APPENDIX J

Assessment of Load Forecast Methodology and Results

January 2012

Powerlink Queensland 2013–2017 Revised Revenue Proposal

Assessment of load forecast methodology and results

Assessment of load forecast aspects of AER's Draft Decision on the Powerlink transmission determination 2012/13 to 2016/17

Prepared for Powerlink

January 2012

ACIL Tasman

Economics Policy Strategy

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Contents

List of boxes

List of figures

List of tables

1 Summary of findings

The main finding from the ACIL Tasman analysis is that the approach used by Powerlink to produce its load forecast largely follows best practice and provides a realistic expectation of future demand. The reasons cited by the AER for rejection of the forecast are unreasonable being based on flawed analysis by EMCa.

The load forecast prepared by EMCa, and used by the AER as an alternative forecast to that presented by Powerlink, suffers from serious misspecification and produces a demand forecast which is strongly biased downwards for a number of reasons.

ACIL Tasman is firmly of the view that the reasons provided by the AER in its Draft Decision for rejecting the Powerlink forecast are not correct. Furthermore, ACIL Tasman believes that it is unreasonable for the AER to have accepted the EMCa demand forecast as a replacement as it is seriously flawed.

Given the flaws we have identified with EMCa's approach, we consider that Powerlink's approach is significantly more reasonable than the AER's alternative.

1.1 Powerlink's forecasting approach

Powerlink relies on inputs from three key largely independent sources namely NIEIR, DNSPs and major customers. However, Powerlink applies its own weather correction and a variety of cross checks to verify the veracity of the forecasts.

It is important that forecasts are capable of being tested and the AER has raised some concerns as to the transparency of the NIEIR model. It is not unusual for there to be elements of a forecasting models that are proprietary – as there is significant commercial value in these models. In our view, the central elements of the NIEIR model are capable of being tested and our testing of the NIEIR model indicates that the outputs of the NIEIR modelling process and the Powerlink forecasting methodology constitute a realistic expectation of the demand forecast over the relevant regulatory period. In fact we were able to show that the NIEIR economic growth forecasts over the past five years have, if anything, tended to underestimate the final outcome.

Other aspects of the Powerlink approach including weather correction coincidence analysis and use of trim factors would seem to be sound and certainly not reason to claim, as has the AER, that the forecast is not a realistic expectation of the future.

1.2 AER Draft decision

The AER rejected the Powerlink load forecast on the grounds that it was not a realistic expectation of demand for the next five year regulatory period. In rejecting the forecast the AER claimed that it contained a systematic upward bias. The AER's main reasons for rejection were:

- use of the "S" curve in weather correction is not appropriate as it produces upward bias in the resulting demand forecast
- relating maximum demand to average temperature is not appropriate and suggested that use of daily maximum temperature was more appropriate for temperature correction of demand
- population as estimated by NIEIR is considerably higher than other forecasts giving the load forecast more upward bias
- electricity prices assumed in the Powerlink modelling are lower than other forecasts again providing inappropriate upward bias to the forecast.

The criticisms were taken from the EMCa report commissioned by the AER to evaluate the Powerlink forecast methodology and results. ACIL Tasman has presented persuasive evidence that the EMCa forecasting approach is flawed resulting in serious downward bias in the results leading to incorrect conclusions. In particular EMCa's linear regression model described in their report to the AER, which relates demand to maximum daily temperature, electricity price and population, represents a misspecification of the econometrics involved. (see Chapter 5)

ACIL Tasman examined each of the AER's reasons for rejection of the Powerlink demand forecast and was unable to find any realistic basis for the conclusions. The following discusses each of the AER's reasons in turn.

Our analysis show the S curve specification is noticeably superior to using a simple linear relationship as it reflects the changing temperature sensitivity at higher and lower temperatures in summer. Furthermore rather than provide an upward bias to the demand estimates, as claimed, it in fact results in lower estimates of the 50 and 10POE demand than the linear approach.

ACIL Tasman has examined the differences between using the AER favoured maximum daily temperature and the daily average temperature and found that the average temperature better explained the variations in daily demand for eight out of the past eleven years. On this basis we cannot accept that use of maximum temperature is a superior approach to using average temperature.

ACIL Tasman accepts that the population level from the NIEIR modelling is higher than other forecasts but, as accepted by AER, the growth rate is consistent with the other forecasts. It is quite inappropriate for AER to use the size of the population as part of its reason for rejecting the Powerlink forecast as it plays no role in arriving at the demand forecast. Even the growth in population is a minor consideration as Powerlink forecast relies in GSP growth not population growth.

Electricity price does affect demand to a very limited degree but with the price elasticity of demand assessed as less than half of that applying to energy consumption(see Footnote 11on Page 37). Even so energy consumption price elasticities are generally significantly less than -1.0. The price coefficient from the EMCa model (as estimated by ACIL Tasman as the model was not supplied by AER in time for to be considered in the report due to confidentiality concerns) implies a price elasticity of demand well in excess of -1.0. This occurs, in ACIL Tasman's opinion, because the price variable in the regression is explaining much of the economic influence on demand. This, we believe, emerges because prices have been raising strongly in recent years while economic growth has stalled.

1.3 EMCa consultant report

ACIL Tasman has presented persuasive evidence that the EMCa forecasting approach is flawed resulting in downwardly biased results and incorrect conclusions. In particular EMCa's model which relates demand to maximum daily temperature, electricity price and population represents a fundamental misspecification of the econometrics involved. (see Chapter 5)

Model specification by EMCa does not incorporate a variable to represent economic growth and as a result the price variable has acted as a proxy particularly as the strong price increases of recent years have been accompanied by low economic growth. The implied price elasticities of demand are multiples of those estimated by others (see Section 5.4.1).

More importantly the next five years is characterised by EMCa as having high price increases and when this is combined with the model misspecification results in unrealistically low demand growth particularly given that the next five years are likely to be characterised by reasonably strong economic growth. ACIL Tasman contends that a model which incorporated economic growth as one of the explanatory variables produces a far more realistic forecast for demand growth (see Section 5.7).

Another downward bias in EMCa's model relates to the fact that the linear regression does not incorporate increasing temperature sensitivity due *inter alia* to increased air-conditioned penetration. This means that the forecast of demand is effectively based on the average temperature sensitivity over the past eleven years rather than on an increasing level which has the effect of biasing downwards the demand forecast (see Section 5.5).

The price series for Queensland used by EMCa in its modelling has been based on the gazetted tariff for residential customers which, in ACIL Tasman's view, does not reflect the price changes which would have occurred in the market as a whole (see Section 4.4).

2 Background

2.1 Purpose of report

In November 2011 the Australian Energy Regulator (AER) released its Draft Decision with regard to the Powerlink transmission determination 2012/13 to 2016/17. The Draft Decision rejected the load forecast submitted by Powerlink and accepted a forecast prepared by Energy Market Consulting associates (EMCa) in association with NZIER. As part of its response to the Draft Decision Powerlink has asked ACIL Tasman to independently examine the load forecast aspects of the Draft Decision and provide a report on its findings.

The report examines the Powerlink forecasting approach as well as evaluating the methodology and data used by EMCa in preparing the load forecast adopted by the AER for its Draft Decision. It analyses the EMCa's forecast to determine whether or not it represents a reasonable expectation of demand for Queensland and discusses the AER's rationale in adopting the alternative forecast. It provides an independent assessment of the specification and performance of the various forecasting methodologies.

The analysis in this report has been based on data both in the public domain and provided by Powerlink and the AER. However details of the regression models developed by EMCa including coefficients and test statistics were not made available by AER for detailed evaluation in time to be considered in the report. In undertaking its assessment ACIL Tasman has been guided by best practice as outlined in the following Section 2.3.

2.2 Outline of report contents and conclusions

The report provides an overview of the forecasting methodology used by Powerlink and a discussion of the basis of these forecasts. It examines the reasons why the AER rejected the Powerlink forecast and provides analysis and comment on them. The EMCa forecast approach and results is examined in detailed and a critique of the methodology is provided.

The report finds that:

- the forecast prepared by Powerlink is a realistic expectation of demand over the relevant regulatory period
- the reasons for AER rejecting the Powerlink forecast are either unreasonable or not relevant
- EMCa's forecast methodology is found to be flawed with a downward bias.

2.3 Forecasting best practice

In assessing the reasonableness of the various forecasting approaches ACIL Tasman uses a best practice forecast check list which incorporates:

- consideration of key drivers
- incorporation of policy impacts
- model validation
- documentation
- transparency and repeatability

2.3.1 Key drivers

Any load forecasting methodology should incorporate the key drivers either directly or indirectly. This includes underlying drivers including; demographic, economic, weather and appliance installation and usage.

The behaviour of key drivers in the future may be quite different than that exposed by recent history, particular for a five year medium term forecast. Hence by explicitly incorporating the key drivers in the forecasting methodology, rather than using simple linear trends based on history, the forecast can more accurately reflect the likely medium term key driver behaviour. Where the forecasts of the underlying drivers are expected to follow a similar pattern to that observed historically, then future energy sales would also be expected to conform to a historical time trend.

2.3.2 Policy impacts

Econometric modelling techniques can be used to establish relationships between electricity usage and the underlying drivers based on historical behaviour. However, in the case of policy initiatives which will be introduced during the forecast period, econometric techniques are not useful as there is no history available. This means that estimates of policy impacts on energy sales need to be calculated separately and then applied as adjustments to the base forecasts.

2.3.3 Model validation

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
- goodness of fit
- in sample forecasting performance of the model against actual data
- diagnostic checking of the model residuals

- out of sample forecast performance

A key aspect of any forecasting methodology is that it should meet minimum accuracy requirements. All models will include approximations by nature of the fact that they are an approximation of the real world and these errors will limit the model's accuracy. In order to assess the model accuracy, its forecasting performance should be assessed using both in-sample and out of sample tests.

An unbiased forecast is one which does not consistently over or under-predict the actual outcomes the methodology is trying to forecast. In and out of sample testing and residual analysis should provide a good indication of any model bias. The results of these tests should be provided to demonstrate lack of bias in the forecasting model.

2.3.4 Documentation, transparency and repeatability

Credible forecasts rely on the forecasting process being transparent, easily understood and well documented.

Documentation should 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 should be clearly described, including:

- variables used in the model
- number of years of data, the reliability of the data and the number of missing data points (if any) used in the estimation process
- estimated coefficients from the model used to derive the forecasts
- details of the forecast assumptions used to generate the forecasts

The process should clearly describe the methods used to validate and select the model. Any judgements applied throughout the process should also be documented and justified. Any further adjustments made to the forecast following application of the forecast methodology should also be documented and justified.

The methodology should be systematic so that a third party can follow a series of prescribed steps to replicate the results.

As a general rule, the documentation should:

- Be clear and concise
- Have clearly defined and outlined processes

- Specify all data requirements and sources

3 Powerlink's forecasting methodology

3.1 Overview

The forecast methodology followed by Powerlink relies to a large degree on inputs from outside sources, namely direct connect customers, DNSPs and NIEIR. However, Powerlink, in addition to its own temperature and coincidence analysis, undertakes checks of reliability and reasonableness on the inputs and forecast results. The overall five stage forecasting process is shown in Box1.

Box 1 **Outline of Powerlink's load forecasting process**

Stage 1 – Bottom-up forecast
Develop a bottom-up state forecast (50% PoE & medium growth) using the demand connection data from Energex, Ergon and the direct connect customers

↓

Stage 2 – Top-down forecast
Review the NIER econometric demand forecast and make adjustments as required based on the latest direct connect customer information

↓

Stage 3 – Align forecasts to Starting value
Reconcile the Bottom-up and the Top-down forecasts to the "starting Value" (temperature corrected 50 PoE peaks from the previous Summer and Winter).

↓

Stage 4 – Reconcile forecasts
Compare and reconcile the Bottom-up and Top-down state forecasts (50 PoE & medium growth scenario)

↓

Stage 5 – Forecast suite
Based on the state forecast developed in stage 4 (50 PoE & medium growth scenario) develop the range of demand forecasts required for network modelling (Low & high growth, 10 & 90 PoE loads and regional peaks)

Figure 1: Demand Forecasting Process

Source: Page 4 of the Powerlink's background paper "Demand and energy forecasting methodology

While Powerlink exercises limited direct control over these external inputs, the fact that NIEIR is used either directly or as a cross check by each of the two

DNSP's and Powerlink should mean that the basic economic and other key assumptions are consistent. Powerlink is satisfied that the DNSP are well placed to contribute to the bottom-up forecast as they are one step closer to the load.

Furthermore, Powerlink reports that trim factors required to align the top-down (NIEIR) and bottom-up (DNSP's) forecasts are small.

3.2 NIEIR econometric load forecast

Powerlink relies on NIEIR to provide forecasts of overall growth in base load. This overall base load growth is applied to the weather corrected demand for the latest year to give the-top down base load forecast.

It is important that forecasts are capable of being tested and the AER has raised some concerns as to the transparency of the NIEIR model. It is not unusual for there to be elements of a forecasting models that are proprietary – as there is significant commercial value in these models. In our view, the central elements of the NIEIR model are capable of being tested and our testing of the NIEIR model indicates that the outputs of the NIEIR modelling process and the Powerlink forecasting methodology constitute a realistic expectation of the demand forecast over the relevant regulatory period

In Appendix A, ACIL Tasman has analysed five years of NIEIR economic forecasts for Australia and Queensland and has demonstrated that, if anything, NIEIR's medium term economic forecasts tend to understate the actual growth.

3.3 Energex and Ergon demand and energy forecast

The DNSP's (ENERGEX and Ergon Energy) provide their forecasts to Powerlink for input to a bottom-up forecast. Powerlink is involved with the DNSPs forecasts and has satisfied itself of the efficacy of the data inputs and approach before relying on these forecasts for its bottom-up approach.

3.4 Powerlink's approach to weather correction

3.4.1 Winter weather correction

For the purposes of temperature correction, the winter period is considered to be the period from mid-May to early September.

Powerlink's approach to weather correcting winter demand entails obtaining a relationship between daily maximum demand and the average of the daily maximum and minimum temperature using linear regression techniques. The regression only includes working days, excluding weekends and holidays. The slope obtained from this regression is the temperature sensitivity and is measured in MW per degree. For the winter period the temperature sensitivity is negative, in that, lower temperatures are associated with higher demands. This occurs because space and water heating loads in winter increase as temperature decreases.

The negative slope of the linear regression line is then used to correct the actual peak demand observed to the 10/50/90 POE demands which corresponds to the 10/50/90 POE average temperatures calculated from a long run temperature series.

The temperature coefficient obtained from each regression, known as the temperature sensitivity is then used to correct the actual peak demand to a long run 10/50/90 POE average temperatures obtained from a long history of weather data.

The formula applied to temperature correct the actual maximum demand is:

Corrected maximum demand = Actual Maximum demand-(Average temp on day of MD -10/50/90 POE average temp)*Temperature sensitivity.

The approach works by shifting the actual MD at the same slope as the regression line to establish the MD that corresponds to 50/10/90 POE average temperatures.

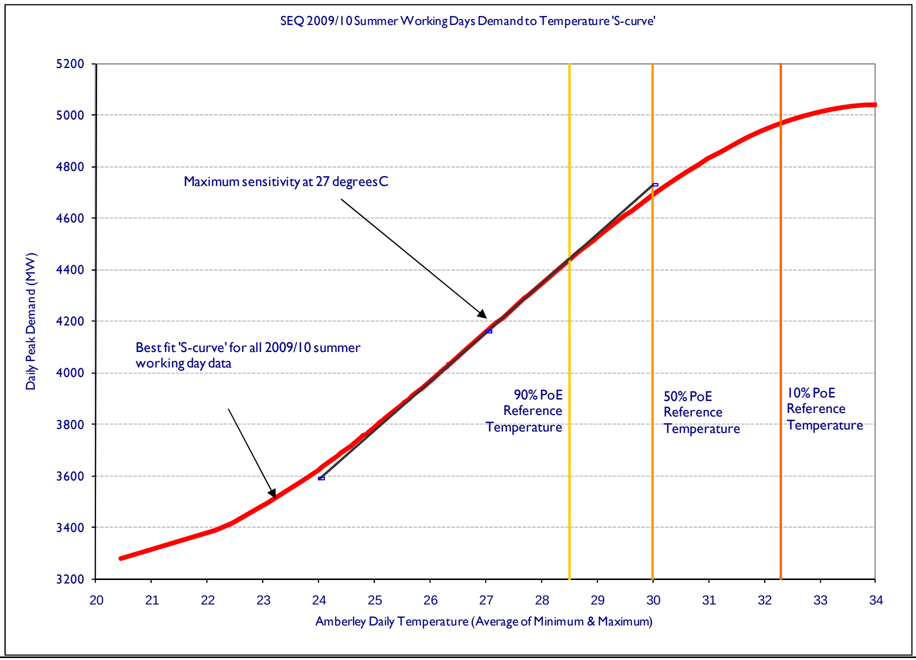
3.4.2 Summer weather correction

Summer is considered to be the period from mid November to mid March. Apart from the South East region, a similar temperature correction methodology is applied for the summer period to that applied in winter.

For the purposes of summer temperature correction for the South East region, Powerlink apply an S curve relationship between daily maximum demand and daily average temperature. The rationale for the S curve is clear. At cooler summer temperatures demand is relatively unresponsive to temperature. As temperature increases, demand becomes more responsive before becoming unresponsive again at extremely high temperatures. In the Powerlink specification, the point of maximum sensitivity is reached at an average temperature of 27 degrees Celsius, before declining gradually. At temperatures above the 10% POE reference point, demand becomes quite unresponsive to further increases in temperature. This corresponds to the point of saturation where all available cooling equipment is running and little or no further demand response is possible.

The characteristic S curve is shown in Figure 1 below.

Figure 1 **S curve relationship between daily MD and average daily temperature**



Data source: Powerlink

The estimation procedure uses working days only as in the case of winter. However, in addition to removing weekends, the holiday period from Christmas to the first week of January is excluded. As in the case of the winter temperature correction procedure, weekends and holiday periods are unlikely to produce peak demand days. ACIL Tasman considers this approach to be reasonable.

Unlike the linear temperature correction regression which is estimated separately on a season by season basis, the S curve uses all available data from the last 12 years which is normalised, presumably for the fact that maximum demand is growing over time. The rationale for using multiple years is that there are sometimes very few observations across the entire S curve in any given season to estimate temperature sensitivity effectively.

ACIL Tasman believes the S curve methodology is a reasonable approach to temperature correction of the South East region of Queensland, and is better able to capture the saturation that occurs at temperatures exceeding the 10% POE reference point. In fact, the use of a linear function can lead to upward biases in temperature correction. To illustrate the point, if a linear method was used to temperature correct an extreme weather day occurring at an average temperature exceeding the true 10% POE level, then the estimated 10% POE demand would be understated.

3.5 Conclusions

Powerlink relies on inputs from three key largely independent sources namely NIEIR, DNSPs and major customers in the preparation of its forecasts. Powerlink consults with each of these sources during the preparation of the load forecast.

On the basis that:

- the approach used by NIEIR produces reasonable results for economic growth (see Appendix A)
- the DNSPs are well placed to undertake bottom up forecasts being one step closer to the potential load developments
- Powerlink's approach including weather correction coincidence analysis and use of trim factors would seem to be sound
- there is careful vetting by Powerlink to ensure consistency and to avoid possible double counting of major loads
- only small trim factors are required to align the top-down and bottom-up forecasts

ACIL Tasman concludes that Powerlink's methodology and data input are sound and should produce forecasts which are a realistic expectation of demand over the relevant regulatory period.

4 AER Draft Decision

4.1 Overview

The AER reached the view that Powerlink's proposed demand forecast is not a reasonable expectation of demand for the next regulatory period. Following this, the AER concluded that Powerlink's load driven capex forecast was not based on a realistic expectation of demand and, therefore, did not meet the capex criteria.

Given its view that Powerlink's demand forecast was not a realistic expectation of future demand, the AER concluded that it should be replaced. It replaced Powerlink's forecasts with alternatives prepared by Energy Market Consulting associates (EMCa).

ACIL Tasman's assessment leads it to the view that the Powerlink forecast is reasonable expectation of demand. Furthermore, its analysis demonstrates that the substitute forecast prepared by EMCa is not a reasonable expectation of demand.

Furthermore in arriving at this conclusion in its Draft Decision, however, the AER made no reference to the Queensland DNSP forecasts it had recently approved and did not attempt to assess the possible implications of using a forecast for Powerlink which was significantly lower than that implied by the recently approved DNSP forecasts.

ACIL Tasman is of the view that AER should satisfy itself that the forecasts it has accepted for the most recent DNSP determinations are consistent with the load forecast applied to the Powerlink determination otherwise an inconsistency will be introduced into the regulatory arrangements. For example, accepting a load forecast for Powerlink's which is significantly lower than implied by the approved DNSP load forecasts could lead to a situation where Powerlink lacks the capability to provide the necessary transmission augmentation to support approved distribution development.

There were two broad reasons for the AER's rejection of Powerlink's demand forecasts:

First, the AER considered the temperature correction method to be inappropriate. In particular it considered that the 'S-curve' approach was upwardly biased and that the use of daily average temperatures was less appropriate than daily maximum temperatures.

Second, the AER was concerned with certain inputs into Powerlink's top down forecast (prepared by NIEIR). The AER considered that forecasts of economic indicators were higher than forecasts from other sources. It also considered that the forecast of electricity price and certain unspecified other inputs were lower than forecasts from other sources.

In both cases the AER was concerned that the input forecasts biased the demand forecasts upwards.

In ACIL Tasman's view, neither of these criticisms are sound. We discuss our views regarding them in the following two sections. Section 4.2 relates to temperature correction. Section 4.3 considers the economic indicators and Section 4.4 considers the AER's concerns with the price impacts.

4.2 Temperature correction

The AER expressed a number of concerns concerning Powerlink's approach to weather correction.

First, it is concerned that Powerlink's use of the 'S-Curve' in temperature correction for the south east region introduces an upward bias to the forecasts. This is discussed further in Section 3.4.2.

Second, the AER considers that Powerlink's use of daily average temperature in forecasting maximum demand is inappropriate. This is discussed in more detail in Section 4.2.2.

4.2.1 *S* curve for South East Queensland (SEQ) region

EMCa makes the criticism that Powerlink's use of an S curve for the SEQ summer season will lead to an upward bias due to the non-linear nature of the curve.

EMCa notes the asymmetric nature of the temperature correction and states that the downward adjustment for days in excess of the 50 POE temperature (30 degrees as a daily average) will be made at the 'flatter' part of the curve leading to less of a downward correction than would be the case if the adjustment was made along a linear curve. While this may be true, EMCa does not point out that the reverse is also true. In fact, on days where the average temperature is below 30 degrees (the 50 POE temperature) the upward correction would be smaller using an S-Curve than it would with a linear curve.

In this particular case, the seasonal maximum demand in recent years occurred on days when the temperature was *below* the 50 POE temperature. Therefore, if EMCa's criticism is to be accepted, the adjustments that were actually made introduced a *downward* bias in the demand forecasts compared to what would have happened with a linear curve. To demonstrate this we have temperature corrected the actual summer season peak for the SEQ region for the last 3 years using a linear temperature correction and the Powerlink S curve methodology. The analysis used working days, excluding the Christmas holiday period. Furthermore, in order to preserve a linear relationship between peak demand and average temperature, days where the average of the daily maximum and minimum temperature was below 23.5 degrees where also excluded.

We have compared the corrected demands from the Powerlink's S curve methodology with those from the linear temperature correction in Table 1.

Table 1 **Comparison of S curve temperature correction with linear temperature correction, SEQ**

Year	Actual Peak	Powerlink S curve 50 POE	Linear temp correction 50 POE	Percent difference	Average temp (day of peak)	50 POE temp	Linear Temp sensitivity coefficient
2008/2009	4635	4907	5156	-4.84%	27.35	30	196.75
2009/2010	4740	4914	4925	-0.23%	28.92	30	171.41
2010/2011	4674	4845	4874	-0.60%	29.05	30	211.01

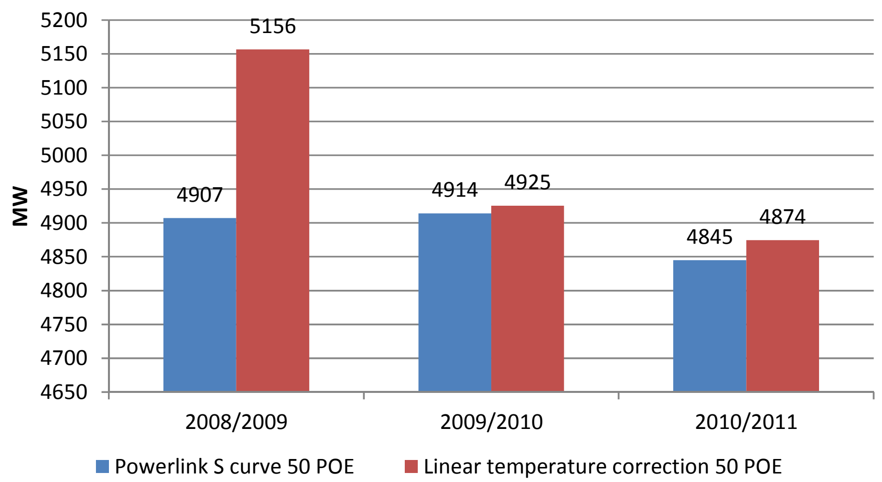
Data source: Powerlink and ACIL Tasman

The results show that the average temperature associated with each of the last 3 summer season peaks for SEQ has been below the 50% POE temperature at Amberley which is 30.0 degrees. In other words, the temperature correction procedure was required to adjust the demand upwards along a flattening curve, which leads to a smaller correction than would occur in the correction was applied linearly. There has been no upward bias in temperature correction over the last 3 years as a result of using the S curve methodology. In fact the linear weather corrected peak demands are higher compared to those of the S curve methodology.

The linear weather corrected 50% POE peak demand for the last 3 years is compared with Powerlink's weather corrected demand in Figure 2. There has been no upward bias over this period because of the S curve. If anything, the S-curve biased the forecasts *downwards* relative to using a linear curve.

ACIL Tasman would also like to note that there are some segments of the S curve that can be approximated very well by a linear approximation. This is evident in 2009-10 and 2010-11 where the S curve corrected demand was biased downwards against the linear temperature correction, but where there was little difference between the two approaches.

Figure 2 **S curve temperature correction versus linear temperature correction, SEQ**



Data source: ACIL Tasman

ACIL Tasman believes that the evidence does not support the claim made by EMCa and accepted by AER that the S curve temperature corrected peak demands will be biased upwards against a linear approach to temperature correction. Indeed, our analysis of the last 3 years suggests that the reverse is the case.

Overall ACIL Tasman considers the S curve approach to be superior to the linear approach as it more closely represents the relationship between temperature and load.

4.2.2 Use of average temperature in weather correction instead of maximum temperature

In its report to the AER, EMCa expresses the concern that the use of daily average temperature as the standard temperature in the adjustment may not reflect the full impact on demand. It suggests that it would be more appropriate to use daily maximum temperature. These assertions also appear to have been accepted by AER.

EMCa claims that the results were mixed, but that the maximum temperature provided a superior fit to average temperature as measured by the regression R^2. ACIL Tasman has not been provided with EMCa's models or specifics regarding the different R^2 values achieved.

ACIL Tasman estimated separate linear regressions for the SEQ region for each summer season from 2000-01 to 2010-11.[1] Separate regressions were estimated relating daily peak demands to daily maximum temperature, daily average ((Max+Min)/2), and both daily maximum and minimum separately. Each regression included a constant.

To reduce bias, the data set was truncated as follows:

- Cool days with average temperatures less than 23.5 degrees were removed for the dataset.
- Weekends and other non-working days were removed from the dataset
- The week before Christmas and 2 weeks after Christmas were removed from the dataset.

Holiday periods and non-working days generally have lower daily peak demands than working days. In order to deal with these, it is necessary either to account for them in any regression model explicitly through the use of dummy variables or remove them from the dataset entirely. We have chosen to do the latter. Failure to account for these days will produce temperature sensitivity coefficients that are biased downwards.

Second, it is necessary to remove cooler days from the regression because these correspond to the part of the curve where peak demand is largely unresponsive to temperature changes. Failure to do so will lead to the slope of the curve not actually representing temperature sensitivity at the higher temperatures.

In theory one should also truncate the other extreme end of the curve as well as this corresponds to times when it is so hot that air conditioner use reaches saturation point and demand becomes unresponsive to temperature changes again. This however is less of a problem because these conditions arise rarely, and may only be observed once in every 10 to 15 years.

The results of the temperature sensitivity regressions are shown in Table 2 below. All of the temperature sensitivity coefficients were statistically significant at the 5% level of significance.

1 For these purposes summer is defined as mid-November to mid-March.

Table 2 **R^2's from linear regressions for each summer season using maximum temp, average temp and both maximum and minimum temperature, SEQ**

Year	Maximum temp	Average temp	Both maximum and Minimum temp
2000/01	0.19	0.28	0.28
2001/02	0.43	0.46	0.49
2002/03	0.36	0.42	0.42
2003/04	0.58	0.74	0.74
2004/05	0.54	0.74	0.84
2005/06	0.74	0.68	0.81
2006/07	0.63	0.64	0.68
2007/08	0.39	0.56	0.55
2008/09	0.73	0.64	0.82
2009/10	0.72	0.69	0.78
2010/11	0.65	0.62	0.69

Data source: ACIL Tasman

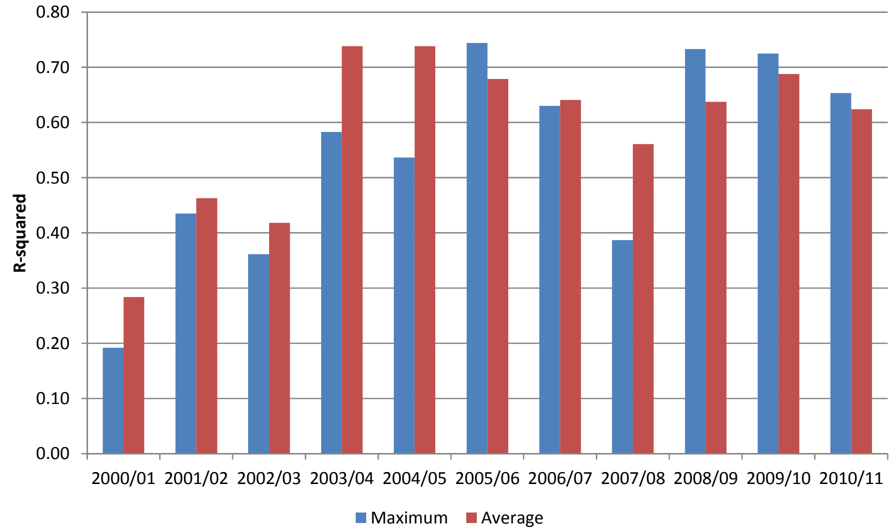
The data show that the results are mixed, but that it is not possible to make the claim that maximum temperature provides a superior fit to average temperature. In fact, in 7 out of 11 years, the R^2 from the temperature sensitivity regression using the average of the daily maximum and minimum was superior to the use of the maximum temperature only.

We note that the maximum temperature provided a superior fit in 2008-09, and was marginally superior in 2009-10 and 2010-11. Interestingly these three years had mild summers in South East Queensland.

The third column in the table shows the R^2 from a regression which included both the daily maximum and daily minimum. The fit from these models was superior to the maximum temperature regressions in every single summer season. This suggests that there is indeed a role for the daily minimum temperature in any temperature correction methodology, and that the use of the daily maximum temperature by itself misses some of the subtle interaction between daily maximum and minimum temperatures in determining the daily peak.

Figure 3 compares the R^2 results from the average temperature versus the maximum temperature regressions.

Figure 3 **Comparison of R^2 by summer season, maximum temperature versus average temperature, South East Queensland**

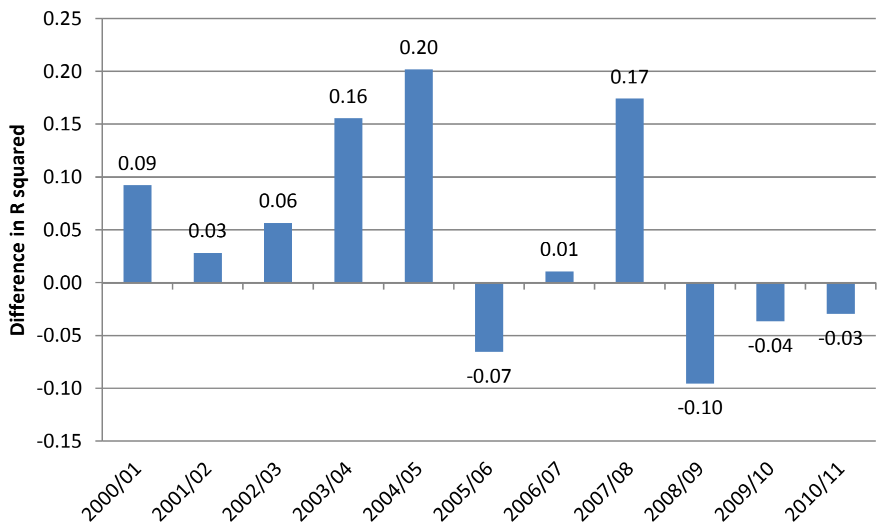


Data source: ACIL Tasman

Figure 4 presents the differences in the R^2's between the average temperature and maximum temperature regressions. The figure shows that the average temperature regressions have performed better in most years of the historical period. Furthermore, they have also outperformed by a considerable margin in these years.

The results do show however, that in the most recent years the relative explanatory power of the maximum temperature has improved and has marginally outperformed the average. We caution however, that this does not necessarily mean that the shift is a permanent one. It could be a result of recent weather conditions, which could shift again.

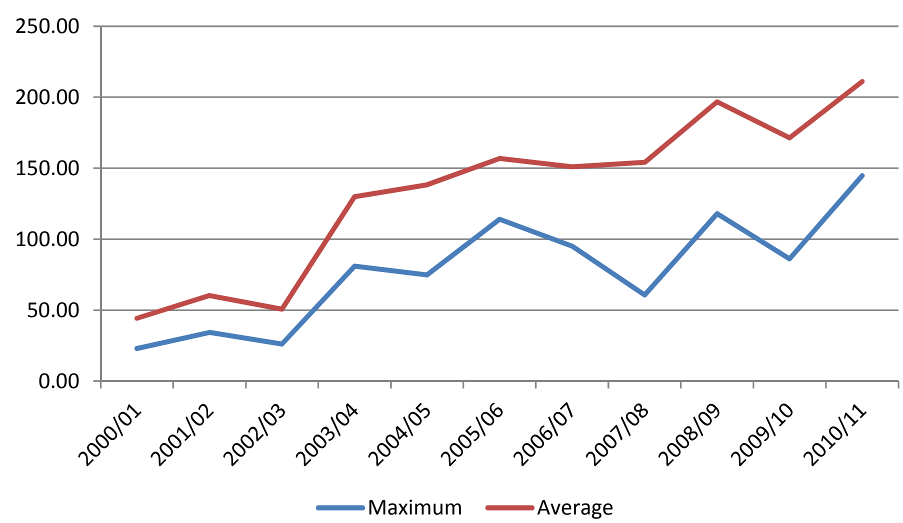
Figure 4 **Differences in R^2 between average temperature regression and maximum temperature regression for South East Queensland**



Data source: ACIL Tasman

The temperature sensitivity coefficients obtained from each of the average temperature and maximum temperature regression are shown in Figure 5 below. Consistent with the decline in Queensland's load factor, these exhibit a rising trend due to an increasing rate of air conditioner and electrical appliance penetration as well as the size of the network increasing.

Figure 5 **Temperature sensitivity coefficients, maximum temperature versus average temperature for South East Queensland (MW per °C)**



Data source: ACIL Tasman

Which variable does better at predicting the weather corrected peak?

The R^2 of the temperature sensitivity regressions measures the overall fit of the model against all working days in the season. Most of these days however, are nowhere near the season peak demand, which drives the need for capital expenditure. It is possible therefore, for a model to have a good general fit across all days in the season, but to have a poor fit when it comes to days that are or are close to the season peak demand. A model like this would be less appropriate for present purposes than one which was more accurate at predicting the season peak, regardless of its performance on other days.

In order to assess this, ACIL Tasman has, calculated the predicted value from each of the models for each actual season peak in the SEQ region given the prevailing weather conditions on these peak days, and compared these values to the actual season peak.

The results are shown in Table 3 and Figure 6. It should be noted that the predicted peak demand values from each temperature sensitivity regression come from the line of best fit estimated by the regression. In reality, the actual peak is driven not only by weather factors but by other random factors as well. The predicted values from the regression line will therefore tend to under predict the actual peak. The solution to this problem is to apply a simulation based methodology which incorporates the regression standard error. We have not done this here, but are presenting the results to illustrate that the average temperature regression model produces predicted values that are closer to the actual peak than those of the maximum temperature regression model.

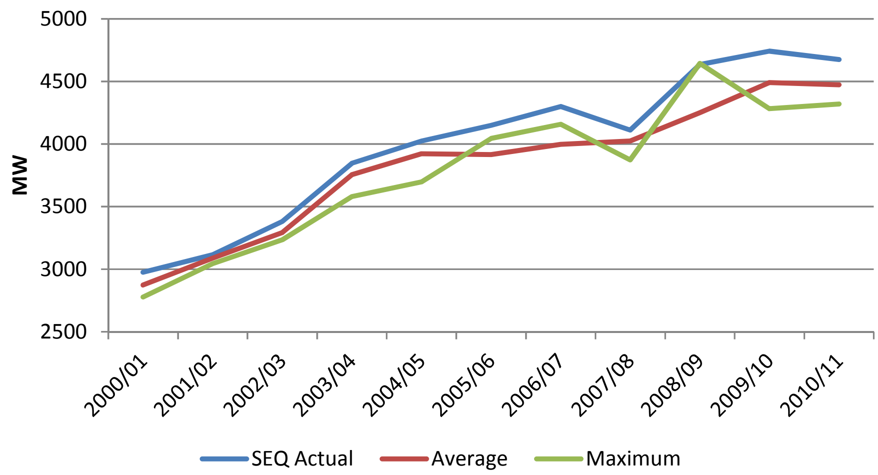
Table 3 **Predicted peak demand values from each temperature sensitivity regression using average and maximum temperatures**

Year	SEQ Actual peak	Average temp model	Maximum temp model
2000/01	2977	2874	2778
2001/02	3115	3090	3045
2002/03	3383	3293	3235
2003/04	3847	3756	3579
2004/05	4024	3923	3698
2005/06	4149	3916	4043
2006/07	4300	3997	4157
2007/08	4112	4025	3874
2008/09	4635	4251	4644
2009/10	4741	4490	4281
2010/11	4674	4473	4320

Data source: Powerlink and ACIL Tasman

The results are shown graphically in Figure 6.

Figure 6 **Model predicted values versus actual SEQ peak**



Data source: ACIL Tasman

The results show that average temperature model has been able to get closer to the actual peak in 8 out of 11 summer seasons. The maximum temperature model was only able to outperform in 2005-06, 2006-07 and 2008-09. It is important to note that while the R^2 of the maximum temperature model is higher in 2009-10 and 2010-11, the average temperature model performed better in terms of explaining the actual SEQ peak in those years. This is highlighted by the percentage errors of each model, which are shown in Table 4.

The reason why the regression results from both methods are almost always lower than the actual peak demand is because the actual peak demand is influenced by other factors apart from just temperature. In particular changing diversity between individual customers, other weather characteristics such as humidity and cloud cover, temperature and other weather characteristics in the period leading up to the peak demand day, time of day and day of the week when the peak occurs, etc. These other factors will almost always see the actual peak demand exceeding the load/temperature regression value and need also to be allowed for in weather correction by applying a simulation based methodology which incorporates the regression standard error.

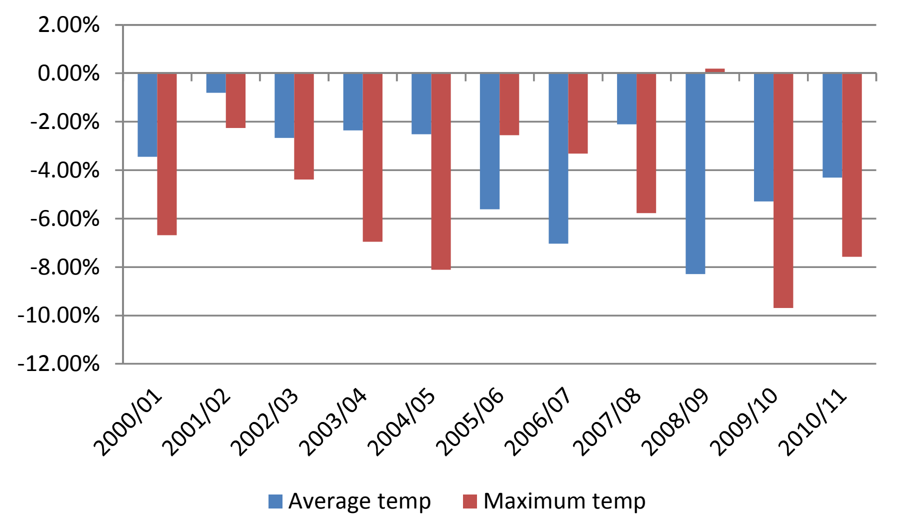
Table 4 **Percentage error of each of alternative temperature sensitivity models, by season**

Year	Average temp	Maximum temp
2000/01	-3.46%	-6.68%
2001/02	-0.81%	-2.25%
2002/03	-2.67%	-4.39%
2003/04	-2.36%	-6.96%
2004/05	-2.52%	-8.11%
2005/06	-5.62%	-2.56%
2006/07	-7.04%	-3.32%
2007/08	-2.10%	-5.78%
2008/09	-8.29%	0.19%
2009/10	-5.29%	-9.70%
2010/11	-4.31%	-7.58%

Data source: ACIL Tasman

The results are shown graphically in Figure 7.

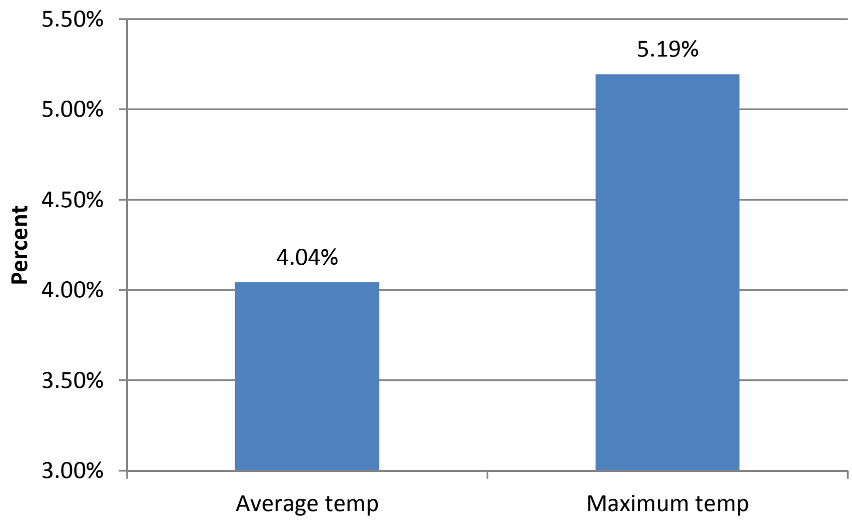
Figure 7 **Percentage error from alternative temperature sensitivity models, by summer season SEQ**



Data source: ACIL Tasman

The mean absolute percentage error (MAPE) of the two approaches is shown in Figure 8. Over the historical period, the average temperature models have had an average absolute error of 4.0% compared to 5.2% for the maximum temperature models. In other words the average percentage errors from the maximum temperature models are 24.8% higher than the average temperature models.

Figure 8 **Mean absolute percentage error (MAPE) of each temperature sensitivity model, 2000-01 to 2010-11**



Data source: ACIL Tasman

ACIL Tasman believes that EMCa have not provided sufficient evidence to demonstrate that the use of the maximum temperature is indeed superior to average temperature in establishing the relationship between maximum demand and temperature.

On the basis of the analysis we present here, we believe that there is considerable evidence that supports the use of the daily average temperature over the daily maximum only, as it does allow the minimum temperature to make a contribution to the daily peak, and has performed better over the historical period.

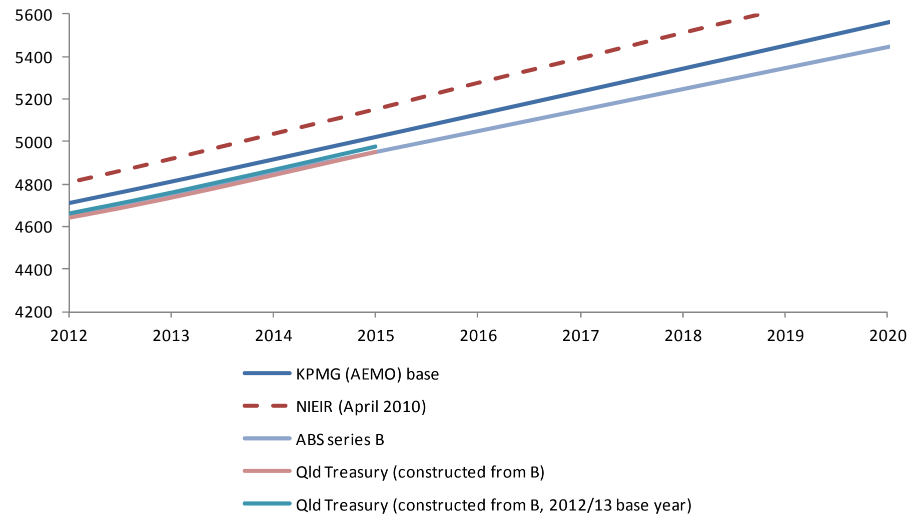
On this basis ACIL Tasman believes that Powerlink's use of average temperature is preferred to the use of maximum temperature alone.

4.3 Inputs to top-down forecast

4.3.1 Population

In its draft determination the AER expressed the view that Powerlink's (NIEIRs) population assumptions were unreasonably high. To support this it produces the following chart (figure 2.5 in Attachment 2 to the AER's draft determination).

Figure 9 **Queensland population forecasts ('000 persons)**



Source: NIEIR, Long Run economic and electricity load forecasts to 2024-25 for the Queensland electricity network, April 2010, p29, KPMG data (prepared for AEMO) obtained from Powerlink, Response to information request EMCa DFR1 of 23 June 2011, received 7 December 2011; Queensland Government State budget 2010-11, Budget Paper 2, p36, Australian Bureau of Statistics, catalogue number 3222.0 *TABLE C3. Population projections, By age and sex, Queensland - Series C*, http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3222.02006%20to%202101?OpenDocument, accessed 7 December 2011

Note: the Queensland Government did not publish population data, only growth rates. The series shown here was constructed from ABS series C. The AER appears to have constructed its Queensland Treasury series by using the ABS forecast until 2012/13 and applying the Queensland Treasury's growth rates from then on. While the impact is small, it is not clear why the AER would not apply Queensland Treasury's growth forecasts consistently for the full period for which they are available.

The AER's primary concern with NIEIR's input assumption is that "while population growth rates appear consistent among the forecasters, NIEIR begins from a noticeably higher base."

In our understanding of NIEIR's approach, this criticism is not pertinent.

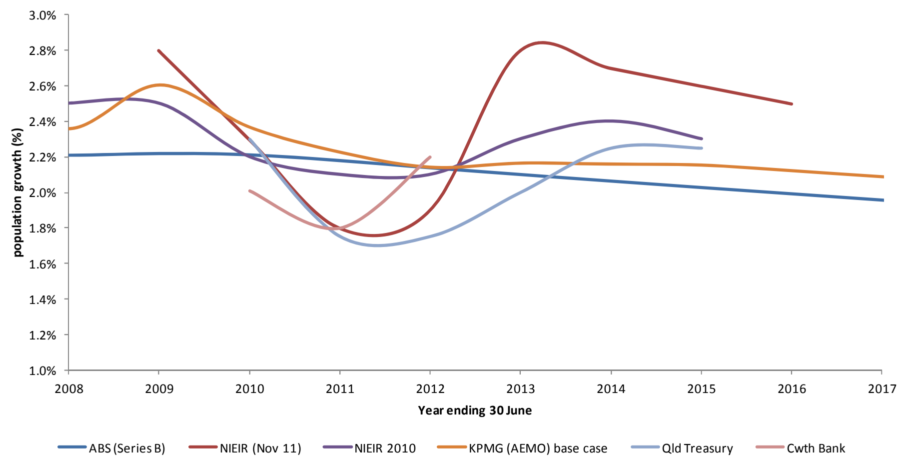
The data plotted in the AER's figure were drawn from a table of outputs in NIEIR's report to Powerlink, not from the inputs to NIEIR's modelling. While we have not discussed the matter directly with NIEIR, in our understanding based on reading of their reports and discussions with Powerlink, NIEIR's modelling relies not on population, but on economic product as measured by Gross State Product. Further, the input to NIEIR's modelling is the *growth rate* of Gross State Product (GSP), not its level.

We note that the AER is satisfied that NIEIR's forecast population growth rate is appropriate. However, this does not form a part of NIEIR's forecast of load.

We understand from NIEIR that the overstated *level* of population is likely to be due to NIEIR's model aggregating population from distribution regions to the State level. There would appear to be some double counting in the way this was done. This has no bearing on the load forecasts themselves.

For completeness, Figure 10 shows the growth rates of the various forecasts shown in the AER's figure and, where available, the high and low case forecasts from the same sources. We have also included population forecasts from the Commonwealth Bank.

Figure 10 **Population forecasts – growth rates**



Source: NIEIR, Long Run economic and electricity load forecasts to 2024-25 for the Queensland electricity network, April 2010, p29, KPMG data (prepared for AEMO) obtained from Powerlink, Response to information request EMCa DFR1 of 23 June 2011, received 7 December 2011; Queensland Government State budget 2010-11, Budget Paper 2, p36, Australian Bureau of Statistics, catalogue number 3222.0 *TABLE C3. Population projections, By age and sex, Queensland - Series C*, http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3222.02006%20to%202101?OpenDocument, accessed 7 December 2011, Commonwealth Bank Global Markets Research, Economics: Update, 17 March 2011

Figure 10 shows that there is a measure of uncertainty regarding the future growth of Queensland's population.[2] It also shows that some forecasters, such as NIEIR and the Queensland Treasury, attempt to forecast the short term cycle in population growth while others such as the ABS and KPMG take a longer term view. Leaving this aside, though, as the AER concluded, the average growth rates are all similar to one another.

NIEIR's modelling methodology does not rely on population as an input. In fact, our understanding is that NIEIR's methodology for forecasting demand does not rely on population at all. Therefore, the AER's view concerning

[2] While the figure doesn't show forecasts for other places, this uncertainty is by no means peculiar to Queensland.

NIEIR's estimate of the *level* of population should have no bearing on its assessment of Powerlink's load growth forecasts.[3]

To the extent that population is relevant to Powerlink's forecasts, which is limited, the important point is that the AER accepts the *growth rates*. Thus, the AER's assessment of NIEIR's population forecasts should not lead to it being concerned about Powerlink's demand forecasts.

4.3.2 Economic product

EMCa does not analyse NIEIR's expectations for growth in economic product in detail, although it makes the general statement that Powerlink's (NIEIR's) assumed macroeconomic inputs are "towards the upper end of accepted forecast ranges."[4]

Given that Powerlink's forecast of load is driven by the forecasts of economic growth by NIEIR, it is important for the AER to consider those forecasts.

In its report, EMCa provides no indication of what it considers to be an accepted range of forecasts of Queensland's economic product. It compares NIEIR's forecasts with those prepared for AEMO by KPMG and notes that NIEIR is more optimistic than KPMG. This is shown in Figure 11, which reproduces EMCa's "Figure 16: Forecasts of GDP (sic) growth rates".

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3 The AER's focus on population may be due to EMCa's view that it is a better choice of input for forecasting demand. As discussed in Section **Error! Reference source not found.Error! Reference source not found.**, we do not share this view.

4 EMCa, op cit, p1

Figure 11 **EMCa Figure 16: Forecasts of GDP (sic) growth rates**

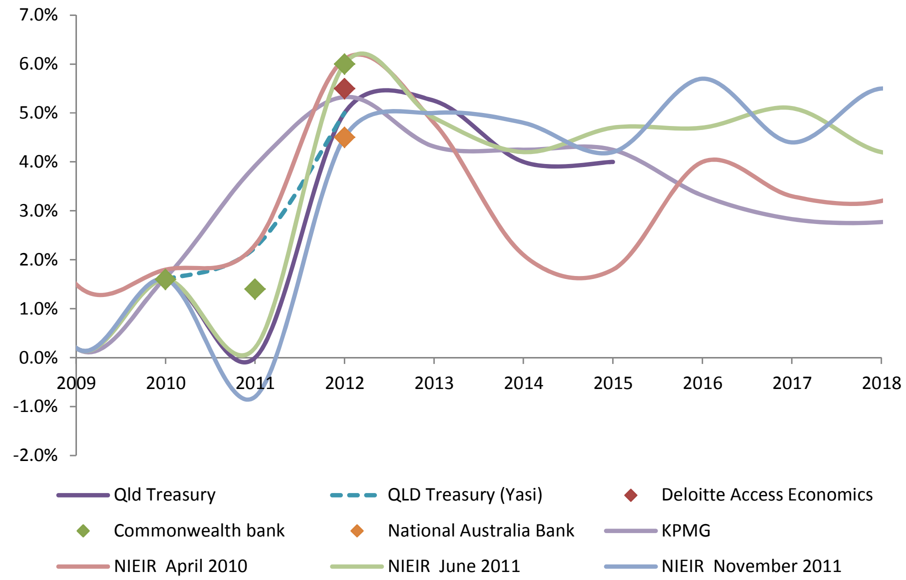
Source: NIEIR, Long run economic and electricity load forecasts to 2029-30 for the Queensland Electricity Network Final report, A report for Network Service Planning Powerlink Queensland, June 2011; KPMG data (prepared for AEMO) obtained from Powerlink,

In Figure 12 we provide a snapshot of various forecasts of economic growth for Queensland. The forecasts are broadly consistent with one another to the extent that they all forecast a single year of very high growth 2011/12 as Queensland recovers from the effects of Cyclone Yasi, the floods of early 2011 and the effect of the global financial turmoil of recent years.[5]

The forecasts differ after 2011/12 in the extent to which they anticipate that growth will remain at high levels or return to lower levels. NIEIR's own forecasts vary in this respect depending on when they were made, reflecting continuing uncertainty surrounding global economic performance. NIEIR's more recent forecasts align more closely with those made by the Queensland Treasury and KPMG (on behalf of AEMO).

[5] At the time of writing, European markets continue to be extremely uncertain, so this last factor may not eventuate.

Figure 12 **Forecasts of GSP growth in Queensland**



Sources: NIEIR, Long run economic and electricity load forecasts to 2024-25, A report for Network Service Planning Powerlink Queensland, April 2010;

NIEIR, Long run economic and electricity load forecasts to 2029-30 for the Queensland Electricity Network Final report, A report for Network Service Planning Powerlink Queensland, June 2011;

NIEIR, Long run economic and electricity load forecasts to 2029-30 for the Queensland Electricity Network Interim report, A report for Network Service Planning Powerlink Queensland, November 2011;

KPMG data (prepared for AEMO) obtained from Powerlink;

Commonwealth Bank Global Markets Research, Economics: Update, 17 March 2011;available at www.commbank.com.au

(Delloitte Access Economics figure) Statement by Deputy Premier, Treasurer and Minister for State Development and Trade Queensland, Hon Andrew Fraser MP, available at http://statements.cabinet.qld.gov.au/MMS/StatementDisplaySingle.aspx?id=77164

National Australia Bank, State Economic Update – 14 October 2011, available at www.nab.com.au

Queensland Government, Budget Paper 2 – Budget Strategy and Outlook, 2011, available at www.budget.qld.gov.au

Powerlink's initial load forecasts were based on NIEIR's April 2010 forecast of GSP growth. As Figure 12 shows, NIEIR's forecast at that time was that growth would be:

- higher than most other expectations in 2011/12 (before the regulatory period begins)
- in the middle when the regulatory period begins in 2012/13
- lower than others until 2015/16
- similar to, although above, KPMG's forecast for the remainder of the regulatory period.

As time has passed and NIEIR's forecasts have been updated to incorporate more information, its growth forecasts have moved towards the centre of the range shown here in the early years of the regulatory period (until 2015). Beyond 2015 the only comparison is KPMG's forecasts, which are for slower growth in Queensland than NIEIR forecasts.

This shows that NIEIRs forecasts of economic growth in Queensland are within the range of other forecasts for the period in which a range has been identified. Beyond that period, they are above KPMG's forecasts.

Other than in 2011/12, which is before the commencement of the regulatory period under consideration, this does not support the conclusion that NIEIR's economic growth forecasts are above the range of forecasts produced by other forecasters. If the AER was to arrive at the view that NIEIR's forecasts are above the range in 2011/12, it should also consider the fact that the same forecasts are at the lower end of the range in later years. While it is not as simple as taking the mean over that time, the forecasts should be considered as a series particularly since the NIEIR forecasts contain a strong business cycle.

4.3.3 NIEIR's historical economic forecast accuracy

In this section we discuss the accuracy and bias of NIEIR's previous forecasts for Australian real GDP and Queensland real GSP. Further details are provided in Appendix A. In this context, forecasting accuracy refers to the magnitude of the errors of NIEIR's forecasts compared to what was actually observed, while bias refers to consistent under- or over-estimates of the forecasts.

Table 5 presents a summary of the accuracy and bias of NIEIR's previous forecasts for the financial year the report was released and for one to four financial years ahead. The forecasts analysed were contained in five years of NIEIR reports up to and including that published in April 2010, the economic forecast that underpin Powerlink's regulatory proposal.

From Table 5 it can be seen that the average error associated with NIEIR's previous forecasts have been higher for the near term, with the largest errors being the forecasts for the current financial year plus one year ahead. Over the medium term (i.e. current financial year plus three and plus four years ahead) the average errors are significantly smaller.

With respect to the bias direction, the Australian forecasts have a tendency to be slight underestimates of the actual growth in the short term but are mixed otherwise. The previous Queensland forecasts however, have consistently exhibited a bias toward underestimating the rate of actual growth.

There does not seem to be much difference between the overall accuracy of the Queensland real GSP forecasts and those for Australian real GDP.[6] Further detail is provided in Appendix A.

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[6] Due to the small sample size, sophisticated statistical tests of the accuracy and relative accuracy of the Australian and Queensland forecasts have not been performed.

Table 5 **Accuracy and bias of NIEIR's historical forecasts of Australia GDP and Queensland GSP compared to history**

	Number of observations	Average deviation (MAE)	Average percentage error (PMAE)	Bias direction
	no.	% points	%	%
Australian real GDP				
Current year accuracy	5	0.4	14.81	–22.3
Current + one year ahead	5	1.4	23.27	–20.6
Current + two years ahead	4	1.2	12.85	26.9
Current + three years ahead	3	0.7	5.50	–50.7
Current + four years ahead	2	0.9	6.10	100.0
Queensland real GSP				
Current year accuracy	5	0.7	16.68	–60.7
Current + one year ahead	4	1.8	19.44	–35.5
Current + two years ahead	3	2.6	17.91	–46.9
Current + three years ahead	2	2.6	13.36	–84.0
Current + four years ahead	1	0.6	2.63	–100.0

Note: NIEIR makes a forecast for the financial year in which the report was released and potentially incorporates one or more quarters of actual data. 'Current year' refers to the forecast for the financial year that the report was released – i.e. 2004-05 for the report released in January 2005, 2005-06 for the report released in December 2005, etc.

MAP - mean absolute error, PMAE - percentage mean absolute error

Data source: ACIL Tasman calculations from previous NIEIR forecasting reports and ABS catalogues 5206 and 5220.

In interpreting the past performance of NIEIR's Australian real GDP forecasts, ACIL Tasman considers the magnitude of the mean absolute error (MAE) for the current financial year plus two, three and four years ahead to be low. For example, the MAE of 1.2 for the current FY plus two years ahead implies that the average forecast real GDP growth over the three years was different by 1.2 percentage points (or approximately 0.4 percentage points per year). The accuracy of the previous short term forecasts seem to be less reliable, and low, on average, but within the range of other forecasters.

Based on this analysis ACIL Tasman contends that the NIEIR forecasts are more likely to underestimate GDP and GSP growth rather than overestimate as claimed by EMCa.

4.4 The impact of price changes

In its draft determination, the AER says that it considers NIEIR's assumptions about future electricity prices to be on the lower end of forecast ranges and that this would bias Powerlink's load forecasts upwards. The AER goes on to say that The Australian Energy Market Commission expects retail prices to increase by 8.1 per cent per year to 2012-13 and that the Queensland Energy Minister expects prices to rise by 10 per cent per year. By contrast, NIEIR's expectations are for more modest price rises.

Regardless of the quantum of price rises that will be experienced in Queensland, neither the AER nor its consultants have given thorough consideration to the mechanism by which price rises would impact maximum demand. In this respect, EMCa appears to treat energy consumption and peak demand as the same thing, or at least to assume that they will respond to price changes in the same way.

In this discussion, as in other parts of its report, EMCa appears to be confusing two distinct concepts. Section 4.4.1 provides a discussion of the difference in these terms and highlights aspects of EMCa's report where it appears that the distinction is not well understood.

Section 4.4.2 goes on to provide a discussion of the impact that price changes can reasonably be expected to have on demand. EMCa criticises Powerlink's demand forecasts for taking insufficient account of recent and future increases in retail prices (headline finding 'f' in the EMCa report to the AER). In Section 4.4.2 we show that *demand* is less responsive to increasing price than *energy consumption*. Given EMCa's apparent confounding of these two concepts, this may explain 'headline finding f'.

Furthermore, it is clearly demonstrated in Section 4.4.2 that price changes have only a minor impact on demand. This section also shows that misspecification of the EMCa model means that it has significantly overstated the relationship between price and demand. In Section 4.4.2 we show that EMCa's model is consistent with elasticity estimates of between approximately -1 and -2. In fact, price elasticity for *energy consumption* has been shown in other studies to be very low (between 0 and -1). It would be even smaller for *demand*.

4.4.1 The difference between energy consumption and demand

EMCa's report appears to use the terms "demand" and "consumption" imprecisely. In our view this indicates that there may be shortcomings in the analysis upon which the AER has based its draft determination.

There is room for confusion between these two concepts because, in economic terms, both can be thought of as demand. However, there are two distinct concepts, and it is critically important that one is not mistaken for the other.

To avoid confusion, we use these terms as follows:

Demand: refers to the quantity of electricity demanded, and supplied, at any given time. Theoretically, demand occurs, and can change, almost instantaneously. In the NEM, demand is usually reported once for each half hour dispatch interval and is the average of instantaneous recordings over the half hour period. Demand is measured in watts (at the network level usually megawatts, or MW).

Energy consumption: refers to the quantity of energy supplied over a longer time. Energy consumption is commonly reported on a monthly, quarterly and annual basis, though any time period is possible. Energy consumption is measured in watt hours (at the network level, usually gigawatt hours, or GWh). Mathematically, energy consumption is equal to the average demand over time.

There are a number of places in which EMCa's report, and therefore the AER's draft determination, confuses the related, but distinct concepts of demand and energy consumption. . For example:

- headline finding 'd' in the EMCa report to the AER is that it has identified structural changes between *demand* and macroeconomic drivers resulting in a declining energy intensity of economic activity in Queensland. This appears to be a reference to paragraph 83 in Section 4.4.2 of the report, where EMCa says that it has identified changes in the relationships between *energy consumption* and macroeconomic drivers over the last ten years. The declining energy intensity of Australian society is well known. However, the relationship between demand and energy consumption is more complex.
- headline finding 'h' in the EMCa report to the AER is that Powerlink has paid insufficient attention to the impact of energy efficiency measures and embedded and distributed generation (p. 2). In our view these interventions are primarily relevant in forecasting energy consumption. Energy efficiency policies typically have little impact on maximum *demand*[7]
- EMCa's discussion of uncertainty (paragraph 72 on p. 16) says that *energy consumption* in Queensland grew steadily from 1960 to the late 1990s and then showed "material year on year variations". EMCa goes on to argue that this is a reason why Powerlink should adopt a range of approaches to forecasting *demand* in order not to be too exposed to the risks. We concur that variability in energy consumption poses forecasting challenges and that is why trends in the load factors require careful analysis to ensure the demand and energy forecasts are consistent.

The apparent confounding of these two concepts is particularly important because this review is solely concerned with Powerlink's demand forecasts. Its energy consumption forecasts are not at issue.

4.4.2 The relationship between price and demand

In economics, the relationship between price and demand is summarised in the price elasticity of demand, often referred to simply as elasticity.

[7] This is the function of demand management policies, although these are not widely used. They are currently under review by the Australian Energy Market Commission.

An elasticity is a measure of the amount that one variable will change in response to a one per cent change in another variable. In the case of price elasticity of demand, it reflects the amount, in percentage terms, by which quantity demanded will increase (decrease) in response to a one per cent decrease (increase) in price.

The price elasticity of demand for different products can vary widely so a price elasticity of demand is not fully defined unless the product being demanded is identified. In this context, it is important to distinguish between *demand* and *energy consumption,* as discussed in the previous section.

Therefore, it is important to distinguish between:

1. the price elasticity of demand for energy
2. the price elasticity of demand for megawatts[8]

The first of these two concepts, the price elasticity of demand for energy, is readily understandable. This is the relationship between the price of energy and the quantity, in watt-hours, of energy demanded over time. Broadly, if price increases, customers might be expected to switch fuels from electricity to gas and, thereby, reduce their consumption. Alternatively, an increase in price might motivate them to improve their energy efficiency and achieve the same outcomes by using less electricity.[9]

The second concept is less widely discussed. It is the relationship between the price of electricity and the quantity that the customer will demand when their demand is at its maximum. This elasticity also deals with reduced consumption in response to increased price, but the reduction must occur at very specific times. Depending on tariff structures, this elasticity might also deal with the possibility that an increase in electricity price might cause a customer to engage in load shifting from times of high price (and demand) to times of lower price (and demand).

These elasticities are not conceptually the same and would take different values.

Our review of the literature in 2010 showed that the majority of studies in this area focus on estimating the price elasticity of demand for energy. Previous studies have typically given little or no consideration to the price elasticity of demand for megawatts.

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8 Given our earlier definition of demand, this would be more accurately named the price elasticity of demand for demand rather than identifying it by the units of measure. However, this is a cumbersome name so we refer to the price elasticity of demand for megawatts.

9 The outcomes in question might range from the level of comfort provided (for a residential customer) to the quantity of aluminium produced (for a commercial customer).

Elasticity estimates for energy consumption were summarised by Fan and Hyndman in 2008.[10] They identified that estimates of the elasticity of demand (for energy consumption) ranges from -0.1 to -0.7 as shown in Table 6.

Table 6 **Price elasticity of energy demand across jurisdictions**

Researcher	Year	Region	Sector	Elasticity
Bohi & Zimmerman	1984	U.S (various utilities)	Residential, industrial and commercial	Residential sector Short-run: -0.2 Long-run: -0.7
Filippini	1999	Swiss (40 cities)	Aggregation	-0.3
Beenstock et al.	1999	Israel	Residential and industrial	Residential -0.21 to -0.58 Industrial -0.002 to -0.44
NIEIR	2007	Australia	Residential, industrial and commercial	Residential: 0.25 industrial: 0.38 commercial: 0.35
King & Shatrawka	1994	England	Residential and industrial	Substitution elasticity Inter-day: 0.1 to 0.2 Intra-day: 0.01 to 0.02
Patrick & Wolak	1997	England and Wales	Industrial and commercial	Water supply industry: -0.142 to -0.27
King	2003	California	Residential	-0.1 to -0.4.
Reiss	2005	California	Residential	-0.39
Faruqui & George	2005	California	Residential, industrial and commercial	Substitution elasticity: 0.09
Taylor et al.	2005	U.K.	Industrial	-0.05 to -0.26

Data source: Price elasticity of electricity demand in South Australia, Shu Fan and Rob Hyndman, Department of Econometrics and Business Statistics working paper 16/10, Monash University, August 2010

The elasticities presented in Table 6 are estimates of the elasticity of demand for *energy consumption*, not the elasticity of demand for megawatts (refer Section 4.4.2). While we are not aware of estimates of the latter, the reasonable expectation is that their absolute value would be lower, not higher, than the

[10] Fan, S and Hyndman, R J "The price elasticity of electricity demand in South Australia and Victoria", 2010. available online, www.buseco.monash.edu.au/ebs/pubs/wpapers/2010/wp16-10.pdf

estimates shown in Table 6. In fact AEMO[11] has estimated that the elasticity of demand for megawatts is less than half the elasticity of demand for energy consumption. Its estimate of elasticity of demand for energy consumption in Queensland is -0.29, which implies that a value of approximately -0.14 or less would be expected for elasticity of demand for megawatts.

As discussed in Section 5.4.1, EMCa's analysis is not consistent with a price elasticity of demand (for megawatts) in this range, implying that its analysis is not valid.

4.4.3 The meaning of price

As discussed in the previous section, ACIL Tasman considers that EMCa and the AER have placed more emphasis on the price of electricity than is warranted for demand forecasts (as distinct from forecasts of electricity consumption).

However, the AER and EMCa appear to have exaggerated the likely effects of 'price' on electricity demand.

In its analysis, EMCa uses a single time series of numbers to represent the price of electricity. It uses this series to analyse variations in electricity demand by all customers in Queensland other than transmission connected customers.

However, in practice, electricity has a large number of prices. Residential and other small customers can choose between various retailers in a competitive market. We understand that, at the time of writing, retailers are offering discounts of up to 12 per cent from the regulated price as gazetted by the Queensland Competition Authority, yet it is this gazetted price that EMCa has used for its analysis.

Another problem with the 'single price' approach is that a large proportion of electricity demand is from large customers. These businesses will typically negotiate prices direct with retailers or may buy on the wholesale market themselves. The price they pay is a commercially sensitive matter, and getting data is difficult. However, it would simplistic to assume that these customers pay the Gazetted price.

11 Taken from the 2010 SA APR (now called SASDO) prepared by AEMO: The price elasticity of annual sales in SA is estimated to be -0.25, with slightly less than half of this elasticity applying to peak demand levels. AEMO reports elasticity in Qld as -0.29, so the target for elasticity for MW is maybe about -0.14 if the relativities between price elasticities of demand and energy are the same in Qld and SA.

4.5 The energy intensity of Queensland's economy

The AER states that Powerlink did not take sufficient account of the declining energy intensity of the Queensland economy in its forecasts. This is another example of the apparent confounding of *energy consumption* and *demand*.

It is true that the energy intensity of Queensland's economy has declined in recent years. To illustrate this, the AER reproduces figures from EMCa showing declines in energy use per unit of GSP (AER figure 2.7) and energy use per capita (AER figure 2.8).

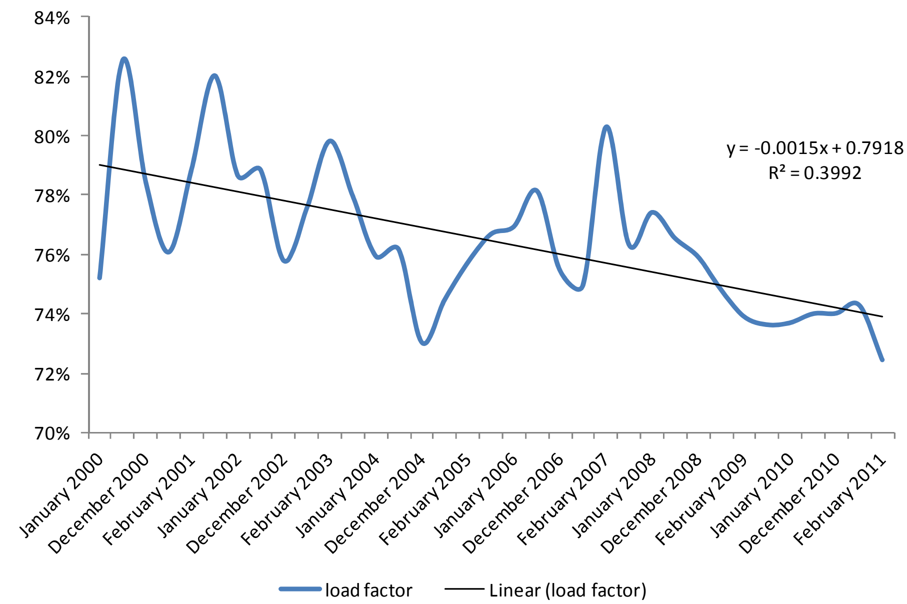
As noted above, while energy consumption and demand are related to one another, there is neither a constant, nor a one-for-one relationship.

The relationship between demand and energy consumption is captured in the load factor, which is the ratio of average to maximum demand.[12] Low load factors indicate that maximum demand is high relative to average demand, so the market is 'peakier' than others with higher load factors.

The load factor in Queensland has been reducing over time, indicating that *demand* and *energy consumption* are growing at different rates. As Figure 13 shows, this has been occurring in Queensland over the last decade, largely due to the increasing penetration of air conditioning.

[12] There is a direct relationship between average demand and energy consumption.

Figure 13 **Queensland load factor 2000 to 2011**



Data source: ACIL Tasman calculations based on AEMO data

The recent decline in Queensland's load factor shows that the decline in *energy consumption* has not been matched by a decline in *demand*. Given the decline in load factor, it is consistent for forecast demand growth to outstrip forecast energy consumption growth.[13]

4.6 Conclusions regarding AER's rejection of Powerlink's forecasts

In conclusion, we consider that the Powerlink forecast methodology is sound and represents a realistic expectation of demand.

AER's reasons for rejecting Powerlink's demand forecasts are flawed because they:

1. are based on a incorrect assessment of the affect of weather on electricity demand
2. are based on dissatisfaction with an input variable (population size) that is not used in the forecasting model
3. overstate the importance of price changes

[13] The declining load factor is also consistent with the conclusion that demand has a lower price elasticity than energy consumption. While both are priced the same, and subject to the same non-price drivers, the growth rates have diverged, therefore demand has been less responsive to changes in those dirvers than energy consumption.

4. assume that demand will respond to drivers in the same way as energy consumption
5. are based dissatisfaction of an input variable (GSP) on the basis that it does not fall into the range of possible forecasts when it in fact it does.

5 EMCa alternative forecast

In light of the fact that it considered Powerlink's forecasts to be an unrealistic expectation of future demand the AER decided to replace them with an alternative set of forecasts. The alternative forecasts were prepared by EMCa.

In this chapter we review the approach EMCa took to constructing those forecasts. We provide an overview of that approach in Section 5.1.

In summary, we consider that EMCa's alternative forecasts are not a realistic expectation of future demand. Nor, in our view, was the method by which they were prepared to be considered superior or to be preferred in any way to Powerlink's method in determining a realistic expectation of the demand forecast over the regulatory period. In particular, we have concerns, which are discussed in the sections that follow, are that:

- EMCa's choice of inputs fail to capture variation in economic activity (Section5.2)
- EMCa's model exaggerates relationship between price and demand because it attributes all of the slowdown in maximum demand in the last few years to rising prices and not reduced economic activity (Section 5.4)
- EMCa's approach to temperature correction disregards the changing temperature sensitivity of electricity demand in Queensland over the last decade (Section 5.5)
- EMCa's model does not perform as well in out of sample backcasting as an alternative based on GSP instead of population (Section 5.6)

For these reasons, we do not regard EMCa's alternative forecasts as a satisfactory alternative to those put forward by Powerlink.

As we show in Section 5.7, if we address only the major flaw we have identified, the omission of GSP from EMCa's model, the forecasts produced by EMCa's methodology are much closer to those produced by NIEIR. While we would not suggest that those forecasts should be taken as alternatives to Powerlink's own, we do take this as evidence that Powerlink's forecasts are reasonable.

5.1 Overview of the EMCa methodology

EMCa produced the alternative forecasts by applying a linear regression approach to forecasts peak demand directly.[14] It explored three methods for doing so.

- Method 1 was to use historical Queensland state level temperature adjusted demand as the dependent variable with a range of demand drivers as independent variables
- Method 2 was similar to Method 1, but used demand data that was unadjusted (for weather) as the dependent variable.
- Method 3 which used a 'naïve' trend analysis applied to Powerlink's temperature adjusted and non-weather adjusted peak demand data.

In each case large mining and industrial loads were added to the forecasts produced using the above methods to produce totals. EMCa and the AER adopted and accepted Powerlink's approach to forecasting large mining and industrial loads as being reasonable. Therefore, the issue is confined to other components of demand.

EMCa's preferred approach was Method 2. Its preferred forecasting model uses population (level), daily maximum temperature and forecast electricity price[15] to forecast demand.

EMCa's model was calibrated using 11 years of historical data, which is all that Powerlink was able to provide. EMCa note that this is a small data set, and that it would be preferable to have more data.

5.2 Model does not capture economic drivers of peak demand

Our first concern with EMCa's model is that it does not capture the economic drivers of peak demand.

Electricity demand is 'driven' by economic and demographic factors in the relevant region. Therefore, a well specified forecasting model should incorporate both of these drivers in its inputs.

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[14] This differs from Powerlink's approach which is to use energy consumption as an input to forecasting demand.

[15] We have assumed that EMCa's price series is a forecast of retail prices. Neither its source, not the method by which it was produced, was specified in the report. However, the levels seem approximately consistent with the Queensland Competition Authority's Benchmark Retail Cost Index approach to setting retail prices. We note that this price applies to only a subset of the customers under consideration here.

EMCa considered two alternative measures of economic activity for its forecasting model, population and GSP. In the final specification, EMCa omitted GSP because "it had little explanatory power in the analysis." It noted that this was probably because "the factors influenced by GSP were covered by other variables, such as population."

It is not clear exactly what EMCa means when it says that GSP had little explanatory power in the analysis. We have taken it to mean that the coefficient on that variable was insignificant.[16]

We are not surprised that GSP was not statistically significant. If it was included together with population in a model specification the high degree of correlation between the two variables would make it more difficult to achieve statistical significance.

The reason for this is that GSP growth is driven by population growth and changes in productivity. In other words, a large part of growth in GSP is driven by rising population itself. This is consistent with EMCa's note.

GSP as an explanatory variable therefore incorporates both the effect of rising population and changing productivity over time. The use of population on its own can only capture part of the story, and will fail to fully capture the impact of changing economic activity over time.

For this reason we believe that GSP is a superior explanatory variable to use in the regression than population when faced with a choice between one or the other.

We do not agree with EMCa's rationale for choosing population over GSP. As far as we are able to see, this choice was made on the basis that, in a model containing both variables, one was statistically significant while the other was not. This is not a valid basis for choosing between these two variables. Rather, the choice should be based on a hypothesis regarding the underlying relationship between electricity demand and its drivers.

A demand forecasting model with explanatory variables that *include* population but *exclude* GSP will fail to capture the effect on demand of changing economic activity unless these two variables are perfectly correlated with one another. In other words, this requires that as population increases (decreases) GSP will increase (decrease) in proportion with it. This has not been true in the past and is unlikely to be so in the future. While changing economic conditions will have some influence population growth, population trends are much more

[16] It may also mean that including it in the model did not improve goodness of fit substantially.

stable than those exhibited by GSP, which also moves due to wide variations in economic output.

It is well known that Queensland's GSP has been substantially lower in recent years than it would have been if not for a series of external events including:

- The global financial crisis and ongoing economic turmoil
- Cyclone *Yasi*
- The floods of early 2011

The effect of these factors is that, in recent years, Queensland's economic growth has been considerably lower than during earlier years, while population growth has continued more or less according to trend. The slowdown in peak demand growth due to declining economic activity is therefore not adequately captured by population. The implication of this is that the failure to account for peak demand changes arising from economic gyrations will lead to biased coefficients on other variables in the model, as the model will mistakenly attribute the impact of declining economic activity to them . This could have the effect of reducing the slope coefficient on the population variable, and make peak demand less responsive to future population growth. Also, if the economic slowdown corresponds to significant price rises as it has, then the model could overstate the effect of price, if a price variable is included in the model specification but GSP is not. This is discussed further in Section 5.4.

Also, by using population as an input instead of GSP, EMCa has assumed that Queensland's economic activity will not change for the duration of the next regulatory control period (i.e. until 2017). While there is considerable uncertainty regarding when Queensland's economy will bounce back from recent difficulties and by how much, the forecasts presented in Figure 12, Page 30 show that forecasters are unanimous that it will bounce back to some extent during the regulatory period. ACIL Tasman is concerned that the EMCa Method 2 will not only lead to biased coefficients arising from model-misspecification , but will also fail to account for an economic recovery after 3 years of being considerably below trend growth.

Comparing the GSP growth forecasts in Figure 12 (p30) with the population growth forecasts in Figure 10 (p27) shows that forecasters are also unanimous that the productivity component of Queensland's GSP growth will improve over the regulatory period, although again they are divided as to the rate.

These figures show that EMCa's Method 2 will seriously understate future growth in peak demand because it assumes that economic conditions will remain unchanged for the duration of the regulatory period.

To account for this, our view is that using GSP instead of population as an explanatory variable is more sound, both from an empirical and theoretical perspective. Even with the empirical observation that in a model containing both population and GSP variables where population is significant but GSP is not, we are of the view that, if either variable is to be omitted, it should be population.

5.3 Biased relationship between population and peak demand

As mentioned in the previous section of this report, the failure of EMCa's Method 2 to capture the economic slowdown experienced in Queensland over the last 3 years will lead to potential biases in the existing coefficients of the model.

Of particular concern is the effect on the relationship between population and peak demand which is a key driver of load growth in EMCa's specification.

By omitting GSP as a variable in the model, EMCa's existing model specification will mistakenly attribute some of the decline in economic activity to the existing variables in the model, the two most important of these being price and population. The expected impact of this misspecification is to overstate the sensitivity of demand to price changes while reducing the sensitivity of peak demand to changing population.

In this section we consider the effect on the relationship between population and peak demand. The relationship between price and peak demand is considered in Section 5.4.

To demonstrate the significance of the effect of the economic slowdown of the last 3 years on the relationship between population and peak demand in EMCa's model specification, ACIL Tasman has estimated the population coefficients measuring the sensitivity of peak demand to changing population for both the full historical sample as well as the period up to the end of 2007-08, before the onset of the economic slowdown. We include the maximum temperature on the day of peak in the model but exclude the price variable, which we believe has serious problems associated with it when used without a variable that captures variations in economic activity (discussed further in Sections 5.2, 5.3 & 5.4).

The results in Table 7 below show a marked increase in the size of the population coefficient when the model is calibrated using only the first 8 years of the sample, thus excluding the impact of the slowdown in the Queensland economy. This illustrates the impact of the reduction in GSP growth on the population coefficient in the model, which is then applied throughout the entire regulatory period and cannot incorporate any subsequent improvement in economic recovery.

Table 7 **Comparison of population coefficients from models with and without the impact of the economic slowdown**

Region	Full sample	Excluding last 3 years	Percent difference
SEQ	0.002315	0.002504	8.16%
SW	0.002844	0.004407	54.96%
CQ	0.002629	0.00378	43.78%
NQ	0.002801	0.004451	58.91%

Data source: ACIL Tasman

Table 8 presents two sets of forecasts derived from each of the regional models of peak demand with population and maximum temperature as the explanatory variables, over the 2 periods, one with the period of reduced GSP growth and one without. The results show that the failure of population to capture the reduction in economic activity will lead to a downward bias in the coefficient and significantly lower forecasts compared to the models where the coefficient on population is not affected by economic conditions. By 2016-17, the DNSP forecasts from the region models using the entire sample are 7.5% below those which exclude the decline in GSP growth from the sample.

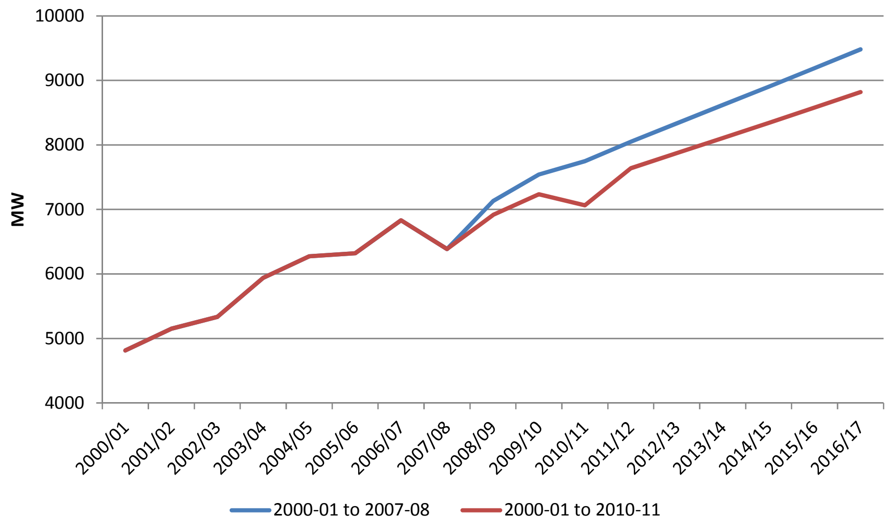
Table 8 **Impact of economic slowdown on DNSP forecasts from a model with population as the key driver**

Year	2000-01 to 2007-08	2000-01 to 2010-11	Percentage difference
2000/01	4813	4813	
2001/02	5152	5152	
2002/03	5333	5333	
2003/04	5937	5937	
2004/05	6274	6274	
2005/06	6319	6319	
2006/07	6829	6829	
2007/08	6386	6386	
2008/09	7128	6915	
2009/10	7541	7234	
2010/11	7748	7063	
Forecast			
2011/12	8049	7638	5.38%
2012/13	8334	7873	5.86%
2013/14	8618	8107	6.31%
2014/15	8904	8342	6.74%
2015/16	9191	8579	7.14%
2016/17	9480	8817	7.52%

Data source: ACIL Tasman

Figure 14 presents the results graphically.

Figure 14 **Impact of economic slowdown on DNSP forecasts from a population driven model**



Data source: ACIL Tasman

5.4 Unreasonable relationship between price and peak demand

Our second concern with EMCa's model is that it suggests a relationship between electricity demand and price that is not consistent with theoretical expectations or other empirical studies.

As part of our review of the AER's draft determination we re-estimated EMCa's model using Method 2.[17] In this model the dependent variable is unadjusted maximum demand. The explanatory variables are price, maximum temperature and population.

The results for the price coefficients for each of the separate Queensland regions are shown below.[18]

[17] It was necessary for us to re-estimate the model because EMCa did not report sufficient detail to enable this analysis.

[18] To account for variation in weather across Queensland both Powerlink and EMCa used the same four regions as described in Section 3.4.

Table 9 **Price coefficients, standard errors and t statistics from Method 2 by region**

Region	Coefficient	Std. Error	t-Statistic	Prob.
SEQ	-42.41226	34.73328	-1.221084	0.2616
SW	-9.345472	4.142103	-2.256214	0.0587
CQ	-20.14785	7.44115	-2.707625	0.0303
NQ	-29.67973	9.259373	-3.205372	0.015

Data source: ACIL Tasman

Using standard hypothesis testing techniques the table above shows that at the 5% significance level only the price variable in the CQ and NQ region equations were statistically significant. At the 1% significance level all 4 regions had price variables that were statistically not significant. This means that there is some uncertainty as to the precision of the price coefficients, particularly for the SEQ region.

Table 10 shows the price coefficients for EMCa's Method 2 but with the price series replaced with the KPMG/AEMO historical price series.

Table 10 **Price coefficients, standard errors and t statistics from Method 2 with KPMG/AEMO price series instead of EMCa prices**

Region model	Coefficient	Std. Error	t-Statistic	Prob.
SEQ	-133.0759	48.63014	-2.736491	0.0291
SW	-8.954881	9.293941	-0.963518	0.3674
CQ	-31.053	18.0616	-1.719283	0.1293
NQ	-4.446964	28.6983	-0.154956	0.8812

Data source: ACIL Tasman

Table 10 shows that the price coefficients using the alternative electricity price series are all insignificant at the 1% significance level, with only the SEQ models price coefficient being found to be statistically significant at the 5% level. This suggests that these coefficients should be treated with caution. However, we recognise that the lack of statistical significance arises because of the small sample size that is used in the model calibration (11 observations). This makes it difficult to obtain statistically significant results. It is possible to argue that a statistically insignificant variable is still economically significant and a necessary inclusion in the model. In itself this is not a significant concern.

Of greater importance is the value of the coefficients themselves. It is important to ensure that the coefficients that any model produces are consistent with both theoretical expectations and other empirical studies. In our view these coefficients are not consistent with either and cannot be relied upon. The reason for this is that the price elasticity of demand implied by these coefficients is outside the range that could reasonably be expected.

This is discussed in more detail in Section 5.4.1.

5.4.1 Price elasticities are outside the range suggested by other empirical studies

The price coefficients in the regression model discussed above (i.e. EMCa's Method 2 model) cannot be interpreted directly other than to note that they have the correct sign, i.e. they are negative, so demand falls when price increases.

To allow the elasticities to be estimated directly, we estimate EMCa's Method 2 model in double log form. When the model is estimated in this form the price coefficient can be interpreted as an estimate of the price elasticity of demand.

Table 11 shows the results.

Table 11 **Price elasticities, standard errors and t statistics from Method 2 in double log form by region**

Region	Elasticity	Std. Error	t-Statistic	Prob.
SEQ	-0.269561	0.182662	-1.475736	0.1835
SW	-0.56566	0.233864	-2.418762	0.0462
CQ	-0.49198	0.179675	-2.738175	0.029
NQ	-0.556153	0.139217	-3.994868	0.0052

Data source:

The magnitude of the coefficients is on the high side of what is expected for Queensland. It should be noted that the SEQ region price elasticity was found to be statistically different from zero at the 5% significance level.

ACIL Tasman is concerned that while these elasticities look to be within the acceptable range for price elasticities of energy (as summarised by Fan and Hyndman and reproduced in Table 6), they are in fact too high to be credible estimates of the price elasticity of peak demand (see discussion at Section 4.4.2).

The impact of these apparently overstated elasticity estimates is that the high price rises expected by EMCa during the regulatory control period will lead to a large reduction in demand.

5.4.2 Why are EMCa's price elasticity estimates unreasonable?

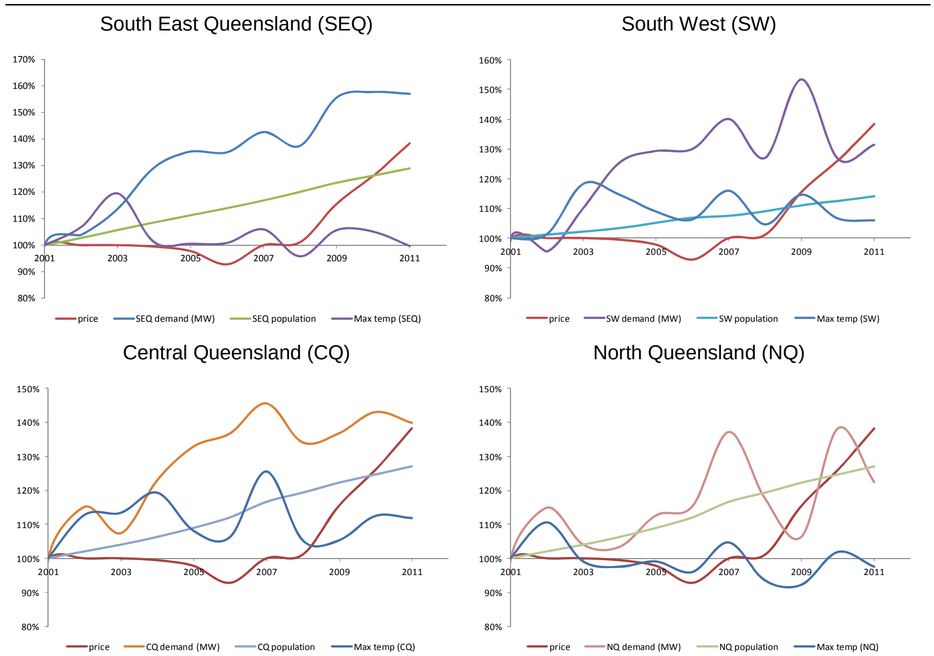
As discussed in Section 5.4.1, EMCa's alternative forecasts imply price elasticity of peak demand estimates that are unreasonable.

We consider that the estimated price coefficients, and therefore the estimates of price elasticity of demand, are likely to be biased by EMCa's decision to use population in place of GSP as the economic input.

It is clear in Powerlink's demand was reduced substantially in 2009-10 and 2010-11 due to reduced economic activity arising from the aftermath of the GFC as well as higher electricity prices (prices increased by in excess of 6% in 2009-10 and 2010-11) and the floods and Cyclone Yasi.

As discussed in Section 5.2, EMCa omitted GSP from its model in favour of population. Figure 15 shows a simple plot of the variables in EMCa's model (expressed as indices with a base year of 2001 to allow them all to be seen on the same scale).

Figure 15 **Electricity demand, population, electricity price and annual maximum temperature in four Queensland regions**



Data source: EMCa data supplied by Powerlink

An inspection of the plots in Figure 15 illustrates that:

- there is a positive relationship between demand and temperature
- population in each of the four regions has grown steadily over the past decade
- electricity price has been more variable than population and grew more rapidly than population in the last three years.

While the demand data in Figure 15 is not weather corrected, because EMCa did not use weather corrected data in its Method 2 model, it also appears that falls in demand coincide with increases in price. This is not surprising.

What is not shown in these plots, and is not accounted for in EMCa's model, is that those reductions in demand also coincide with significant reductions in GSP growth.

Without a GSP variable, EMCa's model appears to have assigned the *entire* reduction in demand to the increase in electricity price. While this is likely to be a factor, we expect that the decline in GSP growth would be of greater importance.

Confirming this expectation, we replaced population with GSP in the regression analysis, and found the influence of the price variable is dampened significantly (see Table 12). This is consistent with the notion that price rises in 2009-10 and 2010-11 are capturing most of the slowdown in peak demand when a lot of the slowdown can be attributed to slowing economic activity which is captured by the inclusion of GSP as an explanatory variable.

All of the price coefficients are statistically insignificant at the 1% and 5% significance levels when population in Method 2 is replaced with GSP as an explanatory variable.

Table 12 **Price coefficients from model with population replaced by GSP**

Region	Coefficient	Std. Error	t-Statistic	Prob.
SEQ	24.67227	31.90287	0.773356	0.4646
SW	-3.621704	3.544341	-1.021827	0.3409
CQ	-8.520458	5.806351	-1.467437	0.1857
NQ	-7.747798	6.916509	-1.120189	0.2996

Data source: ACIL Tasman

Table 13 shows the coefficients as price elasticities derived from the double log version of the same model. The estimated elasticities now range from around 0 for SEQ up to -0.2 for the SW and CQ regions. These values, though all statistically insignificant, are significantly smaller than the in EMCa model specification which included population and excluded GSP. This change arises because the GSP variable is able to capture the impact on peak demand of reduced economic growth, while the EMCa Method 2 specification relies completely on the electricity price.

Table 13 **Price elasticities from model with population replaced by GSP**

Region	Coefficient	Std. Error	t-Statistic	Prob.
SEQ	0.08687	0.163661	0.53079	0.612
SW	-0.204996	0.201567	-1.017012	0.343
CQ	-0.20295	0.136897	-1.482504	0.1818
NQ	-0.126756	0.114205	-1.109903	0.3037

Data source: ACIL Tasman

This, coupled with NZIER's forecast price increases, will further bias the demand forecast downwards.

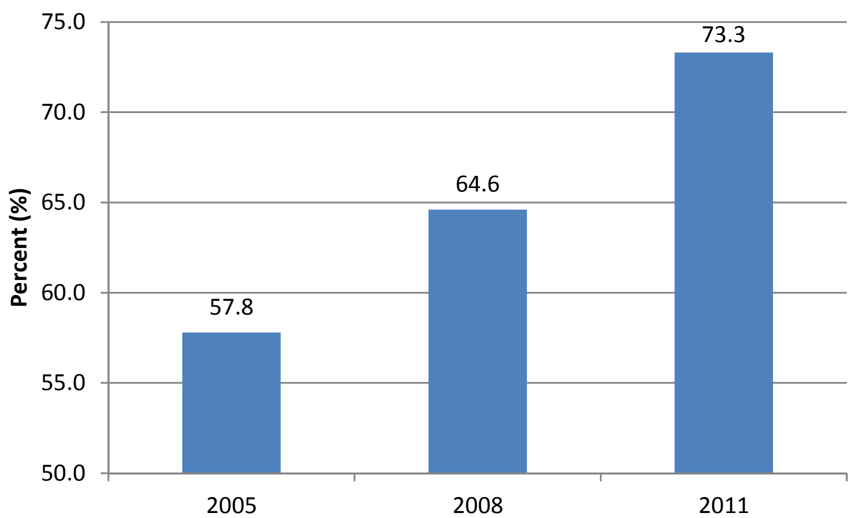
5.5 Maximum temperature coefficient fails to capture increasing temperature sensitivity over time

EMCa's Method 2 model includes maximum temperature on the day of the annual peak in electricity demand in Queensland as a way of controlling for temperature effects because it is based on a series of peak demands that is not weather corrected.

While we agree that weather correction is necessary, we have identified a significant problem with this simplistic approach to doing it. The main issue is that the relationship between weather and demand is taken as the average over the historical period from 2000-01 to 2010-11. By using a linear regression EMCa's methodology forces this relationship to be constant over time.

Far from exhibiting a constant relationship between weather and electricity demand, the period on which EMCa's model is based was characterised by significant structural change. This was driven by increasing penetration rate of air conditioning systems as shown in Figure 16. In addition, the size of the network itself has increased due to rising population. Both these factors suggest that the MW per degree temperature sensitivity of peak demand should be increasing over the historical period.

Figure 16 **Proportion of Queensland households with cooling systems, 2005, 2008 and 2011**



Data source: *ABS, 4602055001DO001_201103 Environmental Issues: Energy Use and Conservation, Mar 2011*

EMCa's decision to assume that the relationship between weather and electricity demand has been constant is likely to understate future demand, even if we assume that air conditioner penetration has saturated and there is no further growth in temperature sensitivity available from this source in the forecast period.

In order to demonstrate the effect of increasing temperature sensitivity over time, we estimated separate daily regressions for each season from 2000-01 to 2010-11 for each working day in each season for the SEQ region. We truncated the data by removing cool days (where average temperature was less than 23.5 degrees Celsius) from the dataset. This is done to remove those observations where demand becomes flat and unresponsive to temperature changes.[19] In this way we largely avoid any bias that would result from the application of linear regression to a non-linear relationship.

These regressions were run using both average daily temperature and maximum temperature as explanatory variables. The results obtained were similar in both cases. Table 14 shows the estimated coefficients for each of the summer seasons from 2000-01 to 2010-11 for both average temperature and maximum temperature. They exhibit a rising trend over time, demonstrating the increase in temperature sensitivity over time.

[19] When temperature falls low enough air conditioners are mainly turned off. As temperature falls further they can't be turned off again so demand stops declining with falling temperature until it is cold enough that heaters start to be turned on.

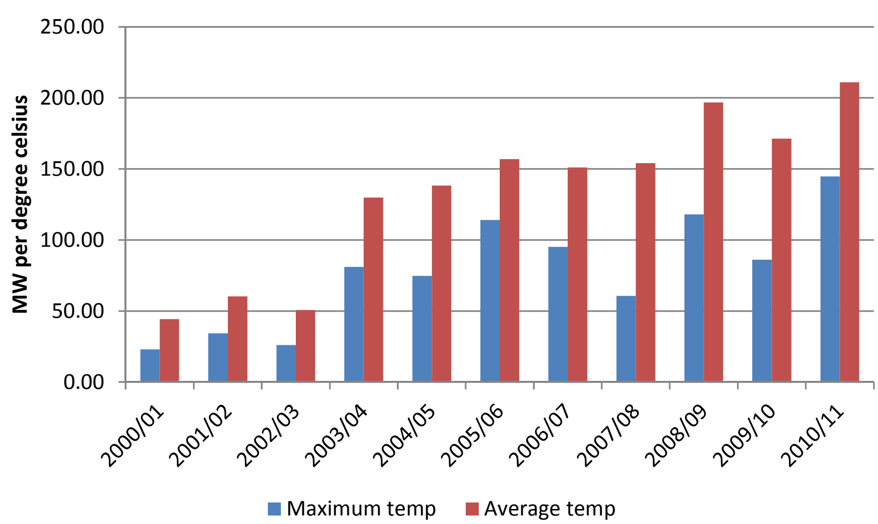
Table 14 **Season by season temperature sensitivity coefficients, South East Queensland**

Year	Maximum temperature	Average temperature
2000/01	22.87	44.23
2001/02	34.31	60.27
2002/03	26.05	50.64
2003/04	81.00	129.90
2004/05	74.69	138.24
2005/06	114.10	156.93
2006/07	95.12	151.02
2007/08	60.60	154.18
2008/09	117.87	196.75
2009/10	86.01	171.41
2010/11	144.80	211.01

Data source: ACIL Tasman

Error! Reference source not found.Error! Reference source not found. shows the estimated coefficients from Table 14 graphically.

Figure 17 **Average and maximum temperature sensitivity coefficients over time, summer 2000-01 to 2010-11**



Data source: ACIL Tasman

5.6 Back-cast model from Method 2 performs poorly against alternative model with GSP as key driving variable

EMCa applies a within sample back-casting to its own model. This is simply running the ordinary least squares regression which minimises the sum of squared errors in the sample. In other words, EMCa chose the model that delivered the highest R-squared.

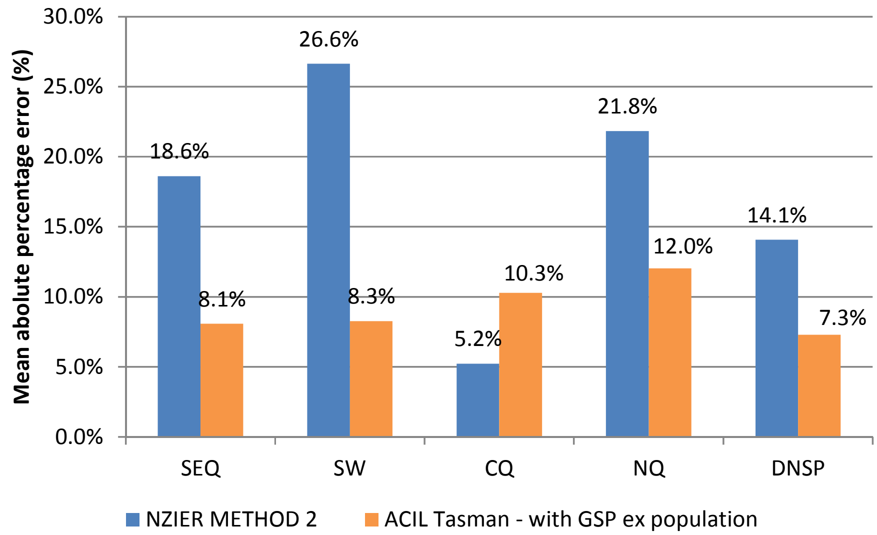
While this is an indication of model fit against the historical data, it is no guarantee that the model is reasonable for the purposes of forecasting. In fact, it is only by sub-setting the historical sample and using the model to forecast out-of sample that a true assessment of the model's forecasting performance can be obtained.

We re-estimated EMCa's Method 2 model using a subset of data to conduct an out-of sample back-casting. The available time series was split so that EMCa's model was calibrated using the first seven years of data. The estimated coefficients from this model were used to 'forecast' peak demand for the remaining four years.

We also performed the same process using a model where we replaced population with GSP as the driving variable. The mean absolute percentage errors (MAPE) of both models for each of Powerlink's four regions are shown in Figure 18 below.

The figure shows that the model with GSP included as an explanatory variable instead of population has greater versatility and been better able to adapt to and capture the slowdown in peak demand that occurred in recent seasons.

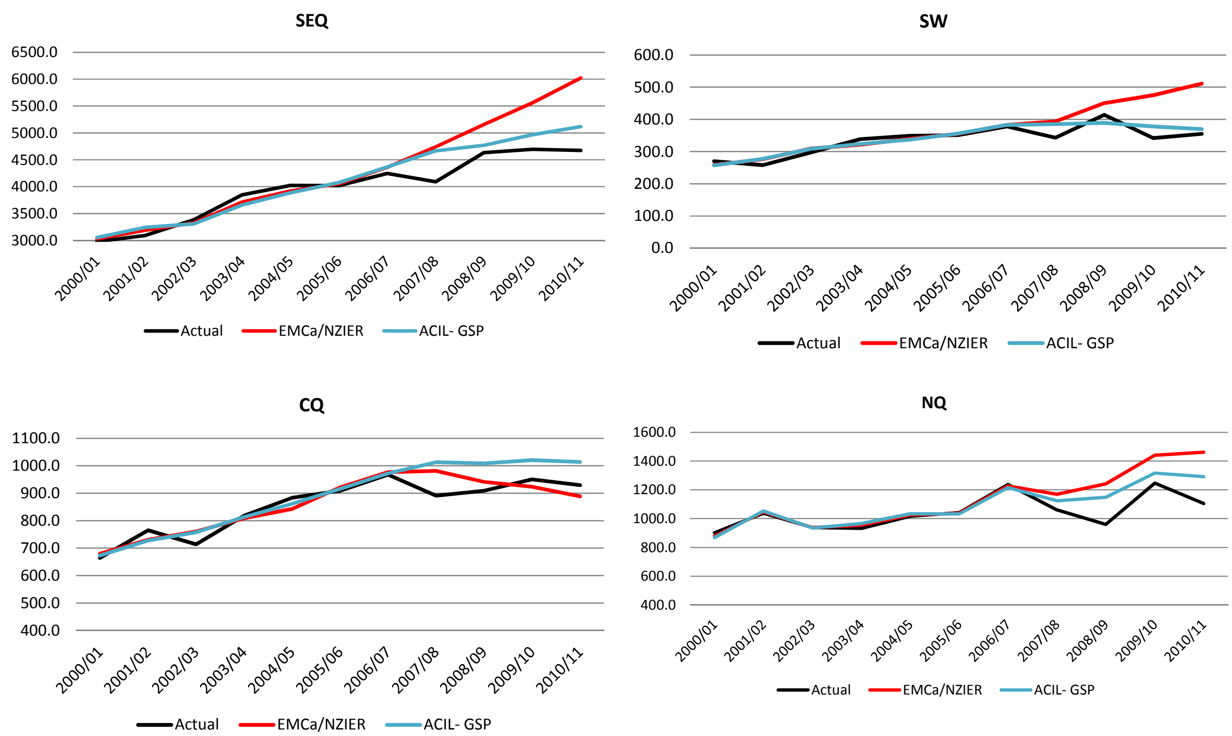
Figure 18 **EMCa versus amended model- 4 year out of sample back cast, Mean absolute percentage error (%)**



Data source: EMCa and ACIL Tasman

The predicted values from each of the two models (including both the in-sample and out-of sample predictions) are plotted against the actual peak demands for each of Powerlink's four regions in Figure 19.

Figure 19 **Actual versus predicted demands from EMCa Method 2 and ACIL Tasman GSP models**



Data source: Powerlink/ACIL Tasman

5.7 Alternative forecasts using GSP instead of population

Although we identify a number of issues concerning EMCa's Method 2 model in the previous section, we consider that the omission of a variable which captures the economic cycle such as GSP in favour of population to be a key factor resulting in a major downward bias in the generated forecasts from the model. This is the case for 2 reasons. First, population growth is relatively steadily over time, and will not respond to improved economic growth outlook for the forecast period. Second, the sluggish economic environment of the last 3 years will result in a lower sensitivity in the model between population growth and peak demand.

Also, an additional benefit of a model based on GSP rather than population is that it would be capable of incorporating any anticipated economic recovery without losing population dynamics, which are a component of GSP growth. By omitting GSP, the EMCa model specification does not allow the forecast economic recovery to translate into higher peak demand over the next regulatory period. This is a major drawback.

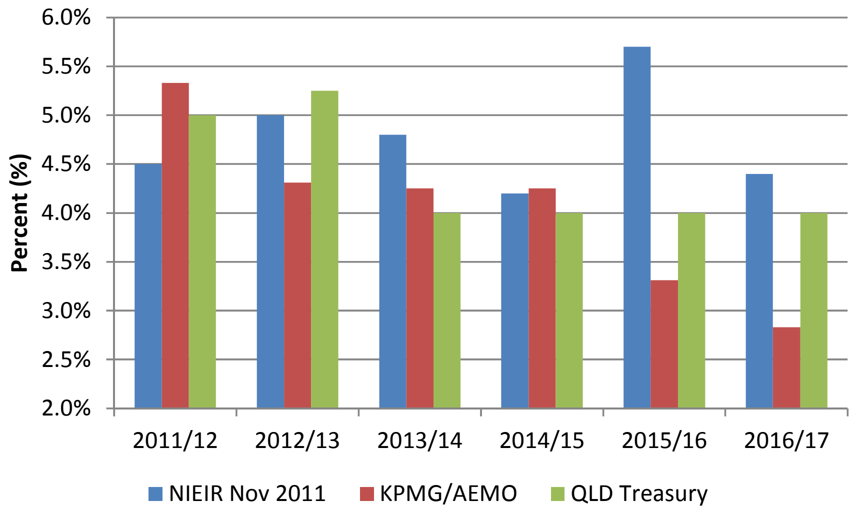
There are also significant issues relating to the exaggeration of price effects due to the failure to suitably allow for variations in economic activity.

The use of a price variable in combination with population is not appropriate due to the simultaneous effects of the slowdown in economic activity with the significant price increases that took place in the last 3 years of the historical series. The subsequent bias in the price coefficients due to the absence of a variable capturing the economic cycle, in combination with EMCa's large price increases in the forecast period, will produce forecasts that are biased downwards.

We consider that a model similar to EMCa's Method 2 model, but with population replaced by GSP as the driving variable, will better control for variation in economic activity. Through its inclusion it will control for the economic cycle and reduce any bias that arises through the misspecification of the model. It will also allow the forecast economic recovery to impact on peak demand, which EMCa's Method 2 cannot do. For simplicity we have made a simple alteration to EMCa's Method 2 by replacing population with GSP. Because the coefficients on the price variable suggest reasonable price elasticities we allow these to remain in the model specification and therefore allow the anticipated price increases to have an effect on demand. This is despite their lack of statistical significance, which is difficult to attain because of the small sample size we are working with.

Using the GSP model we estimate three separate sets of forecasts, one set using the NIEIR GSP base case forecasts from November 2011, one set using the KPMG/AEMO medium case and one set using GSP forecasts from the Queensland Treasury. These are shown in Figure 20 below.

Figure 20 **Forecast GSP growth, NIEIR (November 2011), KPMG/AEMO, Queensland Treasury**



Data source: NIEIR, KPMG/AEMO, Queensland Treasury

Because the Queensland Treasury's forecasts do not extend beyond 2014-15, we assume that the rate of growth in that year will persist for the next two years of the forecast period.

The calculated forecasts from this ACIL Tasman model using the 3 separate GSP assumptions are presented in Table 15 along with EMCa's forecasts from Method 2, NIEIRs most recent forecasts from November 2011 and Powerlink's 2011 APR forecasts.

Table 15 **Comparison of DNSP forecasts**

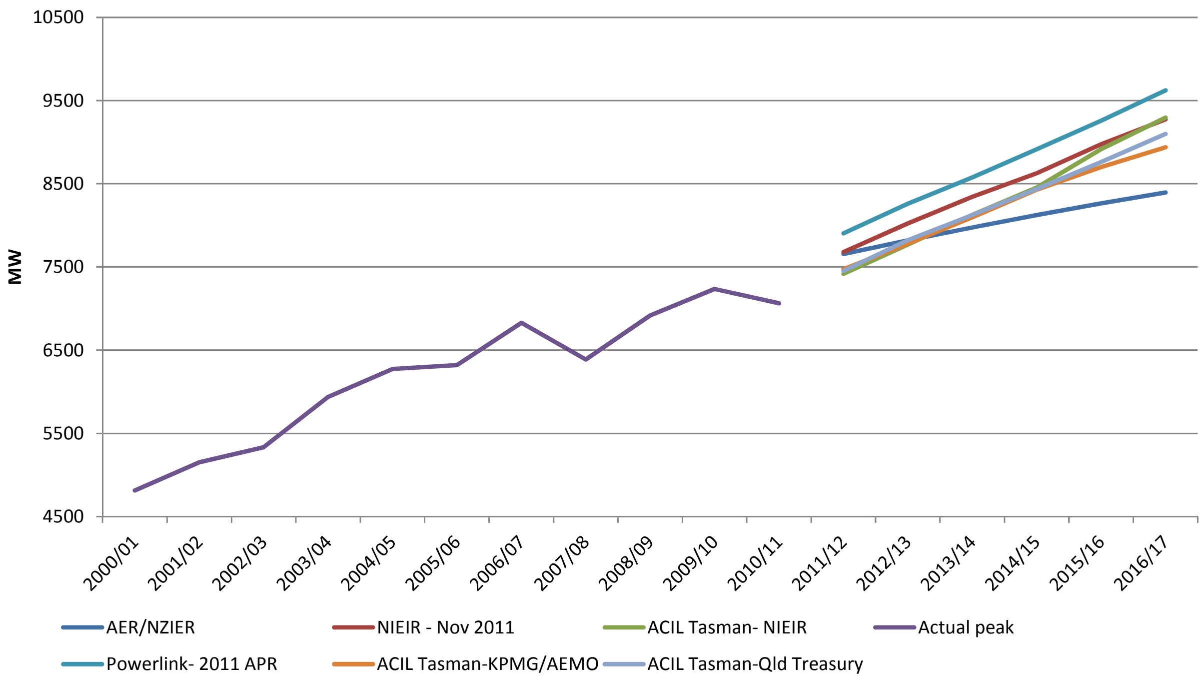
Year	EMCa Method 2	NIEIR - Nov 2011	Powerlink-2011 APR	ACIL Tasman-NIEIR	ACIL Tasman-KPMG/AEMO	ACIL Tasman-Qld Treasury
2000/01	4813	4813	4813	4813	4813	4813
2001/02	5152	5152	5152	5152	5152	5152
2002/03	5333	5333	5333	5333	5333	5333
2003/04	5937	5937	5937	5937	5937	5937
2004/05	6274	6274	6274	6274	6274	6274
2005/06	6319	6319	6319	6319	6319	6319
2006/07	6829	6829	6829	6829	6829	6829
2007/08	6386	6386	6386	6386	6386	6386
2008/09	6915	6915	6915	6915	6915	6915
2009/10	7234	7234	7234	7234	7234	7234
2010/11	7063	7063	7063	7063	7063	7063
Forecast						
2011/12	7655	7680	7904	7417	7472	7450
2012/13	7819	8023	8259	7770	7779	7822
2013/14	7974	8343	8576	8126	8096	8122
2014/15	8122	8626	8915	8454	8427	8435
2015/16	8262	8972	9256	8915	8697	8760
2016/17	8394	9274	9621	9293	8938	9099

Data source: ACIL Tasman

Figure 21 presents the calculated forecasts graphically. The results generally show that when you include GSP into the model (thus excluding population), which captures both population and economic productivity impacts, not just population in isolation, then your forecasts move markedly away from the proposed EMCa/AER forecasts. These lie at the bottom of the range of all possibilities, and do so in our opinion because they fail to capture the impact of any economic recovery that is forecast by a majority of credible firms and agencies (including the Queensland Treasury) as well as overestimating the impact of future price rises due to model misspecification.

Once we capture the impact of the anticipated economic recovery and apply price coefficients that more closely resemble those calculated across a range of more robust empirical studies, we obtain a set of forecasts which more closely resemble those produced by NIEIR and Powerlink, and diverge significantly from those of EMCa's Method 2.

Figure 21 **Comparison of all DNSP forecasts**



Data source: EMCa, NIEIR, Powerlink, ACIL Tasman

ACIL Tasman does not suggest that forecasts produced using this approach are a reasonable expectation of the future electricity demand in Queensland. However, these forecasts do provide strong reason to believe that Powerlink's forecasts are within the reasonable range. Given the flaws we have identified with EMCa's approach, we consider that Powerlink's approach is significantly more reasonable than the AER's alternative.

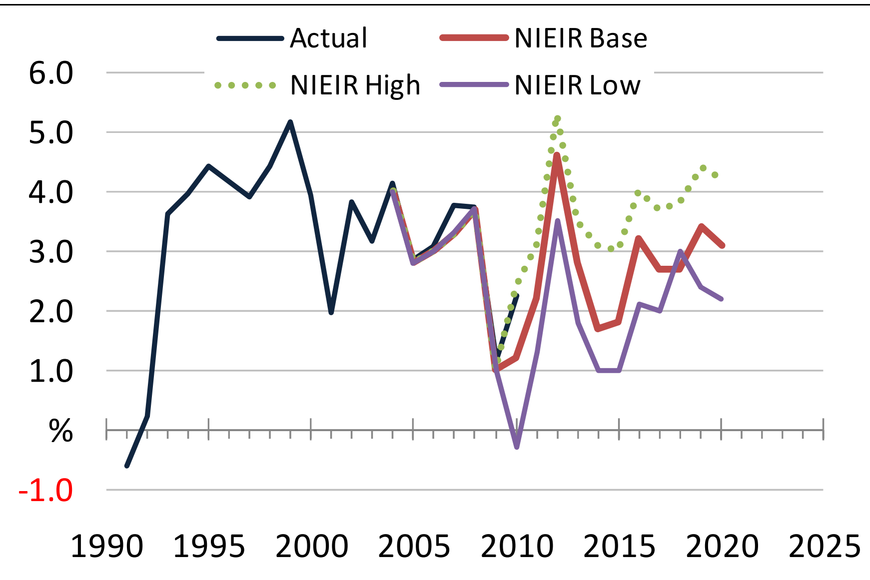
A Assessment of NIEIR forecasts of economic growth - April 2010

This appendix provides an analysis of NIEIR's economic forecast done in April 2010 and assess NIEIRs economic forecasting performance over the past five years.

A.1 Australian real GDP growth

Figure 22 presents the historical annual growth in Australia's real GDP along with NIEIR's forecasts to 2020 done in April 2010. Broadly, NIEIR's Base scenario forecast is projecting the slight downward trend in the rate of annual real GDP growth over the past two decades to continue[20], while the High Scenario has annual growth rates of those experienced in the 1990's (but with the average growth above the 1991-2000 average).

Figure 22 **Historical and projected annual change in Australian real GDP**



Note: All years are financial years ending June 30.

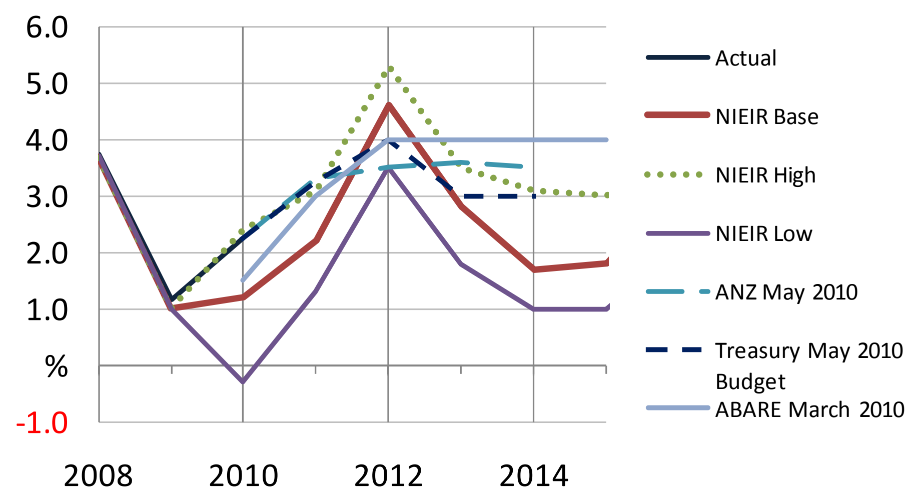
Data source: NIEIR April 2010, ABS Catalogue numbers 5206.0 (quote release date)

Figure 23 compares near term Australian real GDP forecasts from a range of sources including NIEIR's April 2010 forecast. As can be seen, growth for 2009-10 has tracked the NIEIR High scenario. A selection of contemporary

[20] More specifically, average annual growth was 3.32 per cent a year between 1991 and 2000 and 3.00 per cent a year between 2001and 2010. NIEIR's Base scenario has an average annual growth of 2.82 per cent a year between 2011 and 2020.

forecasts from the Commonwealth Treasury, ANZ and ABARE are forecasting average growth to 2013-14 to be between NIEIR's Base and High Scenarios.

Figure 23 **Comparison near term Australian real GDP forecasts from different sources**



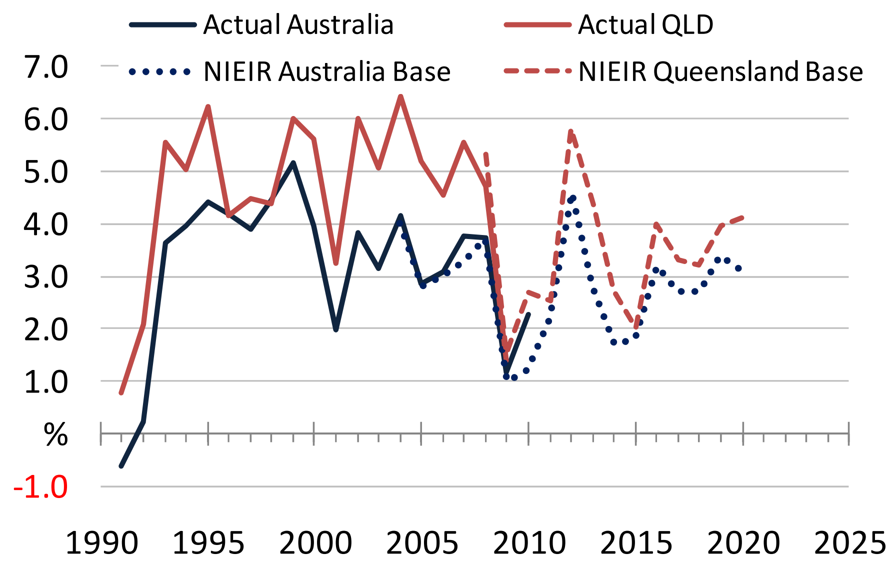
Note: All years are financial years ending June 30.

Data source: NIEIR April 2010. ABS Catalogue numbers 5206.0 (quote release date). Australian Treasury, *Budget 2010-11*, http://www.budget.gov.au. ABARE (2010), *Australian Commodities, March 2010*. ANZ, *Australian Federal Budget Report*, 12 May 2010, http://www.anz.com/resources/3/f/3f93b480426f8c13975e9f9bdc498da1/ANZ-Aus-Federal-Budget-Report-2010-11.pdf?CACHEID=3f93b480426f8c13975e9f9bdc498da1.

A.2 Queensland real GSP growth

Figure 24 presents the historical annual growth in Queensland and Australia's real GSP/GDP along with NIEIR's April 2010 Base scenario forecasts to 2020. Broadly, NIEIR's Base scenario forecast is projecting Queensland to continue to have higher growth than Australia as a whole, but with a narrower gap than recent history.

Figure 24 **Historical and projected annual change in Australian and Queensland real GDP/GSP**

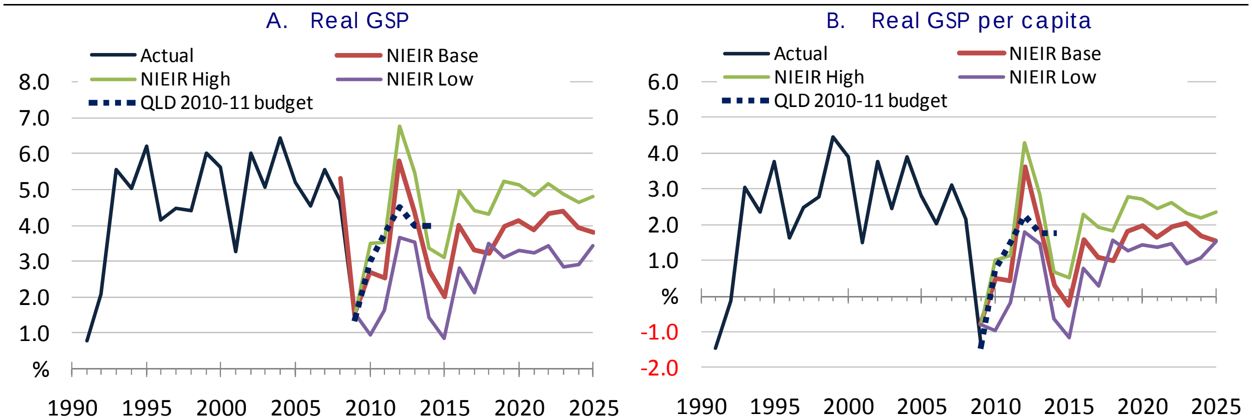


Note: All years are financial years ending June 30.

Data source: NIEIR April 2010, ABS Catalogue numbers 5220.0, 5206.0 (quote release date). Queensland 2008-09 historical GSP growth taken from Queensland Government 2010-11 Budget Paper No 2.

Figure 25A presents all three NIEIR scenarios for Queensland real GSP growth along with Queensland Treasury's assumptions for the 2010-11 Budget, while Figure 25B presents the historical and projected GSP per capita growth.

Figure 25 **Historical and projected annual change in Queensland real GSP and real GSP per capita**



Note: All years are financial years ending June 30.

Data source: NIEIR April 2010, ABS Catalogue numbers 5220.0, 3101.0 (quote release date), Queensland Government 2010-11 Budget Paper No 2 and ACIL Tasman

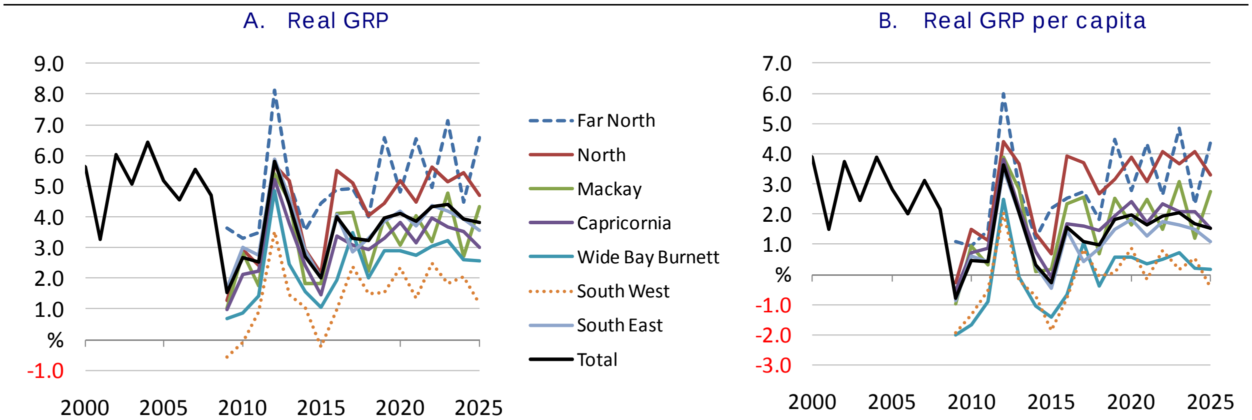
ACIL contends that, on average, NIEIR's Base scenario forecasts seem to align fairly well with expectations and historical growth rates.

It should be noted that NIEIR's assumed High real GSP growth in 2011-12 is not abnormal after a slowdown as experienced in 2008-09 & 2010-11 (compare the growth after the 1991 recession, for example). Hence, even though the projected growth in 2011-12 is significantly above Queensland Treasury's under the Base and High scenarios, we do not deem this to be unlikely after a period of low growth (although it is always difficult to forecast precisely *when* such a turnaround will occur).

A.3 Regional real GRP growth

Figure 26A presents the regional gross regional product (GRP) growth under NIEIR's base scenario, while Figure 26B presents the projected growth in GRP per capita.

Figure 26 **Historical and projected (base scenario) annual change in Queensland regional real GRP and real GRP per capita**



Note: All years are financial years ending June 30.
Data source: NIEIR, ABS Catalogue numbers 5220.0, 3101.0 and ACIL Tasman

As shown in Figure 26A, annual real GRP growth is projected to differ quite significantly by region. In particular, the Far North region is projected to experience sustained, strong growth over the projection period while the South West is projected to have low growth (average annual growth of 5.3 and 1.6 per cent a year, respectively, between 2010 and 2025).

The low GRP for South West clearly does not incorporate the LNG developments which are already having a significant impact on the economy in that region. This suggests that these major developments are not incorporated in the GSP forecasts which seems consistent with the block loads in Powerlink's overall forecast which include allowance for these developments.

A.4 Historical forecast accuracy

In this section we analyse the accuracy and bias of NIEIR's previous forecasts for Australian real GDP and Queensland real GSP. In this context, forecasting accuracy refers to the magnitude of the errors of NIEIR's forecasts compared to what was actually observed, while bias refers to consistent under- or over-estimates of the forecasts.

Box 2 discusses a range of commonly used measures for forecast accuracy as well as the mathematical formulae for calculating the preferred measure for this purpose – the percentage mean absolute error, or PMAE.

Box 2 Measures of forecast accuracy and bias

There are a range of statistical measures that assess the accuracy of a forecast compared with what actually happened. Common measures include:

- Mean error (ME)
- Mean square error (MSE)
- Root mean square error (RMSE)
- Mean absolute error (MAE)
- Mean percentage error (MPE)
- Mean absolute percentage error (MAPE)

The major difference between all these measures is how to add up the errors associated with each forecast – particularly how to add up errors which change sign (i.e. the forecast was below history in one year and above in another). Historically, squaring the errors was a mathematically simple way of converting all errors into the same sign (such as the MSE and RMSE measures) but has the downside that outliers become heavily weighted in the calculation. This property is avoided by the use of alternative functions that use the absolute errors (such as the MAE and MAPE).

Given a suite of possible measures it is good to focus on those that are the most useful for the purpose of assessing the historical accuracy of NIEIR's previous GDP and GSP forecasts. To do this requires some understanding of what the different measures are and any associated weaknesses.

Forecast error and ME

We define the forecasts error to be the difference between the actual growth and the forecasted growth – hence a forecast growth of 3% compared an actual growth of 3.2% has a forecast error of –0.2%. The mean error, or ME, is simply the summation of the errors across all historical forecasts. The problem with the ME measure is that the positive errors can be offset by the negative errors resulting in an average value close to zero.

MSE and RMSE

As discussed above, one way to overcome this is to square the errors prior summation (as is done in the MSE and RMSE measures) but the downside is that outliers gain a disproportionate weight in the final estimate of the average[21] error. A further downside is that the values of MSE and RMSE are not easily interpretable – smaller is clearly better but there is no obvious meaning attached to a value of, say 0.1 versus 1.3.

MAE

As the name suggest, the mean absolute error (MAE) is the average of the absolute errors. Importantly, some meaning can be attributed to the calculated MAE – namely that an MAE of 0.4 implies that the average growth forecast has an error of 0.4 percentage points when compared to what actually happened. Hence, if the average GDP growth over a two-year period was projected to be 10.2 per cent then an MAE of 0.4 implies that the average forecast was 0.4 percentage points different. Unfortunately it is not possible to say which direction (if any) the average forecast was in error from the MAE (i.e. it is not possible to say that the average forecast was 9.8 or if it was 10.6 per cent we can only say that the average [absolute] error was 0.4 percentage points). Another downside of the MAE measure is that although we can place some meaning on the number it is devoid of context. For example, if the actual growth was 50%, then an MAE of 0.4 percentage points is insignificant and we would have confidence in the forecasts. However, if the actual growth was only 0.2%, then the same MAE would make the forecasts seem much less useful.

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21 Technically 'mean error' as the term 'average' can be used to describe the median or mode of the sample. For simplicity, the common usage of 'average' being the mean of the observations is used in this discussion.

MPE, MAPE, PME and PMAE

The mean percentage error (MPE) and mean absolute percentage error (MAPE) measures attempt to place the forecast errors into context against the size of the actual growth. They do this by averaging the relative errors that the forecasts differ from the actual values (and converting to a percentage). The difference between MPE and MAPE is simply that MPE averages the relative errors while MAPE averages the absolute value of the relative errors. An alternative way of calculating the relative error is to compare the sum of the forecast errors to the sum of the actual observations. It is not uncommon to find authors call both methods MAPE. For clarity, we distinguish between taking the mean of the individual percentage errors (MPE) to taking the percentage of the mean errors (PME). Mathematically:

$$MPE = 100 \times \frac{1}{n}\sum_{i=1}^{n} \frac{F_i - A_i}{A_i} \tag{1}$$

$$MAPE = 100 \times \frac{1}{n}\sum_{i=1}^{n} \frac{|F_i - A_i|}{A_i} \tag{2}$$

$$PME = 100 \times \frac{1}{n}\frac{\sum_{i=1}^{n} F_i - A_i}{\sum_{i=1}^{n} A_i} \tag{3}$$

$$PMAE = 100 \times \frac{1}{n}\frac{\sum_{i=1}^{n} |F_i - A_i|}{\sum_{i=1}^{n} A_i} \tag{4}$$

where A_i is the actual observation, F_i is the forecast value and n is the number of observations being compared.

Given the nature of the forecast that we are assessing, the PMAE measure is preferred to the MAPE measure since the absolute error in the GDP/GSP forecasts is of more importance and the absolute errors compared against small actual observations can be given a disproportionate weight.

Bias

In addition to estimating the forecast error, it is useful to obtain an idea about whether there is any systematic bias in the direction of the errors. That is, have the NIEIR forecasts been consistently below or above what actually happened or have they been fairly evenly spread on the up-side and down-side. Following the methodology discussed in Frontier Economics (March 2008), the bias direction can be estimated by comparing the PME and the PMAE measures using the simple formula:

$$Bias\ direction = 100 * \frac{PME}{PMAE} \tag{5}$$

The bias direction will always lie between –100% and +100%. If all the forecasts are consistently above the actual observations then PME will equal PMAE and the bias direction will equal +100%. Conversely if all of the forecasts are consistently below the actual observations then PME will equal the negative of PMAE and the bias direction will equal -100%. For an unbiased forecast one would expect the PME to be close to zero and hence, the bias direction calculation will also be close to zero.

One should be cautious about attaching too much importance to the bias direction value if there are only a small number of observations being compared.

Source: ACIL Tasman

Table 5 presents a summary of the accuracy and bias of NIEIR's previous forecasts for the financial year the report was released and for one to four financial years ahead.

From Table 5 it can be seen that the average error associated with NIEIR's previous forecasts have been higher for the near term, with the largest errors being the forecasts for the current financial year plus one year ahead. Over the medium term (i.e. current financial year plus three and plus four years ahead) the average errors are significantly smaller. There does not seem to be much difference between the overall accuracy of the Queensland real GSP forecasts and those for Australian real GDP.[22]

Table 16 **Accuracy and bias of NIEIR's historical forecasts compared to history**

	Sample size	Average deviation (MAE)	Average percentage error (PMAE)	Bias direction
	no.	% points	%	%
Australian real GDP				
Current year accuracy	5	0.4	14.81	–22.3
Current + one year ahead	5	1.4	23.27	–20.6
Current + two years ahead	4	1.2	12.85	26.9
Current + three years ahead	3	0.7	5.50	–50.7
Current + four years ahead	2	0.9	6.10	100.0
Queensland real GSP				
Current year accuracy	5	0.7	16.68	–60.7
Current + one year ahead	4	1.8	19.44	–35.5
Current + two years ahead	3	2.6	17.91	–46.9
Current + three years ahead	2	2.6	13.36	–84.0
Current + four years ahead	1	0.6	2.63	–100.0

Note: NIEIR makes a forecast for the financial year in which the report was released and potentially incorporates one or more quarters of actual data. 'Current year' refers to the forecast for the financial year that the report was released – i.e. 2004-05 for the report released in January 2005, 2005-06 for the report released in December 2005, etc.

Data source: ACIL Tasman calculations from previous NIEIR forecasting reports and ABS catalogues 5206 and 5220.

With respect to the bias direction, the Australian forecasts have a tendency to be slight underestimates of the actual growth in the short term but are mixed otherwise. The previous Queensland forecasts however, have consistently exhibited a bias toward underestimating the rate of actual growth.

In interpreting the past performance of NIEIR's Australian real GDP forecasts, ACIL Tasman considers the magnitude of the MAE for the current financial year plus two, three and plus four years ahead to be low. For example, the MAE of 1.2 for the current FY plus two years ahead implies that the average forecast real GDP growth over the three years was different by 1.2 percentage points (or approximately 0.4 percentage points per year). The

[22] Due to the small sample size, sophisticated statistical tests of the accuracy and relative accuracy of the Australian and Queensland forecasts have not been performed.

accuracy of the previous short term forecasts seem to be less reliable on average, but within the range of other forecasters.

For comparison, it is not unusual for the Australian Treasury forecasts for the next financial year to change by half a percentage point between the Budget and the mid-year economic forecasts (MYEFO) released approximately 6 months apart. Indeed, the May 2009 Budget papers projected real GDP growth of -0.5% for 2009-10 while the MYEFO projected a growth of +1.5%, with the May 2010 Budget papers projecting a growth of +2.3% (with actual growth being 2.27%).

Although the above comparison is informative, care should be taken in extrapolating any perceived weaknesses to the NIEIR's April 2010 forecasts. First, the analysis is based on a small sample of NIEIR's forecasts. Second, NIEIR themselves may have undertaken a similar exercise and may have adapted their models and/or methodologies to correct for any perceived weaknesses such as the fairly consistent underestimation of the Queensland real GSP growth. Nevertheless, this analysis gives us some confidence that NIEIR's previous macroeconomic forecasts for Queensland and Australia have not been radically different from actual outcomes, particularly over the medium term.

ACIL Tasman
Economics Policy Strategy

Jim Diamantopoulos

Jim is a Senior Consultant in ACIL Tasman's Melbourne office.

He has a strong background in the application of economic, financial and econometric modelling techniques in the analysis of economic problems and issues. Since joining ACIL Tasman, Jim has worked on a range of modelling projects in the energy sector.

Jim is currently advising Aurora Energy on their energy consumption and load demand forecasting methodology as part of their pricing submission to the AER. Jim developed a sophisticated terminal and zone substation load demand forecasting model which formed the basis of Aurora Energy's load forecasts. The model incorporated weather correction as well as adjustments for permanent transfers, major block loads, embedded generation and demand side management initiatives. Jim also developed Aurora's energy consumption forecasts for six customer classes for the next regulatory period, constructing an econometric model that incorporated the key drivers, including economic, demographic and weather variables. To aid Aurora's budgeting and planning process Jim also developed forecasts of the number of new network connections by region and customer class.

Jim was involved in a project for the Australian Energy Regulator reviewing the electricity demand, energy sales and customer numbers forecasts of the five Victorian electricity distribution businesses submitted as part of the latest regulatory pricing review. He critically assessed the forecast input assumptions, the soundness of the forecasting methodologies employed and the reasonableness of the forecast outputs.

In joint project for Energex and Ergon Energy, Jim critically reviewed Energex's and Ergon Energy's summer and winter peak demand and energy forecasting methodology. He developed several methodological improvements, particularly relating to Energex's approach to temperature correction or normalisation. As part of the project he applied a multiple regression and Monte Carlo modelling approach to generate 10 year system level annual summer and winter peak day forecasts at the 10 and 50 POE level. Additional analysis was also conducted at the zone substation, bulk supply and connection point level and further methodological improvements were identified for the client.

Jim was also involved in a project for Energex in Queensland to construct a simulation model of electricity peak demand and energy for the South East Queensland region. The model allows for the analysis of the impact of changes in carbon emissions policies, MRET, electricity prices, trends in appliance energy efficiency and market penetration of various appliances to estimate the impact on both peak summer and winter load and annual energy sales. The model also considers the impact of demand side management initiatives and assesses the likely impact of changes in building efficiency standards, photovoltiac cells and solar hot water systems. Because the model also maps out key economic relationships between demand and economic activity, the model will also be a useful tool to assess the impact of the current financial and economic crisis on peak electricity demand and total energy sales.

Jim was engaged by the WA Office of Energy to create a suite of Excel based simulation models that enable the user to analyse the economics of a range of gas network reticulation options. Options analysed included the development of Greenfield/Brownfield LNG and LPG reticulation options, and the extension of a natural gas pipeline. Capital and operating costs for each of the reticulation options were constructed based on a range of assumptions and the models were solved for a customer per unit gas price that generated a predetermined rate of return to the service provider.

Other relevant projects Jim has been involved in include:

- For the Australian Energy Market Commission, an analysis of the impact of the Small Scale Renewable Energy Scheme (SRES). Specifically Jim developed a non-linear econometric model of the take-up of solar PV installations by state jurisdiction, with the economic payback of installation as the main driving variable.
- Provision of advice to Powerlink in Queensland on their load forecasting methodology with a particular focus on their approach to weather normalisation.
- Econometric analysis and modelling of residential electricity demand for the Australian Greenhouse Office
- Work for ESCOSA in South Australia reviewing SA Water's water and wastewater demand forecasts and associated forecasting methodology

Jim holds a Master of Economics degree from Monash University, specialising in econometrics, a Bachelor of Economics degree with Honours, and a Graduate Diploma of Applied Finance and Investment.

Marcus Randell

Marcus Randell is an economist with over 35 years experience dealing with a broad range of issues in the construction, transport, energy and resources sectors. His work in this area has included analysis of taxation and royalty policy, provision and pricing of infrastructure, industry regulation, project evaluation, and commodity outlooks and price analyses. He has a high level of economic, financial and market modelling skills.

Since joining ACIL Tasman in 1996 he has provided a variety of clients with commercial and strategic advice and modelling on coal industry issues, rail transport, gas and electricity markets, competition policy reform.

Key areas of expertise

A key area of expertise is Marc's high level economic, commercial and financial modelling and analysis skills. He has developed many models to study commercial and market arrangements including ACIL Tasman's initial model of the Eastern Australian Gas Market, network models of gas and water reticulation, models of rail operations, models of mineral royalty alternatives, project financial models, models of energy usage alternatives and cogeneration alternatives.

His expertise also includes:

- development and implementation of mineral taxation and royalty arrangements;
- economic analysis and policy development in the construction industry including industrial relations, taxation, financing and regulation;
- electricity planning including assessment of future electricity requirements and development of strategic and capital investment plans;
- benchmarking and cost benefit,
- infrastructure development, operation, regulation and pricing including bulk haul railways, bulk commodity ports, gas pipelines and electricity generation and transmission facilities; and
- project assessment and risk analysis.

Relevant previous assignments

As Forecasting Coordinator in the Planning Department of the former Queensland Electricity Commission:

- Modelling of electricity load characteristics including econometric analysis of existing and future electricity requirements;
- Economic and demographic modelling to determine future electricity peak demand and energy requirements;
- Provision of analysis and advice in the development of corporate and marketing plans for the electricity industry in Queensland
- Comparative cost analysis of a variety of proposed capital expenditure proposals

As Manager, Resource Economics in the Queensland Department of Minerals and Energy:

- modelling of Queensland's coal rail freight charges and royalty arrangements
- modelling of revised royalty arrangements for base and precious metals in Queensland
- development and assessment of policy options for environmental security arrangements for mining using financial models
- Benchmarking and evaluating performance of Queensland Rail's coal haulage business.

ACIL Tasman assignments:

Marc has been with ACIL Tasman since 1996 and during this time has been involved in a multitude of assignments involving modelling and analysis mainly in the energy and resources and transport sectors. He has a comprehensive knowledge of electricity and gas markets in Australia and extensive project experience in economic market and financial modelling in these areas.

The rail transport assignments have included the preparation of a draft access code, development of a financial model of third party operators, preparation of submissions on rail access, provision of advice on contractual arrangements and the assessment of potential markets for rail transport including FreightCorp and National Rail as part of the financing of the winning bid for these assets.

His assignments in electricity have involved load forecasting, electricity market assessments and pool price projections, identifying and assessing transmission issues, advice on fuel (coal and gas) supply issues and strategies, evaluating capital investment plans, and advice on regulatory issues.

In gas he has provided market assessments for pipeline acquisitions and development, gas price forecasts, advice on supply risks and contractual arrangements and was responsible for the initial development of ACIL Tasman's gas Supply and Demand Model for Eastern Australia.

The ACIL Tasman modelling assignments have included:

- development of a variety financial, network and market models for assignments in the resources and energy area;
- development of a model of gas market possibilities, with particular emphasis on North Queensland;
- modelling and evaluation of electricity generation possibilities in Queensland;
- modelling and advice on coal rail arrangements;
- modelling the economic and social impact of major industrial developments.

Education

B.Econ Australian National University (1974)

Employment History

1996 - Present Senior Consultant, ACIL Tasman undertaking consulting assignments mainly in the resources and energy sectors.

1990-96 Manager, Resource Economics, Queensland Department of Minerals and Energy, providing economic, commercial and financial analysis and advice to the Queensland Government on minerals and energy matters.

1982-90 Forecasting Coordinator, Planning Department, Queensland Electricity Commission. As the principal economist, provided advice on economic and demographic trends, future electricity requirements and corporate and market planning strategies.

1976-82 Principal Executive Officer, Commonwealth Department of Construction leading a small team of professionals involved in policy development and provision of commercial and financial advice on Australia's construction industry.

1975-76	Senior Executive Officer, Commonwealth Department of Social Security.
1974-75	Executive Officer, Enterprise Development Branch, Commonwealth Department of Aboriginal Affairs.
1969-74	Cartographer, Division of National Mapping, Commonwealth Department of National Development.
1963-69	Survey Draftsman, Queensland Departments of Lands and Justice.

Jeremy Tustin

Jeremy Tustin is a senior consultant in ACIL Tasman's Melbourne office. He has a degree in Economics from the University of Adelaide. His background is in competition and consumer protection and economic regulation, in particular in the energy and water sectors.

Energy

Jeremy has expertise in the National Electricity Market. In the electricity sector, he has advised on and prepared submissions relating to issues such as congestion management, appropriate mechanisms of support for renewable electricity generation and energy efficiency.

Jeremy's energy background includes significant experience in greenhouse and renewable policy. He represented South Australia on the National Emissions Trading Taskforce, which was the joint taskforce of Australian States and Territories that was first to propose a cap and trade emissions trading system for Australia. In this area, Jeremy and his team developed and interpreted models of the impact an emissions trading scheme would have on South Australia and in developing a mechanism for offsets. Jeremy was also closely involved with the development of South Australia's solar feed-in law.

In relation to energy efficiency, Jeremy developed a reporting methodology for the South Australian Government's target to improve the energy efficiency of its buildings. He also coordinated interdepartmental activity in relation to that target, developed strategies to achieve it and prepared public reports on progress.

Water

In his role with the Department of Treasury and Finance (SA), Jeremy advised the Treasurer on water policy, both rural and urban. He worked with the Office for Water Security to prepare South Australia's water security plan, in particular to design an economic regulatory regime for the South Australian urban water sector and a cost benefit analysis of a number of possible means of meeting South Australia's urban water demand.

In the urban water sector, Jeremy advised the Treasurer in relation to water and wastewater charges for SA Water. He also prepared the South Australian government's 'transparency statement' to the Essential Services Commission of South Australia concerning the setting of water and wastewater pricing as required by relevant commitments to COAG and under the National Water Initiative.

Jeremy also represented the Department of Treasury and Finance on an interdepartmental committee that developed a policy framework to guide water planning in areas where plantation forestry is a significant land, and therefore water, user. This framework, which is for the use of industry, regional Natural Resource Management Boards and Local Councils as well as the State Government, seeks to balance the social, economic and environmental water needs of South Australia while providing certainty for all industries reliant on water.

Competition and Consumer Protection

Jeremy spent a number of years with the Australian Competition and Consumer Commission, where he conducted investigations and managed litigation in a range of industries and relating to a variety of alleged misconduct. Examples included alleged cartel behavior in the fire protection industry, collusion and alleged misuse of market power in country newspapers and mergers in various grocery industries. He prepared the Australian Competition and Consumer Commission's submission to the (Cole) Royal Commission into the Building and Construction Industry.

Jeremy also has a depth of experience in consumer protection issues, both in policy and practice. On the practical side, Jeremy conducted a number of consumer protection investigations for the ACCC including the *Allans* case, which resulted in a significant fine and has formed the basis for a number of 'two-price advertising' cases pursued more recently. He also worked on a number of other consumer protection cases relating to issues such as GST pricing, unconscionable conduct and misleading or deceptive conduct.

On the policy side, Jeremy spent a number of years as a Research Associate with the Centre for Regulation and Market Research within the University of South Australia where he developed a methodology for quantifying the impact of false advertising and related conduct using discrete choice analysis. During that time Jeremy published papers relating to consumer protection, mergers and trans-Tasman competition regulation.

Selected recent projects:

Jeremy recently conducted (with others) the following projects:

- A review of the electricity sales, customer numbers and maximum demand forecasts submitted by the five Victorian electricity distribution businesses to the AER for the upcoming regulatory period (2011 to 2016).
- A review of the demand forecasts submitted to the Essential Services commission of South Australia by SA Water

- A review of certain principles underpinning the Essential Services Commission of South Australia's upcoming determination of the standing contract price for gas in South Australia

Positions held

2009 ~Senior Consultant, ACIL Tasman

2008 ~2009 Director, Economic Regulation, Department of Treasury and Finance, South Australia

2006 ~2008 Manager Sustainability, Energy Division, Department for Transport, Energy and Infrastructure, South Australia

2004 ~2006 Research Associate, Centre for Regulation and Market Analysis, University of South Australia

1997 ~2004 Australian Competition and Consumer Commission, Senior Investigation Officer, Investigation Officer

Selected Publications

Diepold, B. Feinberg, R. Round, D.K. and **Tustin, J** "*Merger Impacts on Investor Expectations: An Event Study for Australia*", International Journal of the Economics of Business, February 2008.

Round, D.K. **Tustin, J** and Round, K.A. "*Australasian competition law: Issues and lessons – a case study"* paper prepared for "*An International Research and Policy Symposium on* "Competition Policy for International Development, Growth and Trade" , presented by Centre for Economic Policy Research, Brussels, December 9 - 10, 2005.

Kennedy, R Hoek, J and **Tustin, J** "*Smoking Behaviour and Perceptions of Cigarette Descriptors*", ANZMAC conference 2005, University of Western Australia, Perth, December 5-7 2005

Tustin, J "*Measuring the distortionary effect of breaches of consumer protection law – a choice modelling approach*", Industry Economics Conference 2005, La Trobe University, Melbourne, 28-29 September 2005

Round, D.K. and **Tustin, J** "*Consumers as international traders: Some economic and legal issues underlying consumer protection*", Competition and Consumer Law Journal, Volume 12, No. 3, April 2005

Tustin, J and Smith, R. L. "*Joined up consumer protection and competition policy: Some comments*" Competition and Consumer Law Journal, Volume 12, No. 3, April 2005