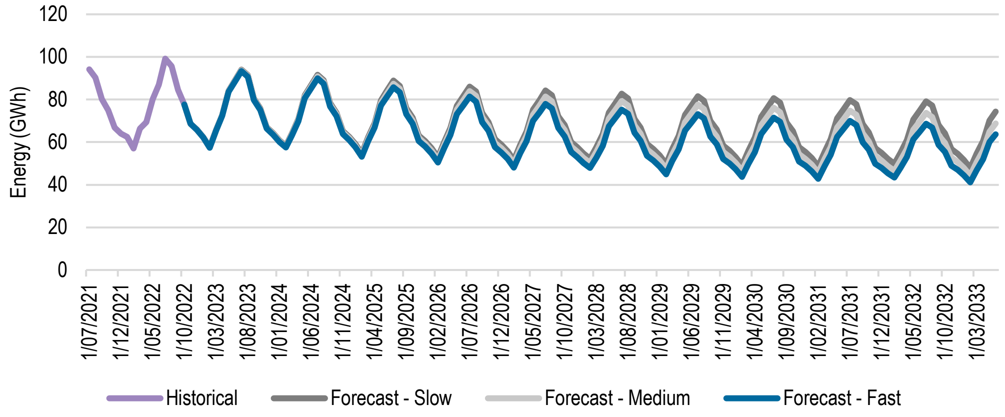
5.2 SAC Small Economy Controlled Tariffs (SACS CTRL ECON)

These tariffs are primarily used to supply hot-water systems and pool pumps. In the East TUOS zone 2 and Mt Isa a significant number of air-conditioners also use this tariff. In all regions, the forecasted number of tariffs continues to decline initially at a similar rate to the historical data and tapers off into the long term as PV installation growth declines. We find this to be a reasonable result. The key driver in decline in controlled load tariffs in all regions is customer PV installation. The number of customers with PV is expected to increase and the historical trend is that some of these customers transfer their controlled loads such as pool pumps and hot water to their primary tariff. The number of customers in the West "Fast" scenario is projected to increase at a higher rate than PV customer installations, so it has the highest energy forecast compared to other regions where the highest energy is in the slow scenario.

5.2.1 SEQ

The SACS CTRL ECON forecasts for the South East Queensland region are shown in the figure below.

Figure 5.1 SACS CTRL ECON Energy Forecasts

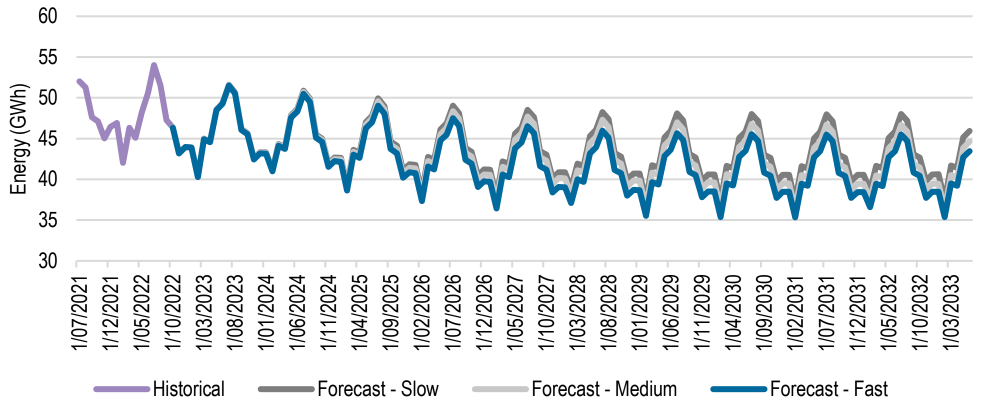


Source: Energy Queensland

5.2.2 East

The SACS CTRL ECON forecasts for the Ergon (East) region are shown in the figure below.

Figure 5.2 SACS CTRL ECON Energy Forecasts

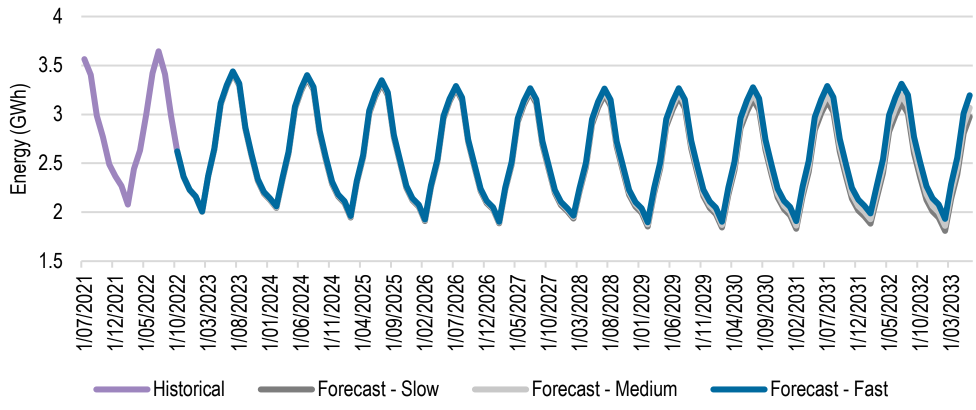


Source: Energy Queensland

5.2.3 West

The SACS CTRL ECON forecasts for the Ergon (West) region are shown in the figure below.

Figure 5.3 SACS CTRL ECON Energy Forecasts

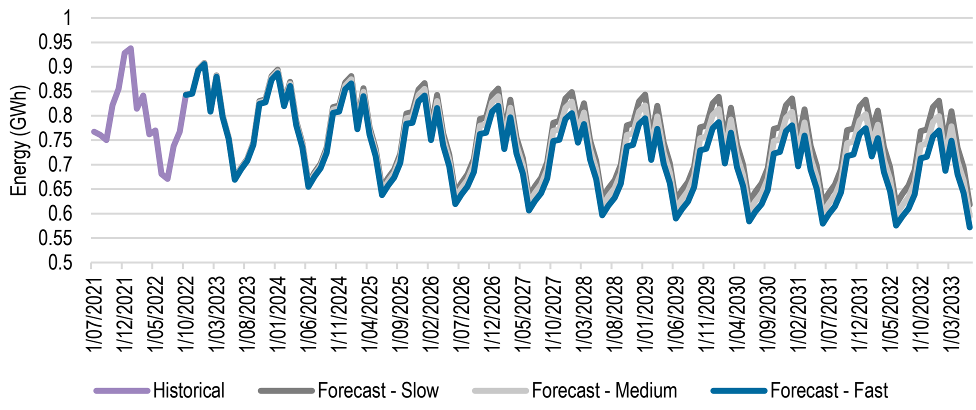


Source: Energy Queensland

5.2.4 Mt Isa

The SACS CTRL ECON forecasts for the Ergon (West) region are shown in the figure below.

Figure 5.4 SACS CTRL ECON Energy Forecasts



Source: Energy Queensland

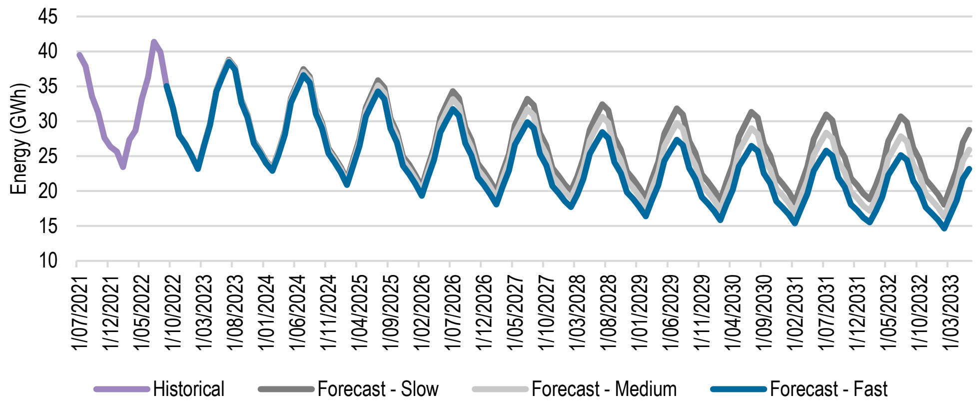
5.3 SAC Small Super Economy Controlled Tariffs (SACS CTRL SUPERECON)

Like the SACS CTRL ECON tariff, the forecasted number of tariffs in all regions continues to decline initially at a similar rate to the historical data and tapers off in the long term as PV installation growth declines. The key driver in decline in controlled load tariffs in all regions is customer PV installations where the customer transfers controllable loads to the primary tariff and operates them to coincide with solar generation. It is reasonable to expect this to continue into the future which explains the forecast downward trend.

5.3.1 SEQ

The SACS CTRL SUPERECON forecasts for the South-East Queensland region are shown in the figure below.

Figure 5.5 SACS CTRL SUPERECON Energy Forecasts

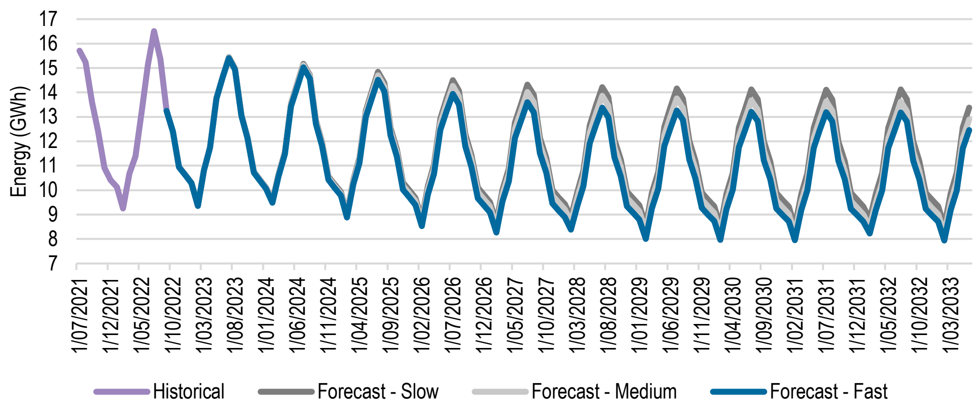


Source: Energy Queensland

5.3.2 East

The SACS CTRL SUPERECON forecasts for the Ergon (East) region are shown in the figure below.

Figure 5.6 SACS CTRL SUPERECON Energy Forecasts

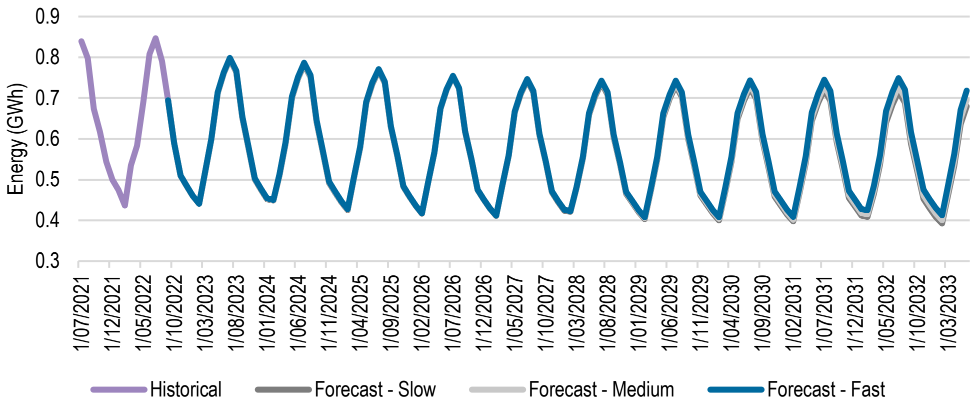


Source: Energy Queensland

5.3.3 West

The SACS CTRL SUPERECON forecasts for the Ergon (West) region are shown in the figure below.

Figure 5.7 SACS CTRL SUPERECON Energy Forecasts

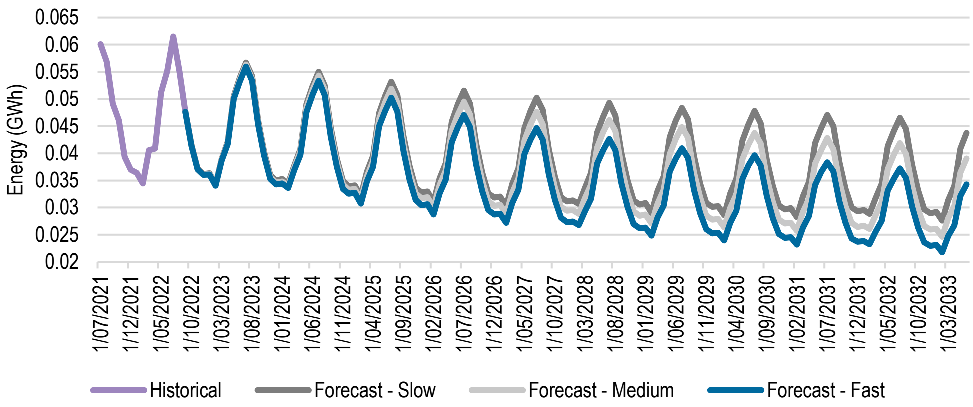


Source: Energy Queensland

5.3.4 Mt Isa

The SACS CTRL SUPERECON forecasts for Mt Isa are shown in the figure below.

Figure 5.8 SACS CTRL SUPERECON Energy Forecasts



Source: Energy Queensland

Review of unmetered supply forecasts 6

Energy Queensland has employed a new methodology for unmetered supply (UMS) forecasts which includes the following key features to improve the predictive ability:

— Fully automated using python code so the process is very transparent and repeatable. Charts and comments are displayed with the code to visualise and explain inputs and outputs.

— Consideration of device level data to consider device replacement programs which are a key driver.

— Replication of the underlying deterministic methodology detailed in AEMO's metrology procedure that generates the billing data. The code to calculate the energy was tested by comparing against historical actuals from 2016 and produced identical results.

The figures below show that forecasted UMS is expected to decrease significantly in SEQ, East, West and Mt Isa over the next ten years. The main driver is streetlight replacement programs:

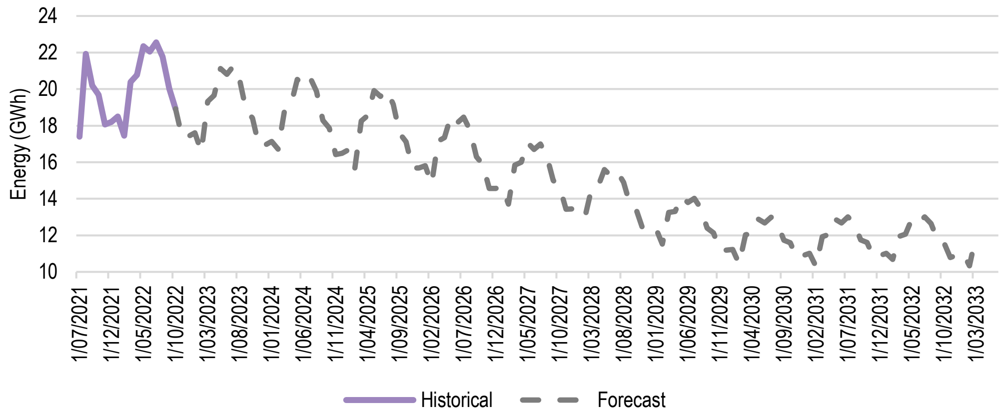
1. 80% of Mercury Vapour Tube luminaires to be replaced by June 2025 (based on 2019/20 FY totals)
2. 100% of all conventional (non-LED) luminaires to be replaced by June 2030

Streetlight devices comprise a significant percentage of unmetered energy consumption which explains the projected decline in all regions.

6.1.1 SEQ

The SAC UMS energy forecasts for South-East Queensland are shown in the figure below.

Figure 6.1 SAC UMS Energy Forecasts

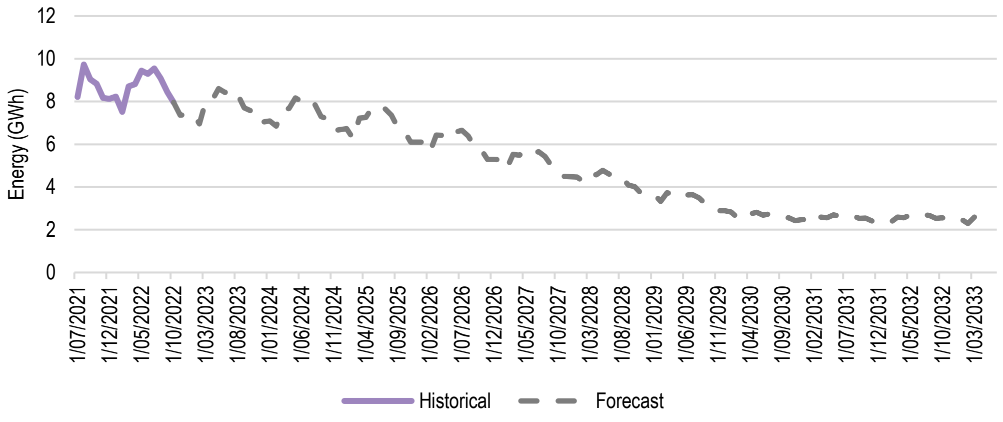


Source: Energy Queensland

6.1.2 East

The SAC UMS energy forecasts for Ergon (East) are shown in the figure below.

Figure 6.2 SAC UMS Energy Forecasts

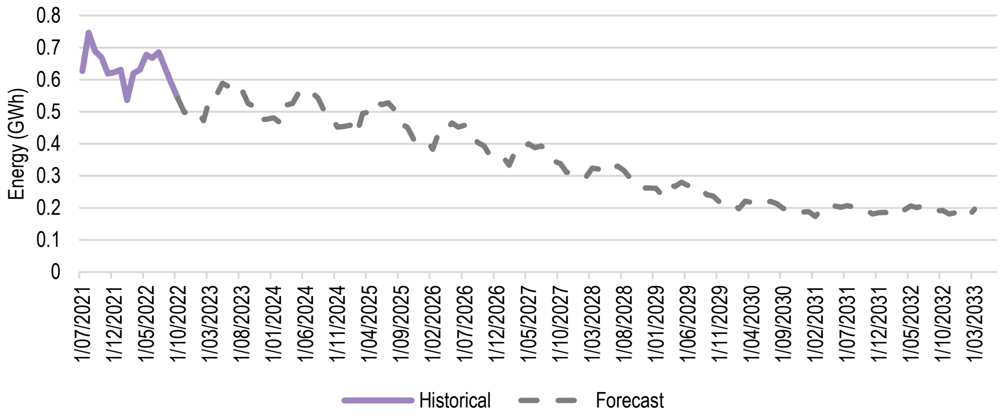


Source: Energy Queensland

6.1.3 West

The SAC UMS energy forecasts for Ergon (West) are shown in the figure below.

Figure 6.3 SAC UMS Energy Forecasts

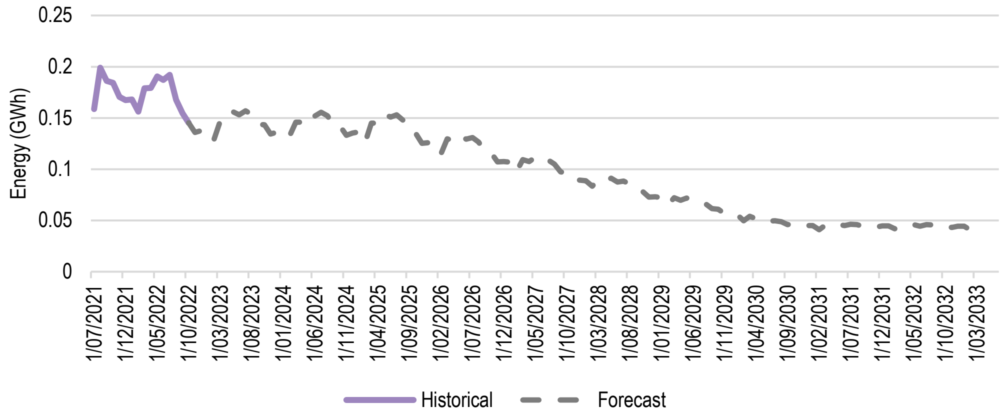


Source: Energy Queensland

6.1.4 Mt Isa

The SAC UMS energy forecasts for Mt Isa are shown in the figure below.

Figure 6.4 SAC UMS Energy Forecasts



Source: Energy Queensland

Review of SAC business tariff forecasts 7

7.1 Assessment of Energy Queensland approach to SAC business tariff forecasts for East, West and Mt Isa zones (Ergon)

The SAC tariff class relates to NMIs connected at LV (<1,000V). SAC BUS refers to all tariffs related to LV connections and customer type of “business”.

Energy Queensland has updated the approach to SAC business forecasts for the East, West and Mt Isa zones to improve the predictive ability of the model and address issues with the previous model. Two econometric models were developed, one to forecast NMI count and another to forecast average purchased energy per business:

1) To forecast the NMI count for each region, time series cross-validation model evaluation was used similar to the approach for regional ICC and CAC forecasts. In the previous model, GSP was included even though a change in GSP may not be reflective of the economic activity in each zone. In addition, the model forecasted the combined total NMI count for all regions and disaggregated to regional level based on the historical NMI count. This could introduce inaccuracy as most regional NMIs are associated with the East zone. If any of the other zones experience a trend opposite to the East zone, the impact is likely to be reduced by it.

2) To forecast purchased energy, linear regression models were implemented in Python code for each region. This has the advantage of increased transparency and repeatability, reduced manual errors and improved speed to produce and update results. The previous process used Excel macros and required significant manual intervention.

7.1.1 Suitability of econometric models

Sample Size

Monthly NMI count data from June 2016 to September 2022 (77 samples) was used as input to the NMI forecast model. Net energy sales data from June 2016 to April 2022 (72 samples) was used as input to the purchased energy model. Because the sample size is greater than 30, there is sufficient data to adequately characterise the underlying data.

The historical NMI count input data was adjusted to remove the impact of the COVID 19 Jobseeker policy and remove a significant number of NMIs reclassified from residential to business between 2016 and mid-2018. The NMI reclassification was due to the introduction of a new enterprise system in Ergon Energy and was no longer present from mid-2018 onwards.

7.1.2 Inclusion of main drivers

NMI count model

Exploratory data analysis to verify NMI Count model

Exploratory data analysis was performed to test whether a linear regression model is suitable to forecast NMI count and can be explained by economic variables such as GSP. It was found to be unsuitable due to lack of predictor variables.

GSP was not found to be a driver of historical NMI count and no other explanatory variables were identified. Time series cross-validation was chosen instead to produce the NMI forecast which we find to be a reasonable approach.

Data cleansing

The historical NMI count data was impacted by events which are irrelevant to the forecast such as Jobkeeper and a reclassification of NMIs due to a new IT system. These were removed from the historical sample data to eliminate the need for additional variables in the model. A key part of building a robust model is to ensure the data is high quality and understand the reasons behind unusual patterns which Energy Queensland have done.

Table 7.1 below shows the results of the time series cross-validation model evaluation.

Table 7.1 Best performing model chosen to produce NMI forecast using time series cross-validation

Region	Best performing model
East	AAdN model (exponential smoothing with additive errors and damped additive trend)
West	AR(3) (autoregression of the order 3)
Mt Isa	Simple Mean

Source:Energy Queensland

Purchased energy model

Energy Queensland included the main drivers of energy usage in their purchased energy model where the estimated coefficients were reliable, statistically significant and of the right sign.

Note that the impact of PV, EV and BESS was removed from purchased energy as these are forecast separately. Purchased energy was normalised to net usage by customer per day (UsgCtDy) by dividing by the NMI count and number of days in month.

The variables considered in the model consist of economic, meteorological and dummy variables to account for government intervention and seasonal variation.

Table 7.2 Variables considered in model

Variable Name	Description	Category
GSP	Gross State Product	Economic
Business Investment	Business Investment	Economic
AvgTemp	Average Air Temperature	Meteorological
ACCHD	Average Cumulative Cooling and Heating Degree days	Meteorological
MaxAppTemp	Average Maximum Apparent Temperature	Meteorological

Variable Name	Description	Category
Ph1Restrict	Phase 1 COVID-19 Business Restrictions[2]	Gov. Intervention
Ph2Restrict	Phase 2 COVID-19 Business Restrictions[3]	Gov. Intervention
Ph3Restrict	Phase 3 COVID-19 Business Restrictions[4]	Gov. Intervention
MthlyBusDays	Monthly Business Days	Calendar

Source:Energy Queensland

Different combinations of the variables were used in the model to test which variables produced the most accurate results. To decide which variables to include in the model for each zone, the Corrected Akaike's Information Criterion (AIC_C) was used to measure model accuracy for each combination.

7.1.3 Approach to model validation

Energy Queensland used the following methods to validate the model, namely assessing:

— the goodness of fit of the regression and predictive accuracy using the AIC measure
— theoretical justification of coefficients
— the statistical significance of the explanatory variables
— consideration of the model residuals for any patterns or signs of autocorrelation

Theoretical justification of coefficients

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

Where variables produced coefficient signs that were contrary to those expected by economic theory, they were discarded from the models. For example, a negative relationship was found between the NMI count and GSP and between purchased energy and GSP, so the GSP variable was discarded from the model.

Goodness of fit test for purchased energy per customer

Table 7.3 presents the model adjusted R^2s for each region's linear regression model. The table shows that each model has a good fit because at least 90% of the variation in purchased energy can be explained by the variables included in the model. As explained above, predictor variables were chosen according to the best AIC score, a measure of predictive accuracy.

Table 7.3 Model R^2 - Purchased energy per customer

Region	R^2	Predictor variables in model
East	93%	AvgTemp, Ph1Restrict, Ph2Restrict, Ph3Restrict, MthlyBusDays

[2] Non-essential business closures with COVID-19 requirements (23/03/2020 – 31/05/2020)

[3] Restricted business closures with COVID-19 requirements (01/06/2020 – 16/11/2020)

[4] Business COVID-19 requirements (17/11/2020 – 16/12/2021)

Region	R^2	Predictor variables in model
West	90%	MaxAppTemp, Ph1Restrict, Ph2Restrict
Mt Isa	94%	GSP, MaxAppTemp, Ph1Restrict, Ph2Restrict

Source:Energy Queensland

7.1.4 Statistical significance and autocorrelation

All variables included in the purchased energy regression models for each region were found to be statistically significant. While there was some mild autocorrelation in the residuals, they are relatively normally distributed and there is no significant change in variance over time which we find to be acceptable.

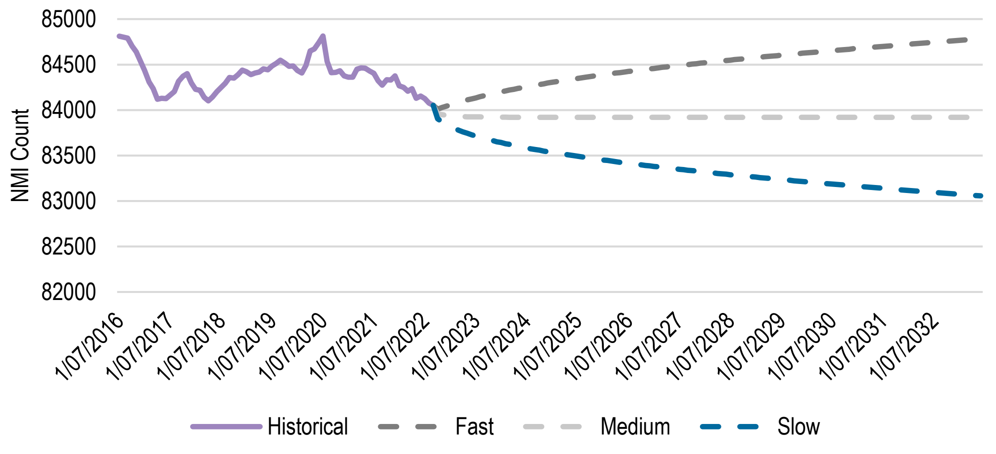
7.1.5 Reasonableness of forecasts

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

Business customer number (NMI count) forecasts

The figures below show that the forecasted customers are expected to remain relatively stable which we find to be reasonable and consistent with historical trends. A very mild decline is forecast in the short term in the East due to a recent decline. Because the model uses additive dampening, the impact of the decline reduces over time to a straight line.

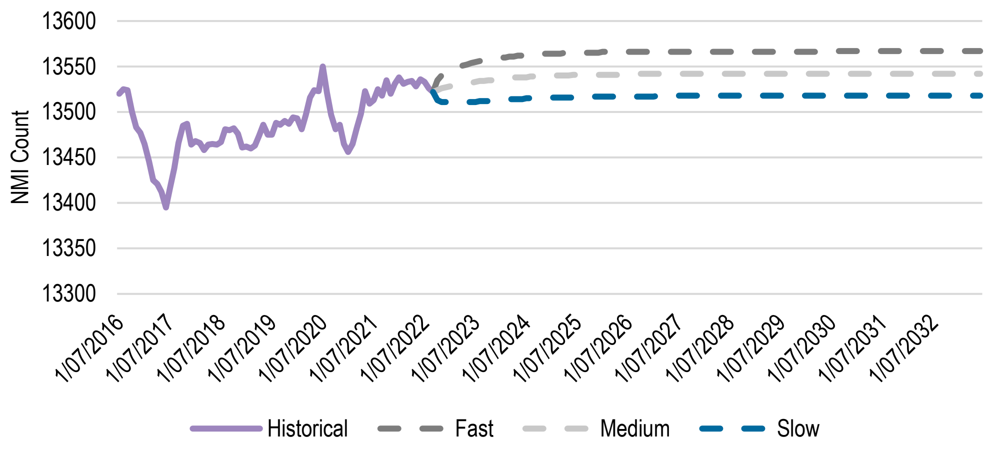
Figure 7.1 East customer numbers, historical and forecast



Source: Energy Queensland

A mild increase is forecast in the West in the medium term which is consistent with the historical growth trend.

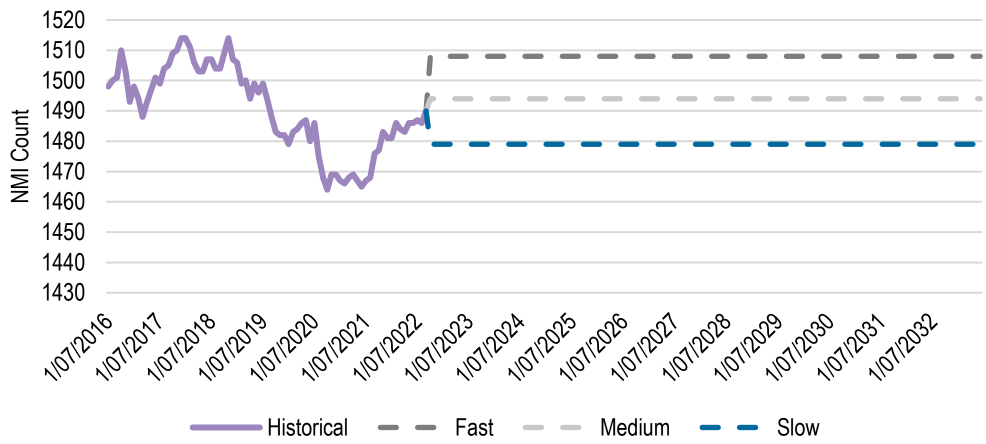
Figure 7.2 West customer numbers, historical and forecast



Source:

In Mt Isa, the mean was used to forecast customer numbers which is reasonable considering the number of customers is small and it is difficult to predict due to high volatility.

Figure 7.3 Mt Isa customer numbers, historical and forecast



Source:

Purchased energy forecasts

Table 7.4 shows that the energy forecasts for the next 10 years have very low average growth rates per annum which are close to zero. This is consistent with very low historical growth over the last four years within the network. In this sense, we consider that the energy forecasts produced by Energy Queensland are reasonable and consistent with the historical behaviour of the network

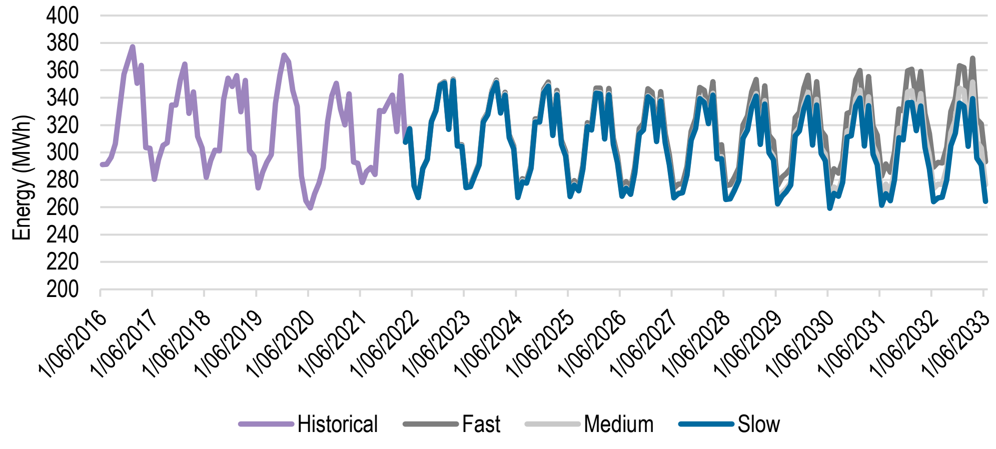
Table 7.4 Historical vs. Forecast Growth Rates

Period	East	West	Mt Isa
2017-2021	-0.72%	-0.49%	-2.32%
2023-2031	-0.09%	-0.34%	0.18%

Source:

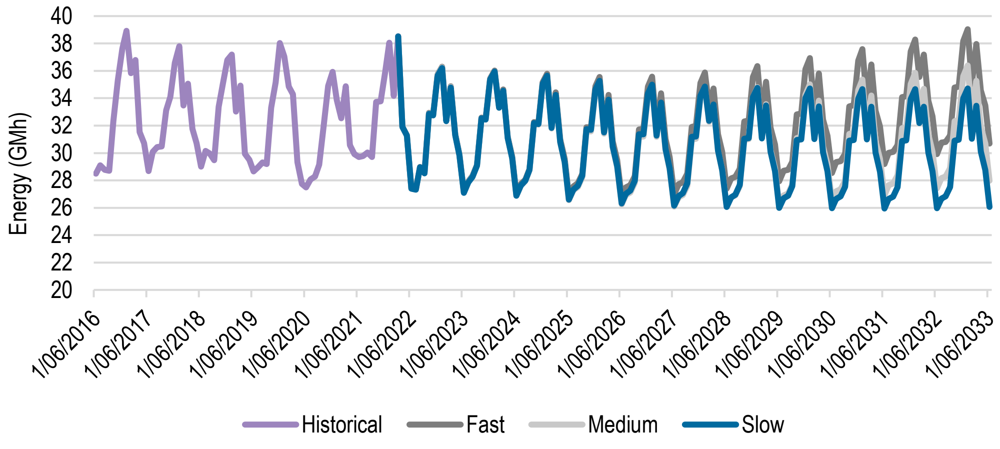
The figures below show the purchased energy forecasts for comparison against the historical data. All scenarios are within reasonable bounds as they do not exceed historical values.

Figure 7.4 East purchased energy, historical and forecast



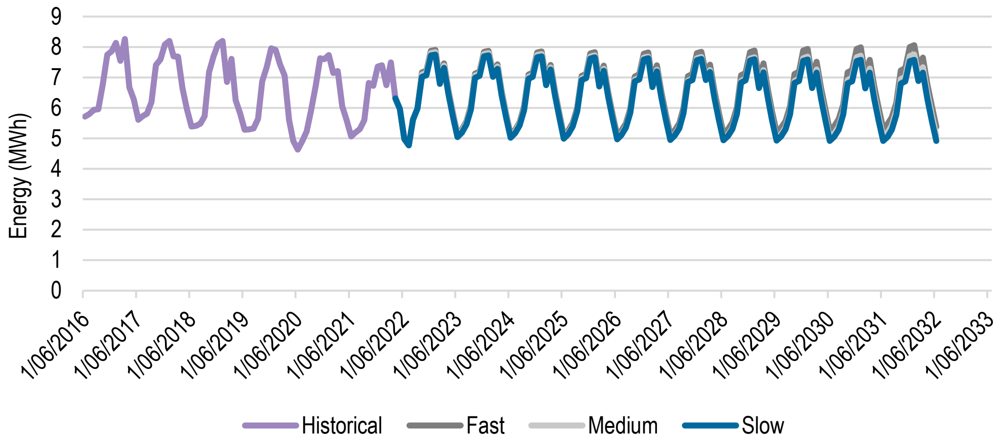
Source: Energy Queensland

Figure 7.5 West purchased energy, historical and forecast



Source: Energy Queensland

Figure 7.6 Mt Isa purchased energy, historical and forecast



Source: Energy Queensland

7.2 Review of South East Queensland (Energex) SAC business tariff forecasts

7.2.1 Approach to SE Queensland SAC business tariff energy forecasting

Energy Queensland use an econometric approach to estimate SAC business tariff forecasts for the Energex region. The approach taken is similar to that used in the residential forecasting.

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

Just like the residential forecasts, a base case model is first estimated which excludes the impact of emerging technologies such as electric vehicles, battery storage systems and solar PV. These are estimated separately and then added to the forecast as a post model adjustment.

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

The process commences with data collection. This includes social and economic factors, weather factors as well as additional variables for external shocks such as COVID 19 and cyclical patterns.

Tests of statistical significance are used to choose explanatory variables which are statistically significant. Diagnostic tests such as tests of serial correlation in the model residuals, tests for heteroscedasticity and tests for multicollinearity are also conducted.

Average per capita consumption regressions were estimated covering the historical periods from March 2008 to June 2022. The main variables included in the Energex business customer model were:

— Average of the daily average temperature
— Accumulated cooling and heating degree days for summer
— Accumulated cooling and heating degree days for winter
— Accumulated cooling and heating degree days for the rest of the year
— Log of the total electricity price
— Gross State Product per customer

— Calendar variables capturing the impact of public holidays and weekends over the Christmas, Easter and rest of the year
— Dummy variable capturing the impact of COVID19
— An autoregressive term to remove any autocorrelation from the model residuals

Table 7.5 presents the estimated coefficients from the Energex SAC business tariff model.

Table 7.5 Model of Energex SAC business energy sales

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	138.758	18.140	7.649	0.000
Average of daily average temperature	2.953	0.179	16.533	0.000
Accumulated CDD and HDD summer	0.184	0.021	8.641	0.000
Accumulated CDD and HDD winter	0.264	0.020	13.196	0.000
Accumulated CDD and HDD rest of year	0.172	0.024	7.120	0.000
Log of total electricity price	-22.066	5.257	-4.197	0.000
Gross State Product per customer	0.010	0.002	5.383	0.000
Weekend/Christmas	-58.611	4.663	-12.568	0.000
Weekend/Easter	-46.576	4.641	-10.035	0.000
Weekend/Rest of year	-39.206	5.220	-7.510	0.000
COVID 19 dummy	-13.797	1.997	-6.910	0.000
AR(1) term	0.7935	0.0500	15.8853	0.0000

Source: Energy Queensland

The final model had an estimated R^2 of 97.4% and all selected variables were statistically significant at the 1% and 5% significance level.

7.2.2 Inclusion of key drivers

Energy Queensland’s approach to business energy sales forecasting for the Energex region includes all the important drivers of energy sales. Economic growth is captured by the Gross State Product variable. Several different weather variables capture weather variations and their impact on business energy sales. The impact of public holidays and weekends and COVID 19 are captured through the application of dummy or indicator variables in the model.

7.2.3 Approach to model validation

The approach taken to model validation for the Energex region SAC business tariff is detailed and comprehensive and closely follows the approach taken for the residential forecasts.

Models are selected using a general to specific approach and statistically insignificant variables are sequentially removed from the preferred model. Just as in the residential models, estimated models for the SAC business tariff in the Energex region are subjected to tests for:

— Serial correlation
— Heteroscedasticity

- Structural breaks
- Multicollinearity

Moreover, the accuracy of the models is assessed by comparing the out of sample model forecasts with observed historical data.

7.2.4 Assessment of key inputs

The main economic and weather inputs used in the SAC business tariff forecasts are the similar to those used in the residential forecasts and are assessed in section 3.1.3. Refer to section 3.1.3 for more details.

7.2.5 Reasonableness of forecasts

In this section we compare the business energy forecasts against historical SAC business energy sales to assess the reasonableness of the forecasts. Any significant deviations from historical behaviour should be easily identified and explained.

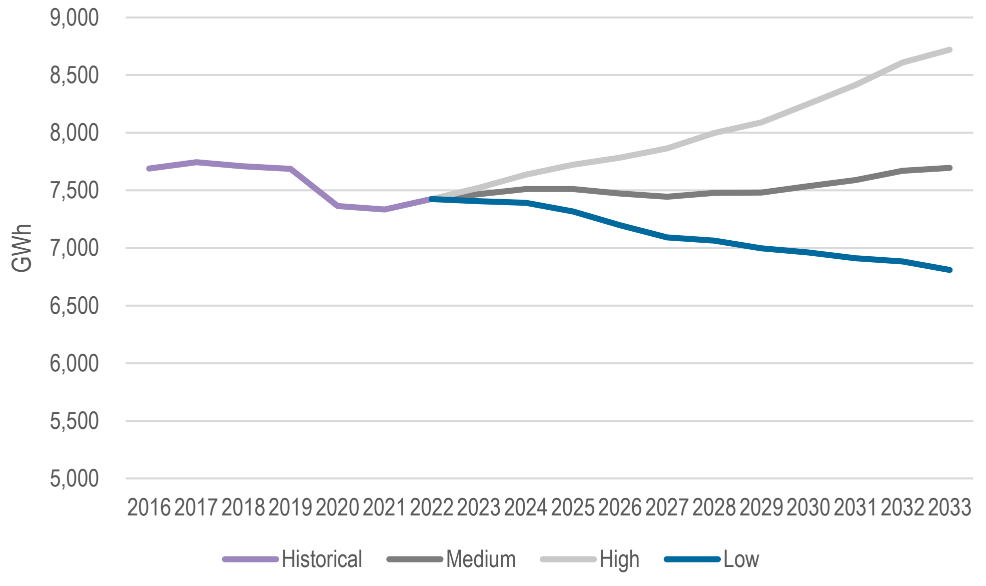
Figure 7.7 shows SAC business energy sales under the low, medium and high scenarios for the Energex region.

Under the medium case, SAC Business energy sales in the Energex network is projected to grow at a rate of 0.3% per annum over the period from 2022 to 2033.

Under the high case, SAC Business energy sales in the Energex network is projected to grow at a rate of 1.5% per annum over the period from 2022 to 2033, while under the low scenario energy sales are projected to fall by 0.8% per annum.

Just as in the residential forecasts, the bands between the low and high expand significantly over the forecast period reflecting the rapidly increasing uncertainty over time. This is reasonable and to be expected.

Figure 7.7 SAC Business energy sales, Energex region, Forecast and Historical



Source: Energy Queensland

Growth is more subdued over the first half of the forecast horizon, but then starts to move higher after 2030 as the uptake of electric vehicles accelerates after 2029.

In our view, the Energex region SAC Business forecasts are reasonable.

7.2.6 Transparency and repeatability

Energy Queensland's document, 'Energy Forecast: Part 3, 2022-23 -2031-32', dated October 2022, describes the approach to forecasting SAC Business energy sales within the Energex and Ergon regions. The document is of a very high standard and describes the models estimated as well as the process involved in reaching the best model in some detail.

The document describes the process of data collection, model estimation and diagnostic checking and model validation very well. It is our view that the document is fit for purpose and adequately describes the forecasting methodology.

In the October 2022 version of the document, the Energex region documentation is presented in an appendix, while only the Ergon region methodology is contained in the main body of the document. This makes the Energex methodology for the SAC Business tariff forecasts appears to be secondary and of less importance than the Ergon region methodology. ACIL Allen therefore recommends that a short section be created in the main body of the document to outline the Energex SAC Business methodology and results. The technical details relating to data analysis and model selection should remain in the appendix.

Recommendations and conclusions 8

It is our view that the forecasting methodology and associated forecasts implemented by Energy Queensland across all its tariff classes and for both the Energex and Ergon region are of a suitably high standard and fit for purpose.

The methodologies applied and forecasts generated are produced in accordance with the best practice principles outlined in section 2 of this report.

Specifically, the forecasting models are transparent and very well documented. They are repeatable based on the information that has been provided within the documentation and associated Excel spreadsheets and Python code.

We recommend a minor change to the 'Energy Forecast: Part 3, 2022-23 -2031-32' document which outlines the SAC Business methodology for both the Energex and Ergon regions. We recommend that a short section be created in the main body of the document to outline the Energex SAC Business methodology and results. Currently they are presented in the appendix of the document.

Where applicable and reasonable, the estimated models contain all the key drivers of energy sales such as economic and weather drivers. The estimated models are validated using well known and accepted statistical methods of model selection, statistical diagnostic checking and out of sample analysis of forecasting errors. In doing so the methodology minimises bias and maximises the accuracy of the forecasts.