Review of forecasting processes used for the SWIS

Prepared for the Independent Market Operator

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ACIL Tasman

Economics Policy Strategy

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Executive summary

The Independent Market Operator (IMO) operates and develops the Wholesale Electricity Market (WEM) in Western Australia. The WEM operates in the South-West Interconnected System (SWIS) which is located in the South West 'corner' of Western Australia. It serves most of Western Australia's population of more than 2 million, with a summer maximum demand approaching 4000MW. The SWIS supplies in excess of 17,000 GWh of electricity each year.

One of the important functions undertaken by the IMO is to ensure there is sufficient capacity to meet SWIS consumer demand. The IMO manages this function through the Reserve Capacity Mechanism (RCM) in which it sets the system capacity requirement, issues sufficient capacity credits to eligible entities (including eligible new entrants) and requires retailers to either acquire sufficient capacity credits bilaterally or from the IMO.

As part of the Statement of Opportunities (SOO) report published every year, the IMO publishes two sets of electricity demand forecasts, one covering annual electricity consumption, the other maximum demand. The forecasts are produced for a 10 year horizon.

It is important to note the current forecasting environment is characterised by a number of uncertainties and structural changes which are having a material effect on energy and maximum demand forecasts across all Australian jurisdictions.

Forecasters nationwide have been reducing their projections due to factors such as:

- A significant rise in the penetration of solar PV systems
- Economic uncertainty associated with the level of Chinese economic activity and consequently the demand for Australian commodity exports as well as uncertainty surrounding the European and US economies
- Changing consumer behaviour in response to significant and unprecedented increases in the price of electricity, partially as a result of the introduction of a price on carbon
- Changing consumer behaviour in response to energy efficiency measures and other factors such as the introduction of time of use tariffs.

Objectives of this review

Under the Market Rules, the IMO's demand forecasting process is required to be reviewed at least once every 5 years. The main objectives of the review are to:

- Assess the demand and electricity sales forecasts and associated methodologies and determine if they are prepared according to best practice demand and energy forecasting methodologies
- Assess the accuracy of the forecasts against what would be considered to be a reasonable level of error and against alternative model specifications
- Identify and recommend improvements to the forecasting methodology to improve performance in terms of accuracy and also the robustness and defensibility of the process to external criticism
- Assess the appropriateness of the methodologies used to account for factors that are not present in the historical data and make recommendations for improvement. These include large block loads, increasing uptake of solar photovoltaic cells and energy efficiency.
- Recommend changes to the Market Rules to enable improved demand forecasting and also to better facilitate the process.

Assessment of the NIEIR and IMO forecasting methodology and process

ACIL Tasman has evaluated the forecasting methodologies against a set of principles which it considers best practice forecasts should incorporate. The assessment is summarised in the following paragraphs.

Inclusion of key drivers in the methodologies

While it is difficult to uncover the underlying structure of NIEIR's proprietary models, it appears that the modelling process for both maximum demand and energy incorporates the expected key drivers of electricity consumption and demand, in particular, the main economic, demographic and weather drivers.

Forecast accuracy and bias[1]

ACIL Tasman has assessed the accuracy and bias of NIEIRs Australian GDP, WA GSP and WA population forecasts, as well as its electricity consumption and summer maximum demand forecasts.

[1] It is important to recognize that we are referring to a statistical notion of bias here that refers to a tendency for forecasts to consistently over or under predict actual outcomes. The use of the term bias in this report in no way suggests any dishonesty or favouritism on the part of the forecaster as may be implied by popular understanding of the term.

The size of the absolute deviation from the true value is measured by the average absolute deviation (MAE) and the average percentage error (PMAE). The bias direction indicates whether there is a tendency for the forecasts to under or over predict over the sample. Definitions of these measures are provided in Appendix A. It is important to note that these calculations are, in this instance, based on a small number of observations. The measures are therefore susceptible to significant movement as a result of the inclusion of new data in the calculation. It is therefore important to keep this in mind when evaluating the results and drawing conclusions on this basis.

The results for Australian GDP and Western Australian GSP show that the average percentage errors of the forecasts are generally less than 10%, which ACIL Tasman considers to be reasonable. The Australian GDP forecasts display a tendency to be biased downwards compared to actual GDP, for near term forecasts, but then exhibit an upward bias for the three and four year ahead forecasts. In the case of Western Australian GSP, NIEIR has historically under predicted with its forecasts. The forecasts have proven to be slightly downwards biased in the earlier part of the forecast horizon, while the size of the bias increases with the forecasting horizon. For the four year horizon, all forecasts of Western Australian GSP under-predicted compared to actual GSP.

The performance of NIEIR's population growth forecasts show that the average percentage error is generally around 10% apart from the 3 year ahead forecasts, which have an average percentage error in excess of 12%. ACIL Tasman also notes that there is a strong downward bias associated with the NIEIR population forecasts.

In terms of the electricity consumption forecasts, the accuracy and bias assessment used non- weather corrected actuals as the limited time and project scope did not allow for ACIL Tasman to undertake a process of weather correction of historical data. Weather conditions in a particular year are a source of deviation of actual outcomes from forecasts and so some care needs to be exercised when considering our analysis.

In terms of electricity consumption, ACIL Tasman considers that the average percentage error of the total electricity sales forecasts is reasonable, generally lying around 5 to 6% of the actual. Apart from public lighting which has a small negative bias, there is a strong upward bias in the forecasts. This bias gets stronger as the forecast horizon increases. ACIL Tasman considers that this upward bias is likely to be a result of overestimated new large loads/block loads which are added onto to NIEIR's base forecasts. This is evident in the larger percentage errors for the industrial sector forecasts, where the new large loads are classified.

The assessment of the maximum demand forecasts shows that the average percentage errors are reasonable, with only a small tendency towards an upward bias in the forecasts. ACIL Tasman considers that NIEIRs maximum demand forecasts have performed reasonably well, particularly after considering the tendency for the large new loads, which are added to the base line NIEIR forecasts, to be overstated.

Models based on econometric methods

NIEIR's models appear to be based on econometric methods that seek to estimate a relationship between maximum demand and electricity consumption and their underlying drivers based on historical behaviour. ACIL Tasman considers that the econometric approach, when applied appropriately is sound.

Weather normalisation

A key requirement of forecasting maximum demand and electricity consumption is to account for movements in weather conditions. NIEIR appears to normalise maximum demand by adjusting a central estimate to account for weather in a deterministic way based on the observed relationship between maximum demand and temperature, i.e. increased (decreased) by a certain number of MW for each degree above (below) the 50 POE level. The estimated relationship between maximum demand and average temperature follows a non-linear S curve, so that the temperature sensitivity of maximum demand will differ by temperature range. While we consider this to be acceptable, this is inferior to the simulation approach which they appear to have developed but are not yet using for their primary forecasts, through their model PeakSim. NIEIR's stated position is that PeakSim, up until very recently was not suitable due to an insufficient time series of market sent out data. Peaksim is run by NIEIR as a cross check against the primary forecast model, but these forecasts are not published. NIEIR states that the forecasts from Peaksim are comparable to the primary forecasts published in NIEIRs report.

Policy variables

NIEIR appears to incorporate adjustments for recent changes to policy that are likely to affect the forecasts, but because of the lack of history are unlikely to be picked up in the econometric modelling. NIEIR appear to have made adjustments for the introduction of the carbon tax and the recent rapid uptake of small-scale rooftop solar PV. ACIL Tasman considers this to be a sound approach to incorporating policy changes into its methodologies.

Model validation and testing

ACIL Tasman recognises that NIEIR has undertaken some tests to validate and test its models. However, ACIL Tasman considers that the lack of an ex-post evaluation of the previous year's forecasts is a shortcoming under the current methodology. ACIL considers that this should be undertaken every year between NIEIR and the IMO, including a detailed analysis of which factors played a role in causing deviations from actual outcomes. This approach should focus on:

- Errors in forecasting the models inputs such as GSP, population and household formation
- Structural issues with the models ability to generate accurate forecasts arising from incorrect relationships between model variables
- Identification of factors that the models are failing to capture- policy changes and new trends and so on

ACIL Tasman considers that this requirement for an annual ex-post evaluation of the forecasts performance could be made explicit within the Market Rules.

Quality assurance of data inputs

From discussions with the IMO, it is evident that there are sometimes inconsistencies between the market sent out data from the IMO and total generation data provided to the IMO by System Management. ACIL Tasman considers that there should be a formal quality assurance process implemented where the datasets are checked and assessed as being free from errors and fit to use in the forecast process. This process should take place inside of Western Power and the IMO, before datasets are provided to NIEIR for use in their forecasting methodology.

Transparency

The current process involving NIEIR lacks transparency. While we understand NIEIR's need to protect its intellectual property, we consider that it would be reasonable for NIEIR to provide significantly more information in relation to the process between the input assumptions and the generated outputs without compromising NIEIR's intellectual property. The current process involving NIEIR relies heavily on NIEIR's judgement which appears to be a routine part of a forecasting model – NIEIR do not simply rely on statistical routines. This judgement is based both on its own expertise and that of other agencies and experts.

While it is clearly preferable for forecasts to be examined in this way a best practice approach would expect that the exercise of any judgement would be set out explicitly, with the forecaster summarising the particular judgements associated with a forecast and describing the analysis underpinning them. This enables the user of the forecasts to form their own view as to whether the forecasts are conservative or otherwise and whether they are suitable for a given purpose.

New block loads

The current approach taken by the IMO to estimate the size and timing of any block loads is to specifically ask the prospective users, as well as Western Power, with whom developers lodge applications, and other government agencies such as the Department of State Development. We note that there is a natural tendency for the developers of large new mining projects to overestimate both the size and the likelihood of their specific project being committed and commissioned. ACIL Tasman recommends that the IMO should be making an adjustment to the estimated block loads to account for this bias. ACIL Tasman notes that the IMO has already made a significant downward revision to the block loads to be included in the 2012 forecasts, compared to previous years. These adjustments are consistent with ACIL Tasman's view that a more conservative approach to estimating block loads be adopted.

Attributes of NIEIRs methodology

While the lack of transparency and detailed information from NIEIR makes it difficult to draw conclusions about its methodology, ACIL Tasman considers that, the NIEIR methodologies appear to have a number of features that are a necessary and desirable part of any maximum demand and electricity consumption forecasting process. On this basis ACIL Tasman generally considers NIEIR's approach to forecasting maximum demand and electricity consumption as being generally sound.

Key recommendations

ACIL Tasman has identified a number of areas where additional analysis and amendments to the current methodology could lead to a more robust and improved methodology.

These are:

- That NIEIR analyses the tendency for its models to under-predict WA GSP and population growth and seek to identify methodological improvements that remove this downward bias
- That NIEIR adopts the use of simulation based weather normalisation methods as the basis for the maximum demand forecasts as soon as it is suitable to do so

- That NIEIR and the IMO consider producing electricity consumption forecasts conditional on different weather scenarios in a way that is similar to the approach taken for system maximum demand.
- That NIEIR and the IMO conduct further analysis of the energy output of solar PV systems in the SWIS, in light of the differences between NIEIR's forecasts and alternative sources such as the ORER.
- That NIEIR and the IMO undertake a detailed ex-post evaluation of forecast performance with a focus on:
  - Errors in the forecast model inputs such as GSP and population growth
  - Structural issues within the models which may lead to less accurate forecasts
  - Identifying factors which the models may be failing to capture such as new behavioural or technological trends and policy changes
- That this ex-post forecast evaluation be conducted annually and that it be required under the Market Rules
- That NIEIR recalibrate its models every year using the latest available information
- That a process of data quality assurance be implemented to ensure that any data used in the forecasting process is free from errors, reliable, complete and timely
- That the Market Procedures be altered to require the timely acquisition of data requested from other agencies or organisations to facilitate the generation of the forecasts
- That NIEIR takes additional steps to improve the transparency of its processes, both of its models calculations between the input assumptions and the generated outputs and any judgements made during the forecasting processes and the underlying rationale behind them
- That the IMO adopt a more critical stance in evaluating new block loads by
  - Applying probability weights to its block load forecasts
  - Heavily discounting or excluding altogether those loads that are expected to come online after 3 years of more
  - That careful consideration be given to the degree of uncertainty associated with new mining loads and that these be reflected in the probability weights
  - That some adjustment be made for the level of coincidence at the time of the system peak and an appropriate coincidence factor[2] be applied to the forecasts block loads

[2] Coincidence factor measures the ratio of the size of a block load coincident with the system peak relative to its system non-coincident peak. An individual load which peaks at the time of the system peak would therefore have a coincidence factor of 1.

- That the IMO puts its contract to provide energy consumption and maximum demand forecasts out to competitive tender on a regular basis, at least every 3 years.

1 Introduction

The Independent Market Operator (IMO) operates and develops the Wholesale Electricity Market (WEM) in Western Australia. The WEM operates in the South-West Interconnected System (SWIS) which is located in the South West 'corner' of Western Australia. It serves most of Western Australia's population of more than 2 million, with a summer maximum demand approaching 4000MW. The SWIS supplies in excess of 17,000 GWh of electricity each year.

One of the important functions undertaken by the IMO is to ensure there is sufficient capacity to meet SWIS consumer demand. The IMO manages this function through the Reserve Capacity Mechanism (RCM) in which it sets the system capacity requirement, issues sufficient capacity credits to eligible entities (including eligible new entrants) and requires retailers to either acquire sufficient capacity credits bilaterally or from the IMO.

As part of the Statement of Opportunities (SOO) report published every year, the IMO publishes two sets of electricity demand forecasts, one covering annual electricity consumption, the other maximum demand.[3]

These forecasts play a key role in the RCM process. The Reserve Capacity Target (RCT) is determined from forecast levels of maximum demand plus an accepted reserve margin. For this reason the accuracy of the forecasts play an important role in determining adequacy of supply. Forecasts that significantly under predict maximum demand could result in insufficient capacity being made available to the market on peak days. On the other hand, forecasts that are too high may lead to electricity prices being higher than necessary through the excessive purchase of capacity credits.

Since 2006, the IMO has engaged NIEIR to produce independent forecasts of electricity sales and summer maximum demand for the SWIS. These forecasts cover a 10 year forecasting horizon and are produced on a financial year basis.

It is important to note the current forecasting environment is characterised by a number of uncertainties and structural changes which are having a material effect on energy and maximum demand forecasts across all Australian jurisdictions.

Forecasters nationwide have been reducing their projections due to factors such as:

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3 Specifically, Chapter 4 of the Wholesale Electricity Market Rules requires median and one in 10 peak demand forecasts under low, medium and high economic growth scenarios.

- A significant rise in the penetration of solar PV systems
- Economic uncertainty associated with the level of Chinese economic activity and consequently the demand for Australian commodity exports as well as uncertainty surrounding the European and US economies
- Changing consumer behaviour in response to significant and unprecedented increases in the price of electricity, partially as a result of the introduction of a price on carbon
- Changing consumer behaviour in response to energy efficiency measures and other factors such as the introduction of time of use tariffs.

1.1 Objectives of this review

Under the Market Rules, the IMO's demand forecasting process needs to be reviewed at least once every 5 years. The main objectives of the review are to:

- Assess the demand and electricity sales forecasts and associated methodologies and determine if they are prepared according to best practice demand and energy forecasting methodologies
- Assess the accuracy of the forecasts against what would be considered to be a reasonable level of error and against alternative model specifications
- Identify and recommend improvements to the forecasting methodologies to improve performance in terms of accuracy and also the robustness and defensibility of the process to external criticism
- Assess the appropriateness of the methodologies used to account for factors that are not present in the historical data and make recommendations for improvement. These include large block loads, increasing uptake of solar photovoltaic cells and energy efficiency.
- Recommend changes to the Market Rules to enable improved demand forecasting and also to better facilitate the process.

1.2 Previous review in 2008

This review follows a review conducted by Frontier Economics in 2008.

In the previous review, a number of recommendations were made concerning the forecasting methodology designed to improve the process.

The key recommendations arising from the previous review were:

- That the Market Rules contain a requirement for a single unconditional forecast of maximum demand
- That NIEIR should provide a single unconditional forecast for maximum demand
- That NIEIR should conduct a conventional backcasting exercise that uses the actual values of the explanatory variables rather than their forecast

values to separate out and identify errors caused by difficulties in the model and model formulation from errors in the forecasts of the explanatory variables

- That NIEIR should further investigate its approach to modelling temperature sensitive load and also the approach to separating base load from temperature sensitive load.
- That NIEIR should improve the transparency of its modelling process
- That the IMO should continue to evaluate the accuracy of its forecasts as part of its annual forecasting cycle
- That the IMO should consider using more than one forecast in its planning process
- That the definition of POE in the Market Rules be clarified.

We note that while not all the recommendations were accepted, the IMO did commission the Monash University Business and Economics Forecasting Unit to produce an alternative set of forecasts in 2011, although these were not used in the 2011 SOO and the IMO did not extend this contract.

Also, NIEIR did conduct a re-evaluation of its approach to forecasting temperature sensitive load which led to the recalibration of its models to correct for an excessive number of air conditioning systems within the SWIS.

ACIL Tasman has conducted its review independently of any recommendations made previously, although this does not necessarily preclude us from reaching similar conclusions in some cases.

1.3 Data provided by the IMO

In order to conduct this review, ACIL Tasman was provided with a number of data sets and reports. These are:

- Half hourly total generation data for the SWIS both on a market sent out basis and generation status review (GSR) basis
- Data on new large loads in the SWIS, both historical and forecast
- NIEIR's annual forecasting reports from June 2006 to June 2012
- Spread sheets containing NIEIR's input assumptions and forecast maximum demand and energy outputs
- Electricity consumption data by customer class
- Temperature data from the Bureau of Meteorology's Perth weather gauge.

1.4 Structure of this report

This report is structured as follows:

- Section 2 of this report outlines a set of best practice demand and energy forecasting principles that ACIL Tasman considers any well developed forecasting methodology should incorporate
- Sections 3 and 4 provide an overview of the NIEIR and IMO approach to forecasting electricity sales and peak demand respectively
- Section 5 provides a discussion of post model adjustments made to account for policy interventions and large loads
- Section 6 critically assesses the methodology adopted by NIEIR and IMO and makes recommendations for improvement
- Section 7 summarises our findings and conclusions.

2 Best practice principles

ACIL Tasman considers that a best practice forecasting methodology would possess the following features:

- It would incorporate forecasts of each of the key drivers of demand, including demographic, economic, price and weather related factors
- Its accuracy would have been assessed, i.e. its ability to predict would have been compared against alternative models, and found to be superior
- The forecasts would have been compared with other independently produced forecasts if these are available and any differences would have been understood and explained
- It would produce forecasts that are free from bias
- The calibrated model would have been subjected to diagnostic checking and statistical validation procedures to ensure that it isn't mis-specified
- The modelling process would be transparent, repeatable and well documented
- The forecasting process would be cost-effective, with the forecasts achieving a suitable level of reliability at minimum cost.

The following sections discuss these attributes in more detail.

2.1 Incorporate key drivers

Any demand forecasting methodology should incorporate the key drivers of demand, preferably directly. These would be expected to include some or all of the following:

- Economic growth
- Population growth
- Growth in the number and size of households
- Weather drivers
- Growth in the number of air conditioning systems
- Growth in the number of heating systems
- Growth in the number and density of other appliances.

An alternative to incorporating drivers explicitly would be to rely on trend analysis. This approach inherently assumes that the drivers of demand in future will continue to reflect past patterns.

However, it is quite possible that the future behaviour of key drivers will be quite different than that observed in history. The longer the forecast horizon, the more likely this becomes. Incorporating the key drivers in the forecasting methodology explicitly, allows future changes in key driver behaviour to be included in the model with the resulting forecasts expected to be more accurate.

2.2 Weather normalisation

A key aspect of any maximum demand forecasting methodology is weather normalisation (or weather correction). It is well established that maximum demand is sensitive to weather as a consequence of heating and cooling loads. Hot conditions in summer or cold conditions in winter (in some places) coincide with maximum demand.

The stochastic nature of weather means that any comparison of historical electricity loads over time requires these loads to be adjusted to standardised weather conditions. Typically, actual demand is standardised to either, or both, a 10 and 50 per cent probability of exceedence level (POE). The 50 (10) POE demand level is the annual maximum demand level that, on average, would be met or exceeded 50% (10%) of the time. It can be thought of as the annual maximum demand that would be observed or exceeded once every two (ten) years on average.[4]

Given that the intent of load forecasting is to forecast maximum demand at a given POE level, any derived relationships with maximum demand that is based on non-normalised data will be susceptible to bias. Conclusions reached on the basis of forecasting with non-weather normalised data are likely to be erroneous and the accuracy of such models would be expected to be compromised. Hence, it is imperative that any demand forecasting methodology incorporate an appropriate form of weather normalisation or correction.

Controlling for variations in weather is also of significant importance for energy forecasting. Unseasonably cooler or warmer summer and winter periods could lead to statistically significant variations in overall annual electricity sales.

The main measures of weather used to capture how warm or cold a given year are cooling degree days (CDD) and heating degree days (HDD). These are calculated by summing the distance between some threshold (usually 18 degrees for the average daily temperature) and the actual daily temperature for all the days in a given year. For cooling degree days (CDD) only the distances in excess of the daily threshold are included in the calculation, while for heating degree days (HDD) only those distances below the average temperature

4 It does not follow from this that half of the maximum demands in any given sample of years are necessarily below the 50 POE level.

threshold are included. In this way, CDD captures how warm a given year is and gives some indication of the requirement for space cooling. HDD is a measure of how cold a given year is and captures the need for space heating.

A further issue to consider in weather normalising peak demand or controlling for weather in energy is to capture the potential impact of long run and permanent changes to weather. A well specified approach to weather normalisation allows for this possibility.

Weather normalisation of peak demand may therefore require that the historical temperature distribution that is used to weather correct peak demand be altered so as to place a greater weighting on more recent data compared to weather patterns that were observed in the distant past, say more than 40 years ago.

In the case of energy forecasting, it is well understood that the historical CDD and HDD time series have tended to exhibit long term trends which should be taken into account in the forecasting process.

2.3 Incorporate policy impacts

Econometric modelling and other techniques can be used to establish relationships between energy consumption/maximum demand and their underlying drivers based on historical behaviour. Inherent in these approaches is the assumption that there is a relationship between demand and each driver and that this relationship will not change during the forecast period.

In some cases, though, changes will occur in the relationships between demand and its underlying drivers. If these changes have not been observed in the past they will not be 'present' in the historical data. Econometric analysis will tend not to account for these changes.

The most common cause of a change in drivers is a change in policy. For example, recent policy efforts to encourage the uptake of solar panels by residential customers in the SWIS (and elsewhere in Australia) have caused the relationship between demand from the residential sector and its drivers to change (downwards).

When a policy change is anticipated it may be necessary to make an adjustment to the forecasts produced by a model or to adjust the model itself. When this type of change is made it should be done transparently, meaning that the size and timing of the adjustment should be set out clearly as should the way the adjustment itself was estimated.

The impact of policy changes could potentially be estimated in a number of ways. Depending on the circumstances it may be possible to infer the impact by:

- A desktop analysis of the likely impact
- Analysing the impact of similar policies introduced in other jurisdictions in Australia and overseas
- Considering the results from organised scientific trials on a subset of the population to be affected by the new policies.

Each of these approaches has its strengths and drawbacks.

The desktop approach is usually the simplest and lowest cost to implement but is characterised by significant uncertainty as it will usually require making numerous assumptions about consumer behaviour, often with limited empirical evidence to support them.

Inferring from the outcome of similar policies in other jurisdictions has empirical strengths but these are limited by differences in characteristics between the jurisdictions or because of variations between the policy initiatives themselves.

The use of organised trials has the benefits of experimental results from a sample of the target population but is hampered by potential problems of sample selection bias and gaming of the results by trial participants.

Any of these approaches will inevitably include a measure of subjectivity and there will often be competing views as to the 'right' answer. To support the veracity of forecasts it is important that the basis on which estimates are made is clearly and transparently articulated. This will allow stakeholders to form their own views as to the appropriateness of the assumptions made.

2.4 Transparency and repeatability through effective documentation

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. These summaries should go beyond general statements concerning the forecaster's preferred approach and be specific about the assumptions and data sources used in preparing a particular set of forecasts.

The functional form of any specified models also should be clearly described, potentially including:

- The variables used in the model
- The number of years of data, the reliability of the data and the number of missing data points (if any) used in the estimation process
- The estimated coefficients from the model used to derive the forecasts
- Details of any assumptions used in generating 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 including the explicit statement of any assumptions used.

2.5 Model validation and testing

Models derived and used as part of any forecasting process should be validated and tested. This could be 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, such as tests for autocorrelation
- Out of sample forecast performance.

Forecasts and forecasting models would ideally be subjected to *ex post* validation through a back casting exercise or similar. *Ex post* validation is not as simple as comparing the actual outcome with the forecast, especially for forecasts of maximum demand. The objective of demand forecasting is (usually) not to forecast the *actual* level of demand, but to forecast demand as it would have been under certain weather conditions, often 50% probability of exceedence.

In anything other than a weather year that accords with the basis of forecasting (e.g. a 50 POE year) actual demand outcomes should be expected to differ from the forecasts. Therefore the backcasting exercise would involve comparing modelled forecasts of history compared with weather normalised data.

2.6 Accuracy and unbiasedness

A key aspect of any forecasting methodology is that it should meet minimum accuracy requirements. All models will include errors 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's 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. In and out of sample testing and residual analysis should provide a good indication of any model bias.

2.7 Discrete block loads incorporated effectively

Apart from the normal organic growth which will occur at the substation level there are also usually larger discrete jumps in demand over time arising from block or spot loads. Block loads arise as new major developments come online, such as new mines. These loads show up as discrete jumps or relatively short ramps in maximum demand and electricity consumption.

Block loads should be incorporated into the forecasts at a level of detail suitable for the forecasts. For example, typically a more granular treatment of block loads would be suitable for distribution system forecasting rather than transmission system forecasting (largely because of the size of systems involved). Forecasting block loads can be difficult and involves the expert knowledge and judgement of local asset managers and planners.

The difficulty in accurately predicting these discrete loads arises mainly because of three sources of uncertainty. These are related to:

- The timing of the new load
- The size of the new load
- The likelihood of the new load going ahead.

ACIL Tasman considers that there will be a tendency within forecasting organisations to overstate the likely size of future block loads. This is because there is often much greater weighting given to the load proceeding rather than not proceeding. The degree of coincidence of the new load with the system peak is also often not evaluated correctly so that the true contribution to the system peak is often less than anticipated. Also, there is often a greater likelihood that a project will experience delays rather than being completed ahead of schedule. These issues should be borne in mind when forecasting and should influence the judgement of the forecaster even if they are not accounted for explicitly.

2.7.1 Potential double counting of block loads

Where econometric analysis is applied to a historical time series and individual block loads are added to the same forecast, there is a prospect of double counting the impact of block or discrete loads. Because block loads are included in the historical data, any fitted regression line will incorporate their contribution to the growth in the peak demand over time. Hence adding expected new block loads to the forecasts may result in double-counting leading to inflated forecasts.

The potential for double counting is typically reduced by applying a threshold to the size of future discrete loads, with only loads exceeding a certain size being added onto the forecast. Smaller loads are assumed to comprise part of the underlying growth determined by the historical trend. Alternatively, where an accurate record of historical block loads is available, the effect of these loads could be removed from the historical time series prior to undertaking any econometric analysis. However, in ACIL Tasman's experience, accurate historical block load data is usually difficult to access.

3 NIEIR's approach to forecasting electricity consumption

This report relates to forecasts of two distinct, but related, quantities, namely electricity sales and maximum demand. NIEIR's methodology for forecasting each of those quantities is different, though ACIL Tasman understands that the methodologies are linked to one another, as are the quantities being forecast.

This section describes ACIL Tasman's understanding of NIEIR's methodology for forecasting electricity sales. Our understanding of NIEIR's methodology for forecasting peak demand is discussed in section 4.

It should be noted that the information provided in the remainder of this section and throughout section 4 is based on information provided by NIEIR to the extent that they have been willing to provide it. ACIL Tasman has not been provided access to the models themselves and so is not in a position to verify that the models have been formulated in accordance with these descriptions.

The descriptions are provided in a factual statement form without continuous qualification that they represent ACIL Tasman's understanding based on the limitations to information and access imposed by NIEIR. This is done for ease of reading. However the qualifications apply throughout. NIEIR forecasts electricity consumption for business and residential customers and public lighting separately. The following sections provide an overview of the approach NIEIR takes to forecasting each of these categories.

The following description of NIEIR's methodology is based on NIEIR's reports to the IMO and on the outcome of a meeting between the IMO, NIEIR and ACIL Tasman in May 2012. At that meeting NIEIR advised that the methodology it used in preparing forecasts for the IMO was substantially similar to that used in other jurisdictions and, in particular, to the methodology described in connection with AEMO's (then VENCorp's) 2009 Victorian Annual Planning Report.

NIEIR's approach to forecasting electricity consumption to business customers in the SWIS is discussed in section 3.1.

NIEIR's approach to forecasting residential electricity sales is discussed in section 3.2. It is linked to the approach for forecasting business sales through the economic drivers of residential sales.

NIEIR's approach to forecasting electricity sales for public lighting is discussed in section 3.3.

The final conceptual step in NIEIR's forecasting approach is to adjust its base forecast to account for anticipated changes in the nature of electricity sales for which the base model cannot account. If, for example, a government policy is expected to drive increases in energy efficiency for which there is no historical experience, the base model is adjusted to account for this. This process is discussed in section 5

3.1 Forecasting electricity consumption of business customers

NIEIR's stated preferred approach to forecasting electricity demand by business customers is to treat electricity as an input to production and therefore to economic activity. In sectors other than residential, NIEIR's forecasts of energy demand are an output of its broader model of the economy, which is the centrepiece of its forecasting approach.

Over the years since its inception, NIEIR states that it has developed increasingly detailed models of the Australian economy. These began with a single national model and now include models of each state and some smaller regions.

An overview of NIEIR's projected outlook for the Western Australian economy is provided in each of its reports to the IMO. The outlook presented in the 2012 report is summarised below.

NIEIR's forecast of economic conditions in Western Australia is a key determinant of its forecast of electricity consumption. Its 2012 outlook is summarised in Table 1.

Table 1 **NIEIR forecasts of economic indicators for Western Australia (annual % change)**

Indicator	2011-12	2012-13	2013-14	2014-15	2015-16	Compound growth rate 2011-12 to 2015-16
Gross State Product	6.8	6.5	4.8	2.6	4.7	5.1
Private consumption	5.5	6.2	6.4	3.9	4.4	5.3
Private business investment	36.5	37.3	11.6	-5.9	-6.4	14.6
Private dwelling investment	-7.8	8.5	7.9	3.5	4.8	3.4
Government consumption	5.1	4.2	4.4	3.6	3.9	4.2
Government investment	2.5	-17.1	-17.3	22.9	16.5	1.5
State final demand	13.1	15.2	7.3	0.3	0.6	7.3
Population	2.6	2.8	2.8	2.7	2.6	2.7
Employment	2.2	4.7	2.7	1.0	2.6	2.6

Data source: (NIEIR, 2012)

NIEIR's June 2012 forecast was for strong growth in Gross State Product (GSP) for Western Australia for the foreseeable future, though there is a softening in growth forecast from 2013-14. Compared to its 2011 report, NIEIR has made a significant upward revision in its economic growth forecast for Western Australian GSP. NIEIR is forecasting an average rate of GSP growth of 5.1% p.a. between 2011-12 and 2015-16, compared with an average rate of forecast growth of 3.1% between 2010-11 and 2015-16 in its 2011 forecasts. This is driven by a significant increase in mining related business investment in 2012-13 and 2013-14, before a decline in 2014-15 and 2015-16, albeit off a very high level.

An important issue is to assess NIEIR's ability to forecast economic growth, over an extended period. Section 6.2 contains a comparison of NIEIR's forecasts of WA GSP and population growth against actual outcomes. As discussed in that section, analysis of NIEIR's forecasting performance over a longer time frame indicates that on average they are consistent over the historical time frame, but they exhibit much greater volatility than is apparent in the historical data with pronounced boom and bust cycles.

NIEIR disaggregates its projection of economic activity in the SWIS by industry class. Then, using electricity intensities for each industry class (discussed below) it indexes growth in economic activity to produce projections of growth in electricity consumption.

Therefore, the key step in NIEIR's approach to forecasting electricity sales to business customers is to link electricity consumption to its forecasts of economic activity.

NIEIR does this by applying an output elasticity of demand for electricity. That is, an estimate of the relationship between electricity consumption and output for each sector. As we understand it, NIEIRs methodology does not allow for changing energy intensity over time.

In some states other than Western Australia, NIEIR has estimated sectoral output elasticities directly. To do this, NIEIR matched individual business customers with their industry class.[5]

This matching process requires that (business) customer details such as name and address are provided to NIEIR. These have not been provided in the SWIS region, so NIEIR has been unable to estimate output elasticities specifically for Western Australia.

NIEIR's report to IMO states that in the absence of estimated output elasticities, it used data obtained from the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) regarding the State-level electricity intensity of industry. From our discussions with NIEIR we understand that in some cases it may have regarded the Western Australian intensities as unsuitable for use in the SWIS context. In those cases NIEIR chose to use intensities estimated in other jurisdictions.

NIEIR's report also states that adjustments were made to the electricity consumption forecasts to the base metals and mining sectors. The changes to the base metals sector were required to account for cogeneration plants at alumina refineries. The detailed rationale for these adjustments has not been provided, nor have the adjustments themselves been specified. This is an example where the forecasting process relies on judgement (in this case NIEIR's judgement) and how the application and use of such judgement should be set out transparently.

3.2 Residential consumption

Residential consumption forecasts were prepared using a model including average consumption per dwelling, weather, real income and electricity prices.

The conceptual approach is divided between existing and new dwellings, with a different average consumption per dwelling assigned in each case. The differences in the average used are driven by factors including Western Australia's recent adoption of a mandatory six star energy efficiency rating for new homes and ongoing changes in appliance efficiency.

5 In practice we understand from discussions with NIEIR that this is typically done using a sample of small and medium business customers.

The residential consumption forecasts are linked to business consumption forecasts through the projection of real income per capita, which is taken from NIEIR's economic model.

Effectively, NIEIR uses its internal projection of new housing construction and an assumed rate of replacement of existing homes and projects consumption forward on a 'per house' basis using an estimate for the likely electricity consumption of an average new home.

Electricity price assumptions are summarised in NIEIR's report to the IMO. They include an adjustment for the carbon price which is to be introduced in July 2012. Prices and the carbon price are discussed together in section 5.2 below.

3.3 Public lighting

NIEIR's report contains no information concerning the way that its forecasts of electricity sales for public lighting were prepared. We understand that, NIEIR bases its forecasts of electricity sales for public lighting in Victoria on its own infrastructure construction forecasts.

Public lighting is a very small proportion of total electricity consumption and is understood to have a very predictable profile. While it would be an improvement if the basis of public lighting forecasts were discussed in more detail, the likelihood is that it would have little effect on the electricity consumption forecasts and none on the maximum demand forecasts given that peak demand tends to occur during daylight hours in summer.

4 NIEIR's approach to forecasting maximum demand

NIEIR's approach to forecasting peak demand in the SWIS can be thought of as dividing demand into four components:

1. temperature sensitive load
2. temperature insensitive load
3. major industrial load
4. embedded generation (negative load).

These four components are forecast independently of one another. The methodologies used to forecast each of them are discussed in turn below.

The following description presents the approach as sequential and staged. This is done for ease of presentation and does not necessarily reflect the sequence in which forecasts are prepared.

The description in this section excludes the process for incorporating block loads because these are estimated by the IMO and added to NIEIR's base forecasts. This process is discussed in section 5.

4.1 Temperature sensitive load

Temperature is an important driver of variation in electricity demand. As NIEIR states, the temperature sensitive component of demand is "unambiguously associated with cooling equipment including air conditioner, fans and refrigerators." (NIEIR, 2011, p. 33)

The first step in forecasting temperature sensitive demand is to estimate the relationship between demand and temperature (i.e. the temperature sensitivity).

To do this, NIEIR disaggregates electricity demand into temperature sensitive and temperature insensitive components by identifying demand on "a mild day" (mild in terms of weather conditions). Demand on this day (or days) is defined as being temperature insensitive demand only.[6] The difference between this demand and the demand observed on other days is attributed to temperature and defined as temperature sensitive demand.

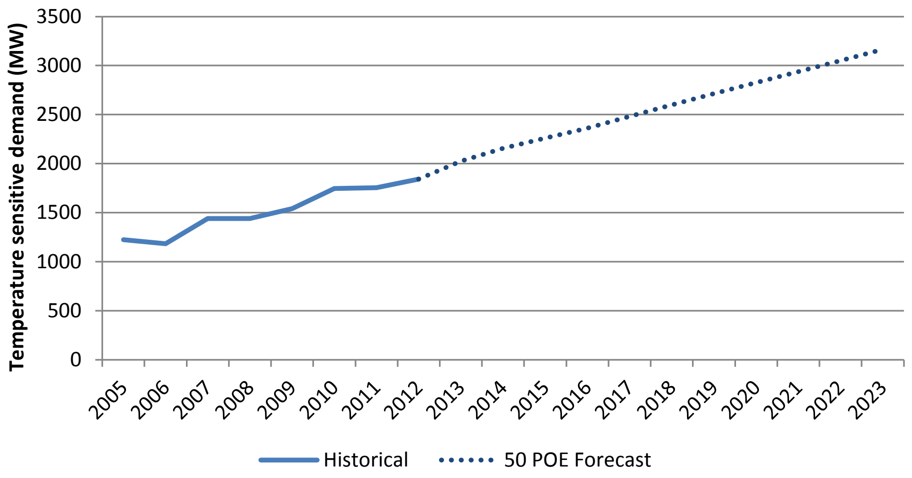
In addition to the direct relationship between temperature and demand, NIEIR has attempted to account for increased penetration of cooling equipment. The

6 NIEIR refers to this as 'base load' demand in its reports.

possibility that temperature *yesterday* might influence demand *today* was also taken into account by using lagged temperature variables (NIEIR, 2011, p. 34).

Figure 1 shows NIEIR's temperature sensitive demand series both historically since 2005 and as projected to 2023.

Figure 1 **Temperature sensitive demand – SWIS, 2005 to 2020**



Data source: NIEIR

Historically, temperature sensitive demand increased at a compound annual rate of 6.0 per cent per annum between 2005 and 2012. However, this growth rate is based on data that has not been weather corrected and so should not be treated as true growth. Part of this variation is due to year on year variability in weather conditions.

In the projection, NIEIR forecasts that temperature sensitive demand, calculated on a 50 per cent POE basis, will grow at an annualised rate of 5.0 per cent per annum to 2023.

NIEIR's forecast of temperature sensitive demand is a function of: temperature along with calendar effects which account for outliers and holidays.

The temperature variable takes account of the ambient temperature in each interval and the daily maximum and minimum temperatures. Together, these are used to estimate the temperature sensitivity of demand in the region in question. This coefficient is then projected forward to take account of changes in the take up of weather sensitive appliances, in particular air conditioners.

Similarly, the estimated coefficients associated with the calendar effects (outliers and holidays) are increased in line with growth in temperature insensitive electricity consumption.

Prior to 2011, , NIEIR had projected a substantial increase in the uptake of air conditioners. In its 2010 report it said:

> The penetration of space cooling equipment has increased dramatically in the SWIS in Western Australia over recent years reflecting:
>
> i. the impact of warm summer temperatures on discretionary purchases of space cooling equipment;
>
> ii. improved marketing penetration and technological advances in space cooling equipment;
>
> iii. the coincident increase in construction activity in both the commercial and residential sectors. The increase in townhouse and apartment construction for residential dwellings are particularly suited to reverse cycle AC units;
>
> iv. the continued ageing of the population and the associated expansion in retirement villages for senior persons.
>
> The annual increase in summer temperature sensitive load since 1999-00 is over four times the annual increase over the first part of the 1990s and explains the steadily rising SWIS summer MDs over the last four years.

As a result, NIEIR modified its methodology to account for this significant increase in the uptake of air conditioners. However, this appeared to overstate the importance of air conditioners in the demand forecasts, which suggests that a larger portion of new air conditioners were used as either replacements or as second (or subsequent) air conditioners in buildings that already had air conditioning. In 2011, NIEIR reduced the assumed impact of incremental air conditioners on maximum demand.

Actual demand as observed is then normalised by adjusting a central estimate to account for weather in a deterministic way based on the observed relationship between maximum demand and temperature, i.e. increased (decreased) by a certain number of MW for each degree above (below) the 50 POE level.

The relationship between temperature and peak demand can also be estimated using a simulation approach. NIEIR's PeakSim model takes half hourly load and temperature data into account to produce a model of the intra-day relationship between temperature and peak demand. Synthetic distributions of demand and temperature are then produced using bootstrapping methods that preserve the relationship between temperature and demand while allowing for the effects of urban and global warming on both recent and future temperature trends. This is done by sampling from recent years with a higher probability than earlier years.

The Peaksim approach was used for the first time in Western Australia in 2011 as a cross check. It has not yet been used exclusively as the basis for forecasts.

4.1.1 Weather normalisation and calculation of the 10 POE and 50 POE maximum demands

In weather normalising maximum demand in the SWIS, NIEIR utilise a temperature distribution derived from the average of the daily overnight minimum and daily maximum temperatures in Perth. The distribution is calculated from a 50 year temperature time series for Perth. The two main Bureau of Meteorology weather gauges used in the calculations are Perth Airport and Mt Lawley. The gauge at Perth Airport closed in 1993, after which Mt Lawley was used as the main data source.

The summer season in NIEIRs methodology is assumed to include the months of December, January, February and the first half of March up to March 15. The summer season is expanded into March to capture the fact that extremely hot days in early March can give rise to peak demand days. Winter is assumed to be June, July and August.

The summer time series used for the purposes of the calculations covers the period from 1960 to 2012. The winter period time series starts from 1970.

The time series of calculated average temperatures in Perth is then used to generate temperature percentiles that correspond to the probability that the temperature in any given year will exceed some level. NIER calculates the 10%, 50% and 90% POE temperatures as a means of calculating the corresponding temperature normalised level of maximum demand.

The 10, 50 and 90% POE average temperatures are shown in Table 2 below.

Table 2 **Perth average temperatures associated with 10%, 50% and 90% POE maximum demands**

	Winter	Summer
10 POE average temperature	7.3	34.6
50 POE average temperature	8.5	32.2
90 POE average temperature	9.2	31.2

Data source: NIEIR (2012) report, Electricity consumption and maximum demand projections for the SWIS to 2022-23

NIEIR then apply an estimated relationship between maximum demand and average temperature which is used to correct the actual observed maximum demand to the 10%, 50% and 90% POE level of maximum demand. They do this by using non-linear switching regression models for temperature sensitive load. The estimated relationship between maximum demand and average temperature follows a non-linear S curve. This means that the ramp up in maximum demand differs by the temperature range. At low temperatures load increases slowly per degree up to 24 degrees Celsius, accelerates per degree up to 27 degrees before slowing down again at higher temperatures. The 10%, 50% and 90% POE maximum demands are then calculated by moving along this non-linear S curve.

4.2 Temperature insensitive load

Temperature insensitive load includes parts of commercial, industrial (excluding major industrial) and residential load.

As discussed below, the key driver of NIEIR's forecasts of temperature sensitive load is air conditioning (space cooling). This does not necessarily imply that air conditioning plays no part in temperature insensitive load. NIEIR leaves room for the possibility that some units may operate during 'base load' times.

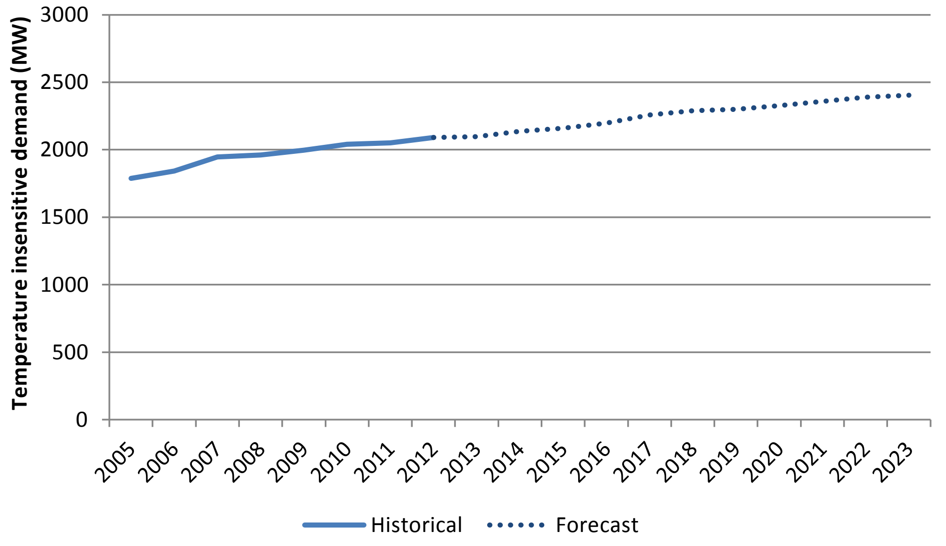
NIEIR calculates the temperature insensitive load by assembling all the 4 pm readings of maximum demand for the season after excluding all non-working days. The maximum demands are then ranked from the lowest average temperature to the highest. The temperature insensitive load is then calculated as the average daily maximum demand over some average temperature range after excluding any identified outliers. For summer, the base load is estimated as the average of all 4 pm maximum demand readings for average temperatures between 19 and 22 degrees Celsius.

As with the forecasts of electricity consumption, which are derived from the same models, NIEIR forecasts temperature insensitive load on the basis that electricity is an input to economic activity (i.e. an input to production). In using forecast economic activity at a sectoral level and the estimated or assumed 'electricity intensity' of each sector, NIEIR forecasts demand at a sectoral level.

Figure 2 shows NIEIR's estimate[7] of the historical temperature insensitive demand along with the projection.

[7] Temperature insensitive demand is not observable as such.

Figure 2 **Temperature insensitive demand – SWIS, 2005 to 2023**



Data source: NIEIR

Historically, NIEIR's estimate of temperature insensitive demand grew at a compound annual growth rate of 2.3 per cent per annum between 2005 and 2012. In the projection, it is projected to grow slower, at 1.3 per cent per annum from 2012 to 2020.

NIEIR's forecast of the temperature insensitive component of peak demand by business customers is linked to its projected growth in business customer electricity consumption. As discussed in section 3.1 above, that projection is driven by NIEIR's projection of economic activity. NIEIR also takes account of appliance take up rates, energy prices and anticipate changes in policy.

Forecasts of the temperature insensitive component of demand by residential customers are driven by average consumption per dwelling, real income, electricity prices and NIEIR's forecasts of population growth.

4.3 Major industrial load and embedded generation

The remaining components of total demand are demand from major industrial customers and demand for street (public) lighting.

Major industrial loads are treated exogenously to NIEIR's model. Their intentions are monitored on a case by case basis and their anticipated load is added to the modelled forecasts in line with those intentions.

Similarly, embedded generators, which reduce peak load from a grid based supply point of view as long as they are operating at the relevant time, are dealt with exogenously from the model on a case by case basis. While Western

Australia has a relatively high proportion of cogeneration compared with Eastern Australian jurisdictions, this consists mainly of a relatively small number of large plants.

As with major industrial loads, the anticipated output of cogeneration plants is subtracted from maximum demand based on the past performance of existing plants and the stated intentions of new plant operators.

5 Post model adjustments

The forecasts prepared by the processes described above are not the IMO's (or NIEIR's) final forecasts of electricity consumption or demand. The methodology described above is not intended to take account of changes in electricity consumption that are not reflected in either the forward price or in the historical data.

It is conventional practice to adjust the forecasts to take account of factors that are anticipated to influence electricity consumption over the forecast period, but that have not been experienced in the past and cannot be 'seen' in the historical data.

In the past forecasts two major adjustments have been made. In 2012, a third was also added. These adjustments are made to account for:

1. Large block loads
2. Greenhouse gas emissions reduction policy
3. Solar panel uptake

Each of these adjustments is discussed in turn below.

5.1 Large block loads

A significant source of uncertainty in electricity consumption forecasts for the SWIS relates to large loads.

The forecasting methodology employed by NIEIR, as with most econometric methodologies, relies in part on the assumption that the relationship between drivers is fixed. In particular, the methodology relies on the assumption that a change in Western Australia's GSP will be associated with a corresponding change in electricity consumption.[8]

However, in some cases, growth can be 'lumpy', with incremental changes in GSP associated with more significant changes in electricity consumption. This can occur when an individual project causes electricity consumption to change substantially, in particular if it begins using electricity before it contributes to increased GSP.

8 The relationship itself is not linear, but is expressed as an elasticity, i.e. the ratio of two percentage changes.

To account for this, the IMO has traditionally made adjustments to the forecasts prepared using the methodology described in the previous sections. Those adjustments have each been associated with identifiable loads[9] and were based on IMO's best understanding of the likely timing and demand of each load. As a result of a tendency to over-predict large new loads, the IMO has adopted a considerably more conservative view on block loads in 2012 compared to previous years.

5.2 Carbon price

The introduction of the carbon price from July 1 2012 makes it necessary for the SWIS forecasts to incorporate any expected effect of the carbon price on both maximum demand and electricity sales in the forecasts.

NIEIR have done this in 2011 by making some assumptions about the total effect of the tax over time on wholesale electricity prices, and then calculating an impact through the application of a price elasticity of demand for electricity.

The impact of the proposed carbon price was first accounted for in NIEIR's June 2011 report covering the forecast period to 2021-22. The underlying assumptions were amended in the 2012 forecasts to reflect the availability of more up to date information.

While we discuss incorporating the impact of the introduction of a carbon price in this section as a post model adjustment, it is important to note that technically the carbon price impact operates in NIEIRs model through the price variable which is adjusted to account for the introduction of a carbon price in addition to other factors which influence price. It is therefore technically not a post model adjustment.

5.3 Solar photovoltaic cells

The IMO has for the first time in 2012, attempted to forecast the contribution to maximum demand and electricity consumption of the rapid uptake of small scale photovoltaic systems (PV) in Western Australia.

Solar PV generation has increased significantly in recent years in response to Government subsidies such as feed in tariffs and the Solar Credits scheme under the Federal Government's Renewable Energy Target.

Small customers installing solar PV have been eligible for various levels of renewable energy subsidy under the Solar Credits scheme through the upfront creation of a multiple of 15 years worth of renewable energy certificates

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9 The loads were identifiable to IMO, though their identities were not always published.

commonly known as RECs (replaced by small-scale technology certificates or STC from 1 January 2011) deemed to be created by the installation (on the first 1.5 kW installed). The initial multiplier for the year 1 July 2010 to 30 June 2011 was five scaling down over time. These deemed REC/STC were usually acquired by the company installing the solar PV in consideration for a reduction in the installation price – hence the Solar Credits program in effect provided a capital cost subsidy.

Due to the unexpected uptake of small-scale solar PV the multiplier schedule has been revised down in effect reducing the capital subsidy available. However the rapid fall in capital costs of solar PV over a similar time period has meant that strong incentives to install small-scale solar PV remain.

Western Australian customers who installed solar PV systems between 1 August 2010 and 1 August 2011 are also entitled to receive a premium feed-in tariff. The payment began at 40 cents per kWh exported for customers who applied for connection between 1 August 2010 and 30 June 2011.

In May 2011 the Western Australian Government announced that its feed-in tariff scheme was to be amended. Customers who applied for connection from 1 June 2011 would receive 20 cents per kWh for electricity they exported. The new payment was only to be payable until the total capacity of solar PV systems installed under the feed-in program reached 150 MW.

The 150MW threshold was reached quickly and, on 1 August 2011, the 20 cent per kWh premium feed-in tariff was closed to new applicants.

Customers who accessed either the 40 or 20 cent per kWh feed-in tariff will continue to receive that payment for ten years. Other customers in the SWIS receive 7 cents per kWh for electricity they export to the grid.

The IMO's 2011 forecasts did not include an adjustment for the uptake of solar PV systems. Notably, the output of solar PV systems is not observed by the IMO directly. It is simply reflected in observed reductions in consumption.

The absence of an appropriate adjustment for PV systems from the 2011 forecasts is likely to have contributed to the forecast electricity sales and peak demand being too high.

While the premium feed-in payments have been closed for new applicants, the upfront cost of PV systems is now significantly lower than in recent years, continues to receive some capital cost subsidy under the Solar Credits scheme and is projected to continue to fall.[10]

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[10] For further discussion see section 3 of ACIL Tasman, "Analysis of the impact of the Small Renewable Energy Scheme", November 2011, available online at

The ongoing uptake of solar systems is expected to further reduce electricity consumption and maximum demand, and hence also reduce the future requirement for generation and demand side management.

The base forecasts for 2012 have been developed on an assumption of 2,000 units installed per month, reducing to 1,750 systems as penetration starts to increase.

The forecasts also assume an increasing system size from 2kW to 2.5kW by 2020.

http://www.aemc.gov.au/Market-Reviews/Completed/impact-of-the-enhanced-renewable-energy-target-on-energy-markets.html

6 Assessment of NIEIR and IMO's forecasting approach to energy and maximum demand

This section assesses the NIEIR and IMO approach to forecasting maximum demand and electricity consumption in the SWIS.

The assessment is made against the set of best practice principles described in section 2 of this report.

6.1 Inclusion of key driving variables

The modelling process for both maximum demand and energy seeks to incorporate the influence of the main economic, demographic and weather drivers.

ACIL Tasman considers this to be an important attribute of any maximum demand and electricity consumption forecasting methodology. By explicitly including these drivers, the models will have the flexibility to account for anticipated changes in the underlying trends of economic and population growth, something that would not be possible if the models were based on more technical rather than fundamental approaches.

However, the problem remains of having to provide forecasts of the input drivers into the modelling process to generate the required demand and electricity sales forecasts. The accuracy of the final forecasts are dependent on the quality and accuracy of the forecasts of these inputs.

NIEIR's report outlines its view of the economic outlook for Western Australia as a whole. However, it provides no information regarding NIEIR's approach to forecasting economic activity in the SWIS region or the inputs it uses in preparing the SWIS region forecasts on the grounds that the details are NIEIR's intellectual property. In meetings, NIEIR preferred not to provide any information regarding these matters other than to say that it applies a Generalised Leontief framework in preparing economic forecasts.

The NIEIR approach to providing information about inputs arguably does not meet the standards of transparency that one might expect for a set of forecasts that have such important consequences for all Western Australian generators and users of electricity.

6.2 Forecast accuracy and bias[11] of economic and demographic inputs

6.2.1 Forecasts of economic growth

NIEIR uses its own internal proprietary models to forecast Western Australian GSP growth and therefore maximum demand and electricity consumption.

ACIL Tasman notes that NIEIR's approach to forecasting GSP appears to be based on a business cycle generated by its models which leaves the demand and electricity sales forecasts susceptible to considerable error if the forecast business cycle does not eventuate, or potentially an even more perverse outcome where the business cycle eventuates but not in synchronism with that forecast by NIEIR. This is particularly so because of the compounding effect of economic growth over time, so that if the first year of the forecast period contains a very high forecast rate of GSP growth which does not eventuate, then this error in growth rate is likely to feed through into the demand and electricity sales forecasts and lead to errors throughout the entire forecast period.

It should be noted that the last 5 years commencing with the onset of the GFC in 2007 have proven to be very challenging time for all economic forecasters. As a small open economy Australia is highly dependent on global economic conditions which have been and continue to be highly uncertain. The US sub-prime crisis was followed by the European sovereign debt crisis which is still unfolding and in all probability still has some way to run. There is also considerable uncertainty surrounding the extent to which the Chinese economy is expected to slow. All these factors play a strong role in determining demand for Australia's natural resources and consequently the health of the underlying economy, particularly in Western Australia.

In this section, ACIL Tasman analyses the accuracy of NIEIR's forecasts of Australian GDP and Western Australia GSP growth.

Australian GDP growth

Figure 3 presents the historical annual growth in Australia's (real) GDP along with NIEIR's forecast to 2022 and the Treasury's forecast to 2014-15. In order to illustrate the evolution of NIEIR's forecasts the figure also shows the

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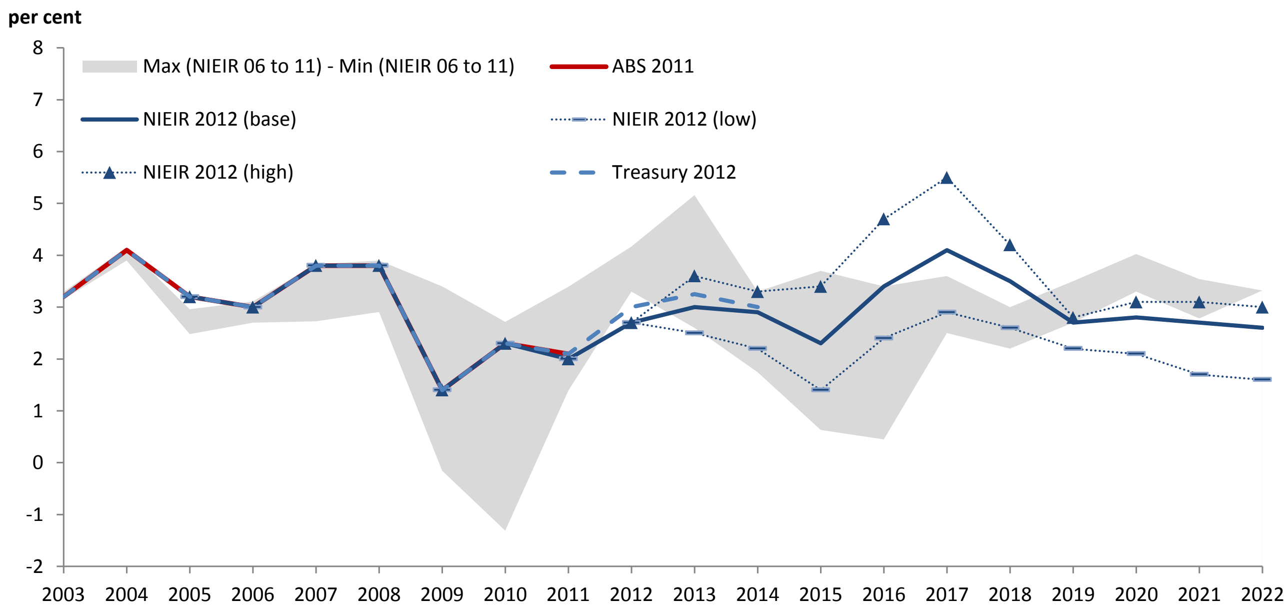
[11] It is important to recognize that we are referring to a statistical notion of bias here that refers to a tendency for forecasts to consistently over or under predict actual outcomes. The use of the term bias in this report in no way suggests any dishonesty or favouritism on the part of the forecaster as may be implied by popular understanding of the term.

differences between the maximum and minimum growth forecast made between 2006 and 2011.

Figure 3 **Australian GDP: NIEIR forecast vs. ABS data and Treasury forecasts**



Note: All years are financial years. Variation in the historical years preceding 2006, denoted by the shaded area, can be attributed to historical revisions by the ABS

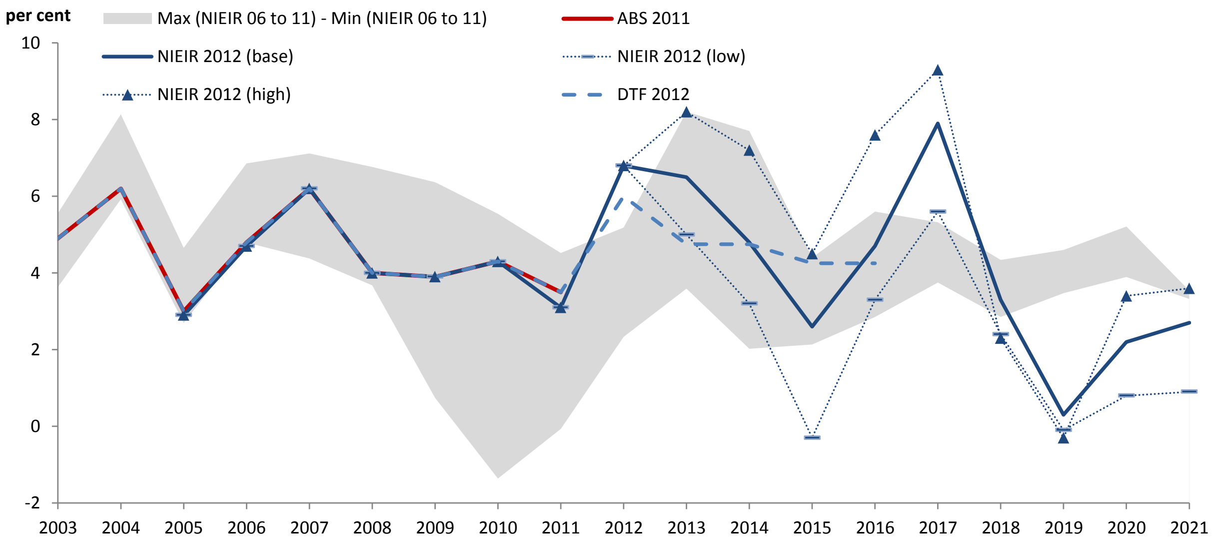
Data source: NIEIR, Treasury Budget 2012-13and ABS cat 5220 table 1

NIEIR's base forecast projects relatively steady growth of around three per cent p.a. This level corresponds to the average annual growth rate of the last decade. NIEIR's forecasts align with the latest Treasury figures. When the forecasts from earlier years are taken into account, NIEIR's predictions appear more volatile than the historic data. Predicted downturns tend to be followed by upswings creating a tendency towards boom and bust scenarios which are not nearly as apparent in the historic ABS data.

Western Australian GSP growth

Figure 4 presents the historical annual growth in Western Australia's real GSP along with NIEIR's forecast to 2021 and the Western Australian Department of Treasury and Finance's (DTF) forecast to 2015-16. To illustrate the evolution of NIEIR's forecasts the figure also shows the differences between the maximum and minimum growth forecast made between 2006 and 2011.

Figure 4 **Western Australia GSP: NIEIR forecast vs. ABS data and DTF forecasts**



Note: Variation in the historical years preceding 2006, denoted by the shaded area, can be attributed to historical revisions by the ABS

Data source: NIEIR, DTF State Budget 2011-12 Paper No. 3 and ABS cat 5220 table 1

Both the NIEIR and DTF Western Australian growth forecasts differ significantly to the Australian GDP forecast. While GDP is expected to grow at average rates over the next few years, NIEIR expect the Western Australian GSP to experience very high growth rates in this period. The tendency in the NIEIR forecast is towards boom and bust which is much more pronounced than in the NIEIR GDP forecast; again high growth is always followed by a low growth phase.

NIEIR expect a growth slowdown in 2014 and 2015. The forecast growth rate is almost two per cent points lower than the DTF forecast. The predicted slowdown falls into a period in which a range of major resource projects are expected to commence production (e.g. Gorgon) while others are expected to be at their construction peak (e.g. Wheatstone). Typically periods in which exports increase and a high level of investment is maintained do not cause GSP growth to stall.

The accuracy of NIEIR's GDP and GSP forecasts are shown in Table 3 below.

The size of the absolute deviation from the true value is measured by the average absolute deviation (MAE), with the average percentage error (PMAE) also defined. The bias direction indicates whether there is a tendency for the forecasts to under or over predict over the sample. Definitions of these measures are provided in Appendix A. It is important to note that these calculations are, in this instance, based on a small number of observations. The measures are therefore susceptible to significant movement as a result of the inclusion of new data in the calculation. It is therefore important to keep this in mind when evaluating the results and drawing conclusions on this basis.

Results are shown for current, one period, two period, three period, and four period ahead forecasts. The results show that the average percentage errors of the forecasts are less than 10%, which we consider to be reasonable.

The Australian GDP forecasts display a tendency to be biased downwards for the current period up to two years ahead, but then exhibit an upward bias for the three and four year ahead forecasts.

In the case of Western Australian GSP, NIEIRs forecasts have historically been below actual GSP. The forecasts have proven to be slightly downward biased in the earlier part of the forecast horizon, while the size of the bias increases with the forecasting horizon. For the four year horizon, all forecasts of Western Australian GSP under-predicted.

Table 3 **Accuracy and bias of NIEIR's economic growth forecasts**

	Sample size	Average deviation (MAE)	Average percentage error (PMAE)	Bias direction
	no.	% points	%	%
Australia real GDP				
Current year accuracy	6	0.58	3.51	-70.51
Current + one year ahead	5	1.56	10.93	-15.73
Current + two years ahead	4	0.76	6.31	-6.00
Current + three years ahead	3	0.51	4.86	81.34
Current + four years ahead	2	0.69	10.17	42.17
Western Australia real GSP				
Current year accuracy	6	1.75	6.57	-6.42
Current + one year ahead	5	2.55	10.99	-1.94
Current + two years ahead	4	1.33	7.04	-46.21
Current + three years ahead	3	0.60	3.99	-63.86
Current + four years ahead	2	1.10	9.99	-100.00

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 5220 and 3101.

As a basis of comparison we have computed accuracy and bias statistics to evaluate the WA Department of Treasury and Finance's forecasting performance for WA GSP.

The results are shown in Table 4 below. NIEIRs GSP forecasts have proven to be moderately less accurate than WA Treasury's over current and current plus one year horizons. Over the current plus two and current plus three year forecast horizons the NIEIR forecasts have outperformed those of the WA Treasury.

Table 4 **Accuracy and bias of WA Treasury's economic growth (GSP) forecasts**

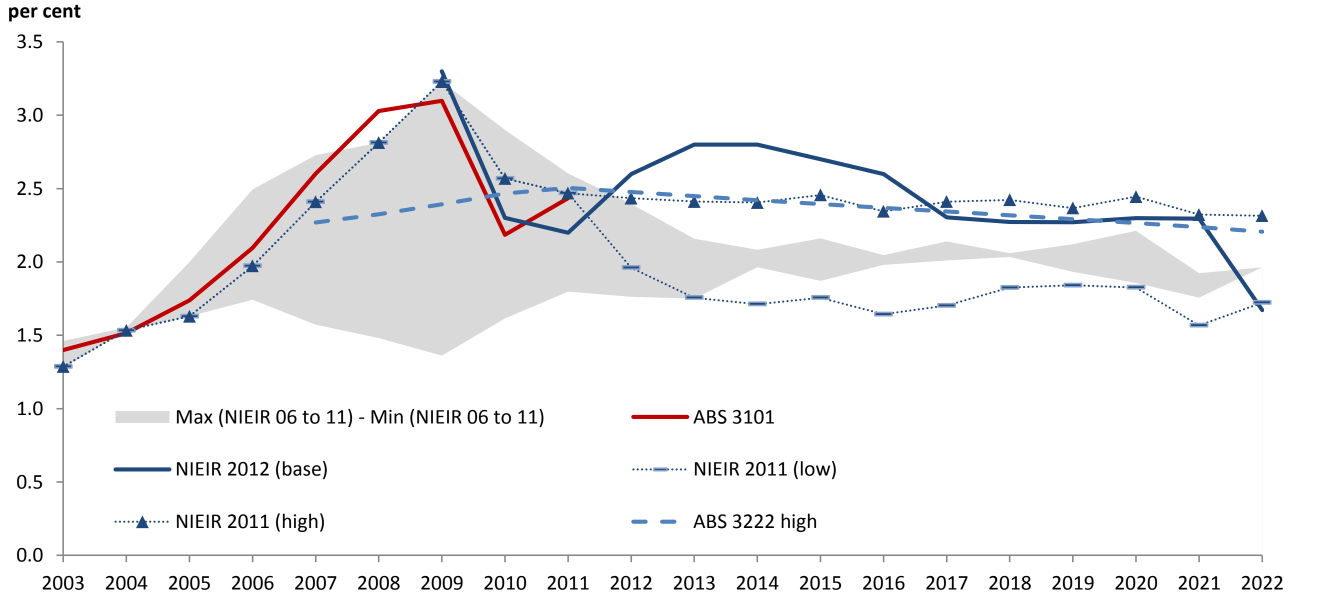
	Sample size	Average deviation (MAE)	Average percentage error (PMAE)	Bias direction
Western Australia GSP	no:	% points	%	%
Current year accuracy	6	1.48	5.56	82.02
Current + one year ahead	5	2.07	8.92	-25.60
Current + two years ahead	4	1.70	8.99	-25.00
Current + three years ahead	3	0.60	4.00	100.00
Current + four years ahead	2	0.60	5.45	100.00

Data source: WA Department of Treasury and Finance

6.2.2 Forecasts of population growth

Figure 5 presents the historical annual population growth in Western Australia along with NIEIR's forecast to 2022 and the ABS forecast for the same period. In order to illustrate the evolution of NIEIR's forecasts the figure also shows the differences between the maximum and minimum growth forecast made between 2006 and 2011.

Figure 5 **Population Western Australia: NIEIR forecast vs. ABS data and ABS forecasts**



Data source: NIEIR and ABS cat 3101 and cat. 3222 (high scenario)

First it is important to note that NIEIR seems to have adopted a revised population forecast methodology for their 2010 forecasts. The pre 2010 forecasts are very conservative and project only four years ahead. The 2010 and 2011 forecasts in contrast project until 2022. It is also interesting that NIEIR's historic numbers do not align with ABS numbers. NIEIR has stated that they use their own series of historical population.

Until the 2012 forecast NIEIR's base forecast appeared conservative. After peaking prior to the GFC, population growth slowed down. NIEIR expected a continuation of this trend and growth rates to stabilise around two per cent. The latest ABS estimates in contrast suggest a reversal of the downward trend took place in 2010-11. NIEIR has acknowledged this and corrected the forecast upward. Averaging almost three per cent the latest population forecast is well above the 2011 high scenario as well as the ABS high scenario.

The performance of NIEIR's population growth forecasts are shown in Table 5. The results show that the average percentage error is generally within 10% apart from the 3 year ahead forecasts, which have an average percentage error in excess of 12%.

However, ACIL Tasman notes that there is a strong negative bias associated with the NIEIR historical population forecasts.

Table 5 **Accuracy and bias of NIEIR's population forecasts**

	Sample size	Average deviation (MAE)	Average percentage error (PMAE)	Bias direction
	no.	% points	%	%
Western Australia Population				
Current year accuracy	6	0.65	4.20	-61.53
Current + one year ahead	5	0.75	5.77	-91.02
Current + two years ahead	4	0.98	9.08	-100.00
Current + three years ahead	3	0.98	12.69	-100.00

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 5220 and 3101.

ACIL Tasman considers that the NIEIR forecasts of Australian GDP, Western Australia GSP and population growth are reasonably accurate in terms of the average percentage error. However we consider that the negative bias associated with the longer horizon forecasts for Western Australia GSP and population growth offers some scope for improvement in forecast performance.

6.2.3 Conclusion – forecasts of economic drivers

ACIL Tasman recommends that NIEIR analyses the tendency for its models to under-predict Western Australia GSP and population growth over longer time horizons, and as a result of this analysis identify methodological improvements that seek to rectify the negative bias.

As these variables are key inputs into the energy and maximum demand forecasting process, any improvements in the ability to forecast the inputs should lead to improved energy and demand forecasts.

6.3 Maximum demand and energy forecast accuracy and bias

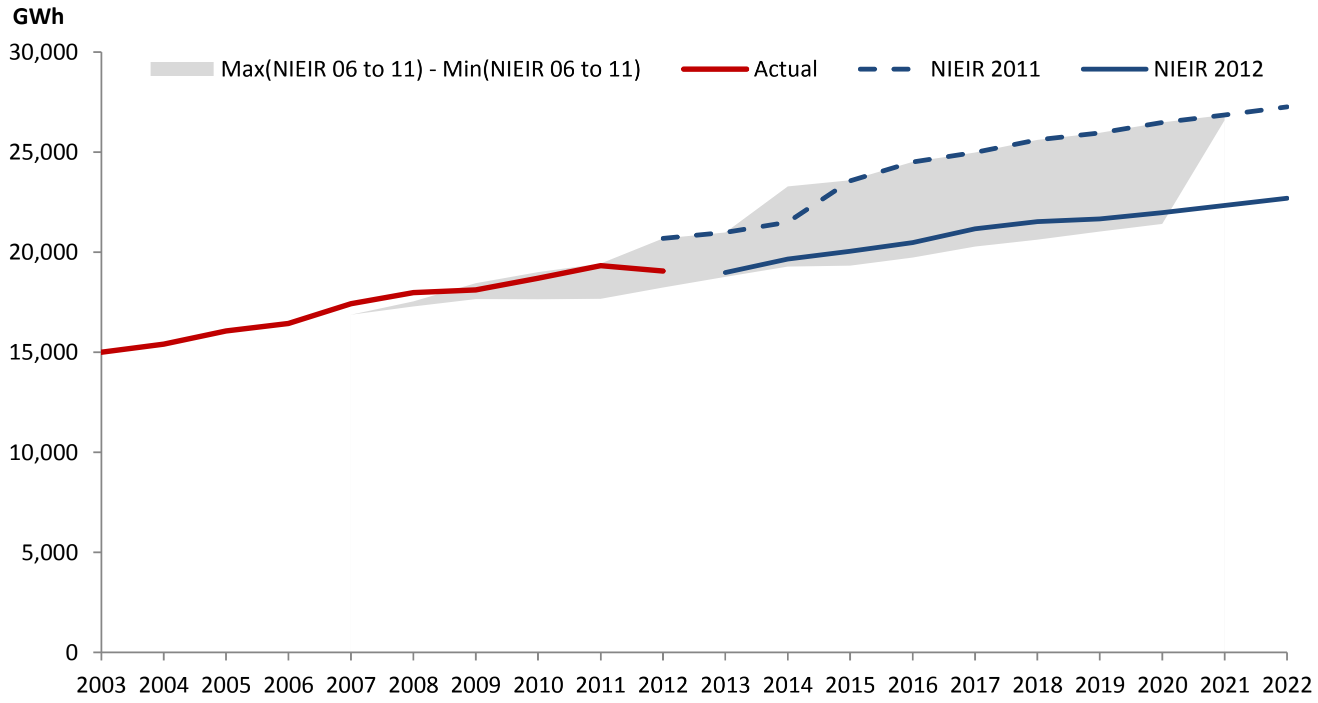
In this section we specifically analyse the performance of the energy consumption and the maximum demand forecasts. We use the forecasts provided by NIEIR from June 2006 to June 2012.

6.3.1 Energy consumption forecast accuracy and bias

Figure 6 shows actual electricity sales for the SWIS region as well as NIEIR's base forecasts from June 2011 and June 2012, and the difference between the maximum and minimum forecast for each year in the forecasting horizon (as shown by the area shaded in grey).

The figure shows that the electricity consumption forecasts follow a fairly narrow range in the early part of the forecast horizon which tends to get wider over longer time horizons. This is expected given the compounding effect of small variations in the rate of underlying growth between the sets of forecasts.

Figure 6 **Electricity consumption: NIEIR forecasts vs. Actuals**

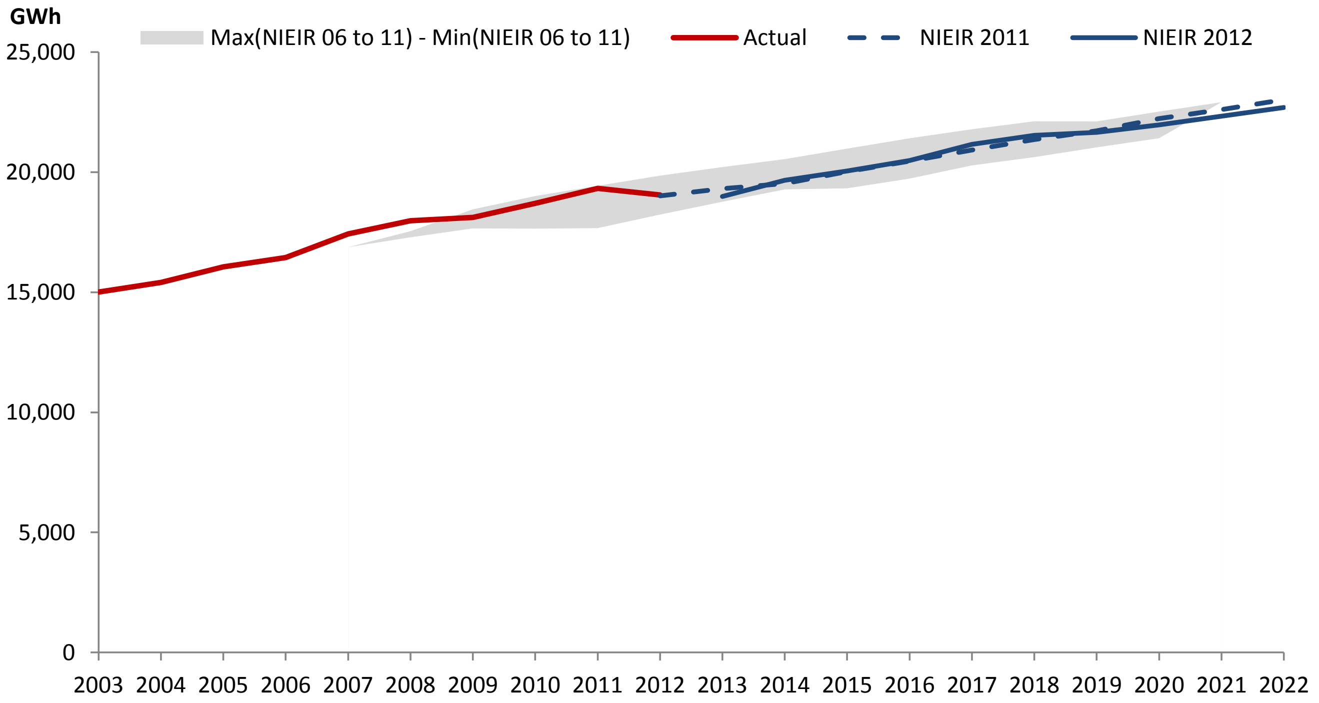


Data source: NIEIR and ACIL Tasman

Figure 6 shows a major downward adjustment in the 2012 electricity consumption forecasts relative to 2011. This is largely the result of a downward revision in the number and size of new large loads which appeared to be overstated in the 2011 forecasts. Neither this adjustment nor any initial overstatement can be attributed to NIEIR as these new large loads are provided to NIEIR by the IMO and added to the NIEIR base level forecasts.

Figure 7 shows the NIEIR 2011 and 2012 forecasts but with the large new loads for these years removed from the totals. The two sets of forecasts now track quite closely with the 2012 forecast slightly above the 2011 forecast for most of the forecast period.

Figure 7 **Energy consumption: NIEIR forecasts vs. actuals (excluding large new loads)**



Data source: NIEIR and ACIL Tasman

Table 6 shows the accuracy and bias statistics of the electricity consumption forecasts over time horizons up to four years ahead. Results are presented for total consumption and by sector.

It is important to note that the forecasts are evaluated against non-weather corrected actuals. One of the sources of deviation between electricity consumption and the observed actuals in any given year will therefore be the weather conditions in that year. This is of greater importance to the forecasts of maximum demand which are affected by weather conditions on a single or small number of days compared to electricity sales which are influenced by weather conditions over the course of the whole year.

For this reason, some care needs to be exercised when comparing the forecast energy consumption with what is actually observed. This is more important for the time horizons which have fewer observations available to use in the error calculation. As the number of observations increase the effect of extreme weather years is averaged out of the calculation. For this reason the error calculations based on the shorter forecast horizons can be considered to be more reliable than those error calculations on more distant forecasts.

The results show that NIEIR's residential forecasts have generally performed better than those for the commercial and industrial sectors. The best performing forecasts were those for public lighting. This is not surprising as public lighting follows a very stable growth path and is not affected by factors such as weather conditions.

ACIL Tasman considers that the average percentage error of the total electricity consumption forecasts is reasonable, generally lying around 5 to 6% of the actual.

However, apart from public lighting which has a small negative bias, there is a strong upward bias in the forecasts. This bias gets stronger as the forecast horizon increases. This is evident in Figure 7 with the historical data tracking along the bottom end of the NIEIR forecast range and actually falling below the bottom of that range in the last year.

ACIL Tasman considers that this upward bias is likely to be primarily a result of overestimated new large loads/block loads which are added onto to NIEIR's base forecasts. This is evident in the larger percentage errors for the industrial sector forecasts, where the new large loads are classified. In response, the IMO has adopted a considerably more conservative approach to the estimation of new large loads in its 2012 forecasts.

Table 6 **Electricity consumption: Accuracy and bias of NIEIR's forecasts compared to history**

	Sample size	Average deviation (MAE)	Average percentage error (MAPE)	Bias direction
	no.	GWh	%	%
Total				
One year ahead	6	752.07	5.34	84.66
Two years ahead	5	898.96	6.38	75.79
Three years ahead	4	601.45	4.22	100.00
Four years ahead	3	951.10	6.72	100.00
Residential				
One year ahead	6	176.43	3.55	78.52
Two years ahead	5	173.12	3.42	98.87
Three years ahead	4	216.50	4.20	100.00
Four years ahead	3	323.03	6.32	100.00
Commercial				
One year ahead	6	207.40	4.61	69.21
Two years ahead	5	311.08	6.89	49.47
Three years ahead	4	161.10	3.53	99.29
Four years ahead	3	286.60	6.33	100.00
Industrial				
One year ahead	6	398.10	9.12	89.42
Two years ahead	5	429.20	9.87	83.15
Three years ahead	4	228.50	5.23	98.62
Four years ahead	3	341.87	7.86	100.00
Public lighting				
One year ahead	6	3.78	2.59	-35.39
Two years ahead	5	3.83	2.57	-15.97
Three years ahead	4	3.32	2.20	-10.71
Four years ahead	3	1.38	0.91	-29.16

Data source: ACIL Tasman analysis of NIEIR and IMO data

Note: This analysis does not include NIEIR 2012 forecast because the relevant actual data has not been released yet.

The results above show the performance of the forecasts by themselves without any point of comparison. One difficulty with conducting the analysis in this way is that the forecast statistics are susceptible to the effect of large unpredictable exogenous events which can skew the performance results. This issue is exacerbated by the fact that the overall sample of forecasts is quite small.

For this reason, ACIL Tasman considers that it is useful to compare the NIEIR forecasts with a set of forecasts from an alternative set of models. We do this by generating electricity consumption forecasts from two simple models, the first being a linear time trend through the historical data and the second being a first order autoregression where the current value of electricity sales is a linear function of last year's electricity sales.

A comparison between the NIEIR forecasts and the two alternative models is shown in Table 7. The results are mixed. The results show that NIEIR's residential sector electricity sales forecasts perform better across every time horizon, except the one year ahead horizon where it marginally underperformed. The results differ for the commercial and industrial sectors which have higher percentage errors for the one and two year ahead forecasts compared to the alternative naïve models. The NIEIR forecasts then exhibit superior forecasting accuracy for the three and four year ahead forecasts for these sectors.

Table 7 **Electricity consumption: NIEIR's accuracy compared to naïve models**

	Sample size	NIEIR	Naïve model 1 Y_t=a+b*t	Naïve model 2 Yt=a*Y_{t-1}
	no.	MAPE (%)	MAPE (%)	MAPE (%)
Total				
One year ahead	6	5.34	2.82	2.34
Two years ahead	5	6.38	3.96	3.43
Three years ahead	4	4.22	5.49	6.10
Four years ahead	3	6.72	6.97	8.83
Residential				
One year ahead	6	3.55	3.51	3.22
Two years ahead	5	3.42	5.19	5.40
Three years ahead	4	4.20	6.80	7.73
Four years ahead	3	6.32	8.83	11.58
Commercial				
One year ahead	6	4.61	3.02	2.56
Two years ahead	5	6.89	4.45	4.73
Three years ahead	4	3.53	6.61	8.21
Four years ahead	3	6.33	8.50	11.97
Industrial (excl 2002)				
One year ahead	6	9.12	4.82	3.38
Two years ahead	5	9.87	8.03	5.56
Three years ahead	4	5.23	12.70	11.97
Four years ahead	3	7.86	16.86	17.60
Public lighting				
One year ahead	6	2.59	0.91	0.93
Two years ahead	5	2.57	1.25	1.63
Three years ahead	4	2.20	1.72	2.89
Four years ahead	3	0.91	1.71	3.26

Data source: ACIL Tasman analysis of NIEIR and IMO data

In total, the NIEIR forecasts perform worse over the shorter time horizon, but outperform the naive models over a 3 and 4 year forecast horizon. ACIL Tasman considers that this underperformance in the short term is likely to be due to the addition of large new block loads that have proven to be overstated.

This can be seen in Table 8 below, which shows the one and two year ahead forecast average percentage errors for the NIEIR forecasts with and without the block loads added to the energy forecast. The average percentage error of the forecasts improves significantly when the new large loads are removed. This suggests that the underlying NIEIR forecasts perform reasonably well.

Table 8 **Electricity consumption: Accuracy and bias of NIEIR's historical forecasts compared to history**

	Sample size	Average deviation (MAE)	Average percentage error (MAPE)	Bias direction
	no.	GWh	%	%
Total				
One year ahead	6	752.07	5.34	84.66
Two years ahead	5	898.96	6.38	75.79
Total excl. block loads				
One year ahead	6	347.04	2.48	65.59
Two years ahead	5	574.51	4.07	62.12

Data source: ACIL Tasman analysis of NIEIR and IMO data

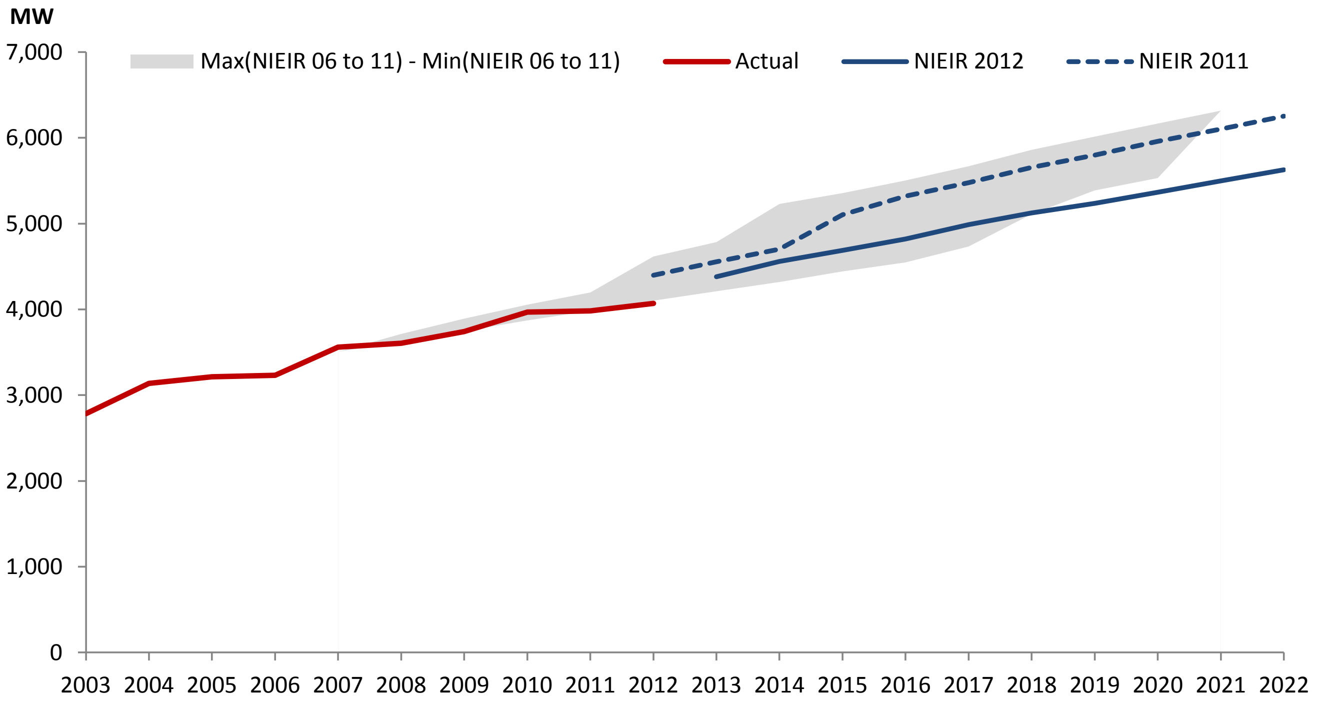
6.3.2 Maximum demand forecast accuracy and bias

In this section we assess the forecast accuracy and associated bias of NIEIRs summer 50 POE maximum demand forecasts over one to four year horizons.

Figure 8 shows NIEIR's 2011 and 2012 50 POE forecasts against the actual peak demand from 2006 to 2012. The grey shaded area shows the range of forecasts for each year of the forecast period, giving an indication of how NIEIR's forecasts have evolved from 2006 to 2011.

The figure also shows a significant downward revision between the 2011 and 2012 forecasts. As in the case of electricity sales, this adjustment is due to a downward revision in the size and timing of new large loads expected to come online in the future.

Figure 8 **Maximum demand: NIEIR 50% POE forecasts**



Data source: NIEIR and ACIL Tasman

Table 9 shows the accuracy and bias statistics for NIEIRs 50% POE forecasts.

The table shows that the average percentage error for the NIEIR maximum demand forecasts is generally good with an average error of less than 4% for total maximum demand forecasts up to 4 years ahead. The results show that there is a tendency for the forecasts to over predict actual maximum demand.

Table 9 **Maximum demand: Accuracy and bias of NIEIR's historical forecasts compared to history**

	Sample size	Average deviation (MAE)	Average percentage error (MAPE)	Bias direction
	no.	MW	%	%
Total				
One year ahead	6	149.37	3.84	78.75
Two years ahead	5	160.82	4.02	100.00
Three years ahead	4	126.25	3.13	98.85
Four years ahead	3	154.20	3.83	57.85
Base load				
One year ahead	6	24.78	1.23	-17.01
Two years ahead	5	24.84	1.22	-10.14
Three years ahead	4	21.60	1.06	-29.86
Four years ahead	3	27.43	1.33	4.98
Temperature sensitive				
One year ahead	6	76.28	4.81	76.10
Two years ahead	5	106.28	6.21	100.00
Three years ahead	4	108.73	6.12	88.87
Four years ahead	3	97.60	5.42	42.96

Data source: ACIL Tasman analysis of NIEIR and IMO data

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The table also shows that the forecasting methodology performs significantly better at predicting base load compared to temperature sensitive load. This is expected as base load behaves in a far more stable way compared to the temperature sensitive load.

The results also show that NIEIR has tended to over predict the temperature sensitive load, particularly over the one, two and three year ahead forecasts. As a result, there is also an upward bias for the maximum demand forecasts overall.

It should be noted that the tendency for NIEIRs temperature sensitive forecasts to be overstated has been due to an overestimation in the growth of air conditioning systems within the SWIS. As a result NIEIR recalibrated its model in 2011 to reduce the assumed number of air conditioning systems in the SWIS, after recognising that the number of historical replacements and non SWIS installations may have been higher than originally assumed. The recalibrated model also assumed a lower utilisation rate for air conditioners in the SWIS than previously.

Again we note that the results in Table 9 are based on actual maximum demands that are not weather normalised. As mentioned previously, basing the analysis on non-weather adjusted data can be misleading if the observed maximum demands differ markedly from the corresponding 50 POE maximum demand.

ACIL Tasman has recalculated the average percentage error and bias direction based on temperature corrected maximum demands. The approach adopted was simply to estimate a relationship between daily maximum demand and the average daily temperature for each summer season from 2006-07 onwards using regression analysis. We remove all non-working days such as weekends from the analysis and also cooler days where the average temperature was less than 20 degrees Celsius. We do this to remove the non-temperature sensitive part of the dataset.

The prevailing average temperature on the day of the system peak is compared to the long run 50 POE average temperature for Perth and an adjustment made to the observed maximum demand to reflect a movement along the regression line to the 50 POE level of maximum demand. This is done by multiplying the temperature sensitivity coefficient by the difference between the average temperature on the day of system peak and the 50 POE average temperature.

This approach to temperature correcting a single observation is likely to produce a biased estimate of 50 POE maximum demand. However, it is considerably simpler than applying more complicated simulation methods which were well beyond ACIL Tasman's scope and would have required significantly more time to complete.

Table 10 shows the actual summer maximum demands and their temperature corrected counterparts.

Table 10 **Temperature normalised maximum demand, 2007 to 2012**

Year	Actual maximum demand (MW)	Average temperature on day of peak	50 POE average temperature	Temp sensitivty MW/degree	Temperature corrected (MW)
2007	3559	30.5	32.7	81.7	3739
2008	3604	29.8	32.7	99.5	3893
2009	3741	31.7	32.7	115	3856
2010	3969	32.7	32.7	107.5	3969
2011	3982	31.8	32.7	130.0	4099
2012	4070	32.3	32.7	117.5	4116

Note: Actual demand values are presented on a GSR basis

Data source: ACIL Tasman

Table 11 shows the average deviation, percentage error and bias direction for NIEIRs summer 50 POE forecasts against the weather corrected history. The results show a considerable improvement in the average percentage error for all forecast horizons except the two year ahead forecasts for which the average percentage error increased. In addition, while the tendency for upwards biased forecasts remains it is reduced considerably using this revised data set.

Table 11 **Maximum demand: Accuracy and bias of NIEIRs forecast compared to weather normalised history**

	Sample size	Average deviation (MAE)	Average percentage error (MAPE)	Bias direction
Total	no:	MW	%	%
One year ahead	6	144.32	3.66	-4.79
Two years ahead	5	187.04	4.64	25.30
Three years ahead	4	111.41	2.75	49.42
Four years ahead	3	112.72	2.77	30.65

Data source: ACIL Tasman analysis of NIEIR and IMO data

ACIL Tasman therefore considers that NIEIRs maximum demand forecasts have performed reasonably well, particularly after considering the tendency for the large new loads to be overstated as these loads are provided by the IMO and are added to the base line NIEIR forecasts.

Table 12 compares the errors from NIEIR's models against the naïve forecasts generated by a simple time trend and a first order autoregressive model. The results again show that NIEIR total maximum demand forecasts perform worse than over 1 year and 2 year ahead forecasts, while outperforming over longer horizons.

ACIL Tasman considers that as in the case of the energy consumption forecasts, the performance of the NIEIR shorter horizon forecasts is adversely affected by the inclusion of overinflated block load forecasts.

Of some concern however, is the inability of the temperature sensitive forecasts to outperform a simple linear time trend against which the NIEIR forecasts are compared. ACIL Tasman considers that this may be an area where further improvements in forecast performance could be achieved following further analysis. However, because the recalibration of NIEIRs model took place only in in 2011, the first revised forecast only features once in the one year ahead statistics. It is therefore too soon to know definitively if the upward bias in the temperature sensitive load forecasts has been resolved.

Table 12 **Maximum demand: NIEIR's model compared to naïve models**

	Sample size	NIEIR	Naïve model 1 Y_t=a+b*t	Naïve model 2 Yt=a*Y_{t-1}
	no.	MAPE (%)	MAPE (%)	MAPE (%)
Total				
One year ahead	6	3.84	2.44	3.14
Two years ahead	5	4.02	3.12	4.04
Three years ahead	4	3.13	3.84	5.04
Four years ahead	3	3.83	4.94	7.69
Base load				
One year ahead	6	1.23	2.08	2.16
Two years ahead	5	1.22	2.32	2.64
Three years ahead	4	1.06	2.67	3.16
Four years ahead	3	1.33	3.20	4.24
Temperature sensitive				
One year ahead	6	4.81	3.37	6.30
Two years ahead	5	6.21	2.64	7.25
Three years ahead	4	6.12	1.54	6.01
Four years ahead	3	5.42	4.10	13.18

Data source: ACIL Tasman analysis of NIEIR and IMO data

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6.4 Model structure and approach

6.4.1 Models are based on econometric methods

NIEIR's models appear to rely on econometric methods that seek to estimate a relationship between peak demand and electricity sales and their underlying drivers, based on historical behaviour.

ACIL Tasman considers that this approach, when applied appropriately, is sound.

The econometric approach breaks down when trying to determine the impact of events and policies that have no historical precedent. This will be the case for the breakthrough of new technologies and for the implementation of policy initiatives which are likely to significantly affect consumption and peak demand. In this case, a simulation approach is preferred where a number of assumptions are made regarding the take-up of the new technology or customer behavioural changes arising from the introduction of a new policy. Using the simulation the total impact on peak demand and electricity sales is then calculated. It has become established practice to then modify the forecasts derived from the econometrically based models to take account of these estimated impacts.

Because the approach has a statistical basis, the modellers have at their disposal a range of model selection and statistical validation techniques that would not be otherwise available.

6.4.2 Disaggregation of temperature sensitive and temperature insensitive load

In an earlier review of NIEIR's forecasting process, Frontier Economics recommended that this process should be modified to integrate it with the process for estimating temperature sensitivity of demand. We agree that it would be an improvement to the forecasting methodology if it's sensitivity to individual judgements could be reduced. It is not necessarily clear that integrating these two steps would be an improvement, but we agree that this may be an area where improvements could be made.

At present, the approach is highly dependent on NIEIR's choice of a mild day where it is assumed that there is no temperature sensitive demand. There is some difficulty associated with this approach as peak demand in a given summer will produce quite a wide range of demand estimates for a given average temperature. One improvement to the process would be for NIEIR to clearly and transparently specify the days it identifies as mild.

6.5 Weather correction

A key requirement of forecasting maximum demand and energy is to account for movements in weather conditions. Failure to do so can result in errors in ascertaining the underlying growth rate of both peak demand and energy and will likely lead to biased forecasts, particularly if the earlier or later seasons in the sample have been subject to extreme weather conditions.

ACIL Tasman therefore views weather normalisation to be a key aspect of any energy and peak demand modelling system.

6.5.1 Approach to weather normalisation of maximum demand

NIEIR currently applies weather normalisation by adjusting observed maximum demand in a deterministic way based on the NIEIR assessed relationship between maximum demand and temperature. NIEIR have also run a simulation approach for the first time in 2011, however, this was not used as a basis for the forecasts.

The simulation[12] approach, known in NIEIRs methodology as Peaksim, uses a long time series of historical weather data from suitably chosen weather gauges in Perth. This data is used to generate a synthetic temperature and residual series, which is then input into models to generate a synthetic distribution of maximum demands. A key aspect of generating the synthetic temperature series is to preserve the correlation structure of the original historical data.

NIEIR has stated that up until recently, it did not have a sufficiently long time series of market sent out data to revert fully to the use of Peaksim. ACIL Tasman recognises this. However, we recommend that the weather normalisation process move to the use of a full simulation methodology as soon as possible.

NIEIR stated that it runs the simulation model Peaksim as a cross check on the primary system maximum demand model. These forecasts are not published in their report but are used as a post modelling evaluation check.

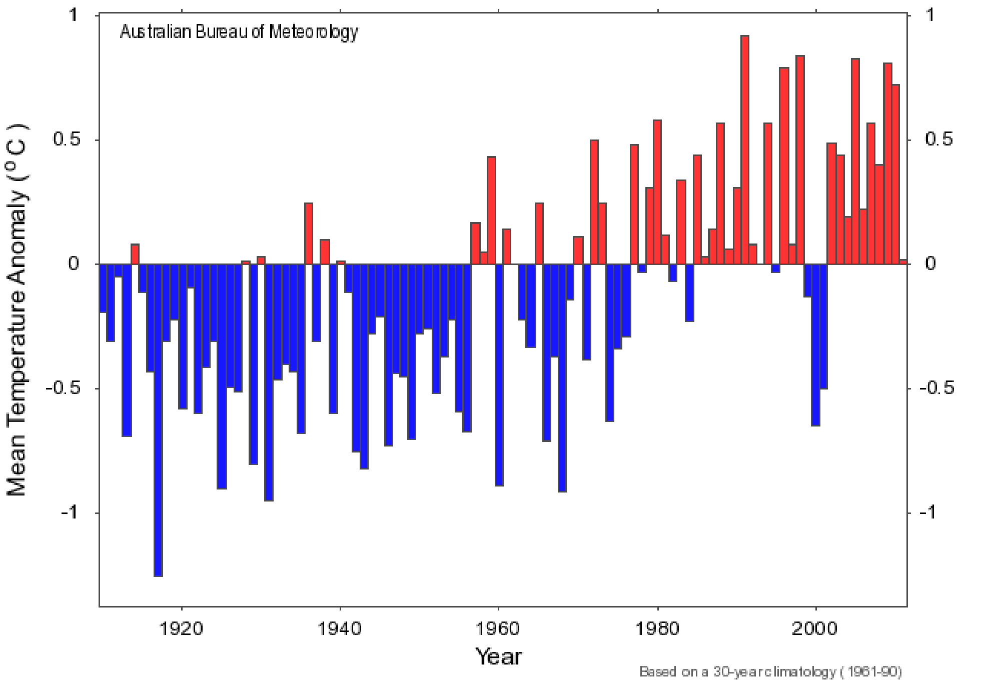
ACIL Tasman has not been able to obtain detail about the underlying structure of the equations driving the weather normalisation process. This makes it difficult to make judgements that are specific to NIEIR's process. However, the simulation approach to weather normalisation is now quite commonly applied across a number of jurisdictions for the purposes of weather normalising peak demand. It has a number of advantages over other methods that use regression analysis to correct a single peak demand, the main one being that it also incorporates the error structure of the regression models. If this is not done then there is some likelihood that the weather normalised peak demand estimates will be biased.

According to NIEIR, the forecast results obtained from Peaksim do compare favourably to those of the primary model. This suggests that there is little evidence of bias in the primary forecasts currently.

Another characteristic of long run weather behaviour is that there has been a tendency towards warmer temperatures over time. Figure 9 shows the deviation of annual average temperatures in Western Australia from the 30 year average for the period from 1961 to 1990. The figure shows a clear long term warming trend. A key question in weather normalisation is therefore whether this long term weather pattern can be expected to continue or whether it is likely to reverse.

12 Some examples of Australian businesses that adopt a simulation approach to forecasting system maximum demand are Energex and Ergon Energy in Queensland and AEMO.

Figure 9 **Long run average temperature deviation, Western Australia**



Data source: Bureau of Meteorology

It is ACIL Tasman's view that it is reasonable to factor in some degree of warming over time into the weather normalisation process for peak demand and also for electricity sales. NIEIR states in its June 2011 report to the IMO that the sampling methods used in the normalisation process allow for the effects of urban and global warming on past and future climatic conditions. While ACIL Tasman has been unable to explicitly verify the NIEIR approach as the models have not been made available, ACIL Tasman considers this approach, as stated, to be reasonable.

It is our view that NIEIR's current approach to weather normalisation appears appropriate. However, we consider that simulation methods are superior to other alternative approaches and recommend that the basis of the forecasts shift to the use of Peaksim or the equivalent as soon as it is reasonable to do so.

6.5.2 Provision of weather dependent electricity consumption forecasts

Currently, NIEIR produce forecasts conditional on weather for maximum demand only. Forecasts of electricity consumption have been produced according to high, medium and low economic growth scenarios, but have not been produced under varying weather conditions.

This has typically been the traditional approach used in energy consumption forecasting as a few extreme events can play a very important role in peak demand and assessing the need for underlying generation capacity but the same few events may not affect the annual energy consumption by much at all.

However, the behaviour of weather across an entire year can make a significant difference to the overall level of electricity sales, with colder than average winters and hotter than average summers adding to consumption in a given year compared with the average.

In order to assess the influence of weather on monthly and annual electricity sales ACIL Tasman devised a simple model which assumes that monthly electricity sales is driven by weather conditions, a certain level of fixed consumption and a time trend.

To estimate the coefficients for the econometric model we regressed monthly electricity sales (in MWh) on time, heating and cooling degree days (both to the basis of 18 degrees) and an intercept to account for block loads. This analysis found a highly significant functional relationship. The table below summarises the key statistics.

Table 13 **Test statistics**

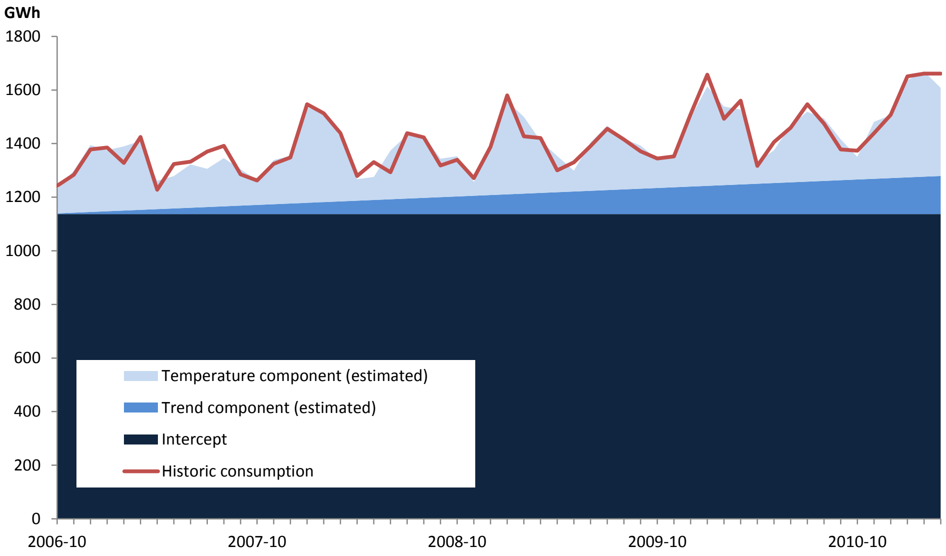
	Time	Cooling Degree Days	Heating Degree Days	Intercept
Coefficients	2,634	1,467	1,415	1,137,000
p-value	5.24E-12	< 2e-16	2.68E-16	< 2e-16
Std error	293	79	118	13210

R^2=0.92, Adjusted R^2=0.91

F-statistic: 190 on 3 and 50 DF, p-value: < 2.2e-16

Figure 10below illustrates the contribution of the three components to the overall estimates. It shows that they reproduce the historic data well.

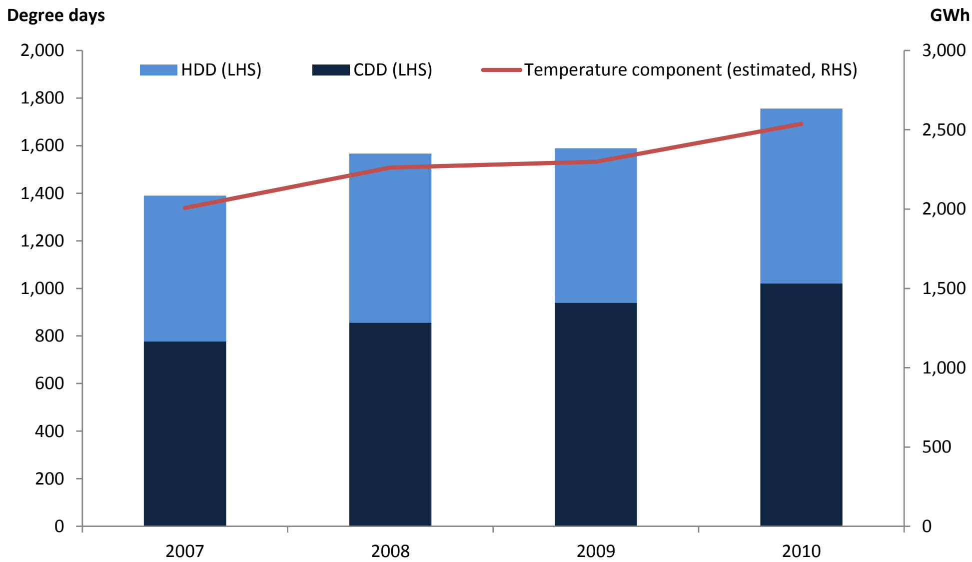
Figure 10 **Electricity sales: Historic and estimated components**



Data source: Historic data from NIEIR

Having established the functional relationship it is possible to investigate if temperature effects would be expected to largely cancel each other out on an annual basis. For this purpose, in Figure 11, we summed up the monthly estimated temperature consumption component (red line) as well as the number of heating and cooling degree days (light and dark blue bars). If weather effects cancelled each other out over the course of a year, one would see a straight red line and equally high blue bars. Since the line is not straight, it is evident that weather has a significant impact on annual electricity sales.

Figure 11 **Estimated temperature component vs. HDD and CDD**



Data source: Temperature data from NIEIR

ACIL Tasman therefore considers that some consideration should be given to producing electricity sales forecasts under three separate weather scenarios, in much the same way as is currently done for peak demand.

The ease to which this is done will depend somewhat on the underlying structure of NIEIRs energy forecasting models. However, given that weather is likely to be a key input in the model then it should not be difficult to produce forecasts on the basis of separate weather scenarios, such as 10% POE, 50% POE and 90% POE.

6.6 Policy variables

6.6.1 Carbon price

As mentioned previously, NIEIR incorporate the impact of the introduction of a carbon tax on energy consumption and maximum demand by making some assumptions with regard to the total effect of the tax over time on wholesale electricity prices, and then calculating the expected effect on electricity consumption and demand through the application of a price elasticity of demand for electricity.

The key assumptions NIEIR used in its 2011 report under the base case was for a carbon price of $25 per tonne in 2014, rising to $45 per tonne in 2020 and $60 per tonne in 2030. At that time, the federal Government had announced that the Carbon Pollution reduction Scheme (CPRS) would be deferred until after 2013. In terms of the effect on the wholesale electricity price above the business as usual case, prices were to be 20% above the BAU price in 2014, rising to 40.5% in 2020 and 60% in 2030 as a result of the introduction of the carbon price.[13]

The carbon price assumptions in NIEIRs 2012 report reflect the change in Federal Government policy which mandated the introduction of a carbon tax from July 2012 before the introduction of an emissions trading scheme in 2015. Under NIEIRs modelling assumptions, the carbon price commences at $23 per tonne in 2012 and rises by 2.5% per annum in real terms until 2023.

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[13] ACIL Tasman notes that the longer term price rise assumptions are potentially excessive and do not appear to reflect the gradual lowering of the carbon intensity of the Australian electricity sector, including the Western Australian WEM, with an increased emphasis on efficient combined cycle gas and renewables. Hence even though the carbon price may have more than doubled by 2030, the level of pass through of carbon costs (which are driven by plant tat the margin across the load curve) would have expected to halve and the absolute level of pass through would not be expected to be too different using the NIEIR carbon price trajectory. However, ACIL Tasman notes that this is unlilkely to have a significant effect on the shorter term forecasts which are of most interest to the IMO.

Real price impact and price elasticity of demand

The ultimate effect on both electricity sales and peak demand is then calculated by applying the NIEIR assumed own price elasticity of demand for energy to the calculated increase in the real price of electricity arising from the introduction of the carbon tax.

Although we have not been provided with the price elasticity NIEIR use for the SWIS, NIEIR have previously done work in the area to determine a appropriate price elasticity for the NEM. Based on a review of Australian and overseas literature and their own work, NIEIR have estimated the own price elasticity of demand to be -0.25 for residential demand, -0.35 for commercial demand and -0.38 for industrial demand.

Table 14 **Long run own price elasticity of demand by sector**

Sector	Price elasticity
Residential	-0.25
Commercial	-0.35
Industrial	-0.38

Data source: NIEIR (2006)[14]

These estimates of the price elasticity of demand for electricity are in ACIL Tasman's view within the generally accepted bounds of what can be considered to be reasonable estimates of the own price elasticity of demand for electricity.

It is important to note however, that these elasticities were estimated over a time period (between 1980 and 1995) when the real price of electricity behaved differently compared to more recent price increases from 2009-10 onwards. This suggests that there is a high degree of uncertainty associated with the true degree of price responsiveness that will result both as a result of the carbon tax, other environmental related charges (RET and feed-in tariffs) and network and distribution charge related price increases.

The price elasticity of demand can be expected to be different to what has occurred historically due to the magnitude of the price change and the different position of electricity charges in terms of absolute and relative prices. However, this difficulty will only be resolved in the future when empirical studies are able to shed further light on the demand response arising from the most recent price rises.

Despite these difficulties, ACIL Tasman considers that the approach that NIEIR uses is a sound approach to incorporating the carbon price into its methodology.

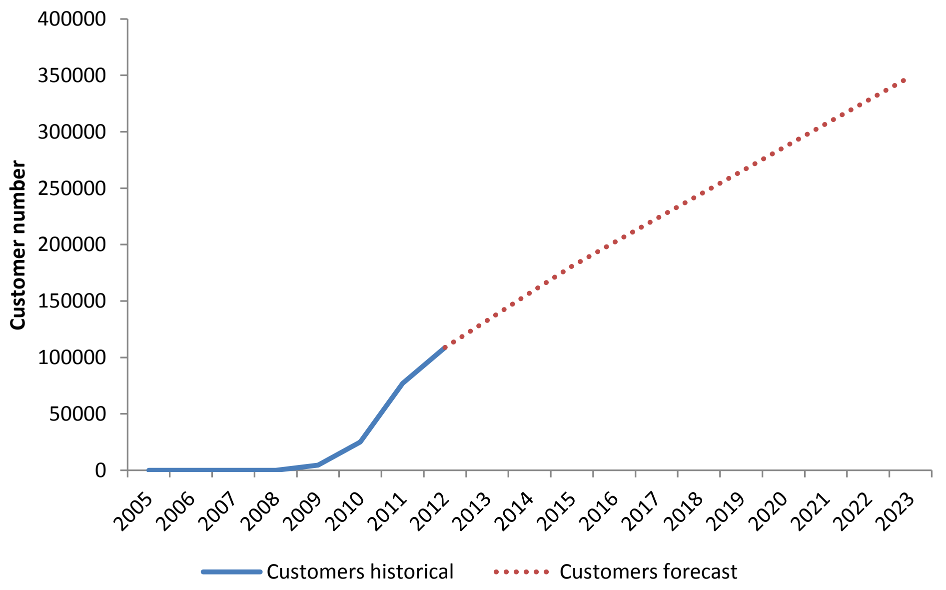
[14] NIEIR (2006) 'The Own price elasticity of demand for electricity in the NEM'

6.6.2 Solar photovoltaic cells

The impact of photovoltaic cells is being incorporated into NIEIRs forecasts for the first time in 2012. This follows the rapid uptake of solar PV systems in the last few years in response to the introduction and subsequent downsizing and closure of the Western Australian government's premium feed-in tariff scheme.

Figure 12 shows NIEIR's projection of the uptake of solar PV systems in the SWIS.

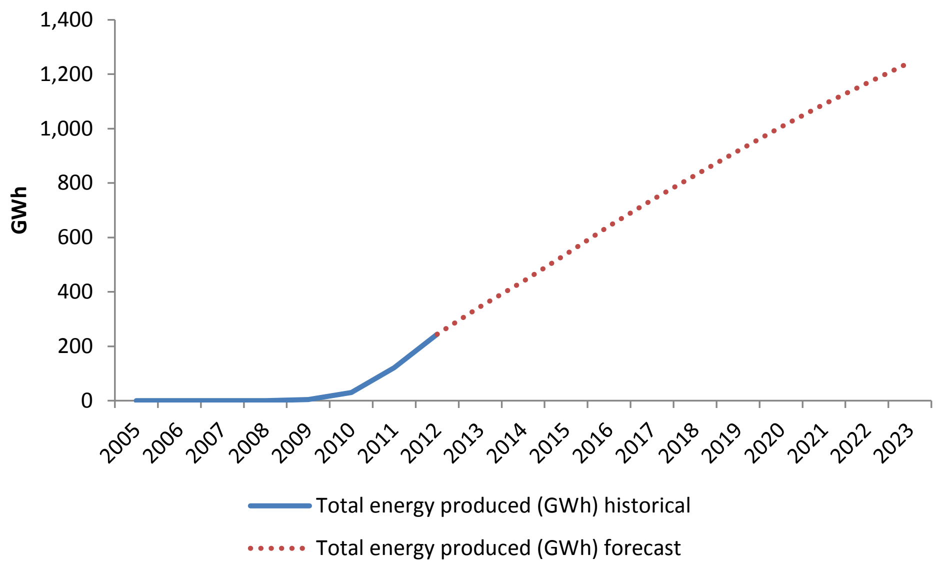
Figure 12 **Solar PV systems – number of installed systems, SWIS, 2005 to 2023**



Data source: NIEIR

Figure 13 shows the projected energy output from those systems.

Figure 13 **Solar PV systems – total energy output, SWIS, 2005 to 2023**



Data source: NIEIR

The total solar PV load and associated energy output is calculated and then deducted from the base level forecasts.

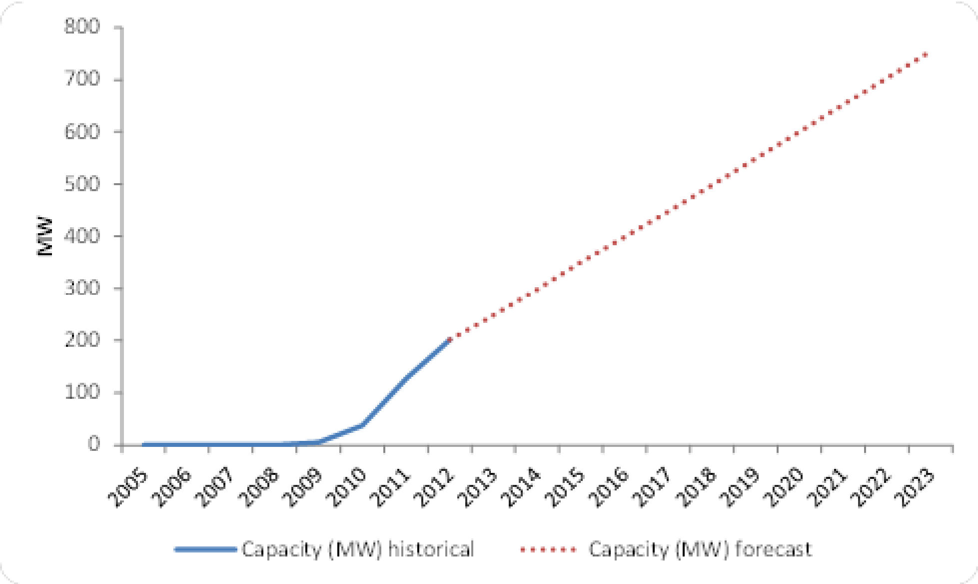
Three components of the forecast are discussed below:

1. The projection of total installed capacity
2. The projection of total energy output (GWh)
3. The projection of impact on peak demand (MW)

Projected installed capacity

NIEIR projects ongoing take up of solar PV systems will be in line with the rapid rates observed recently. This projection is shown in Figure 14 below.

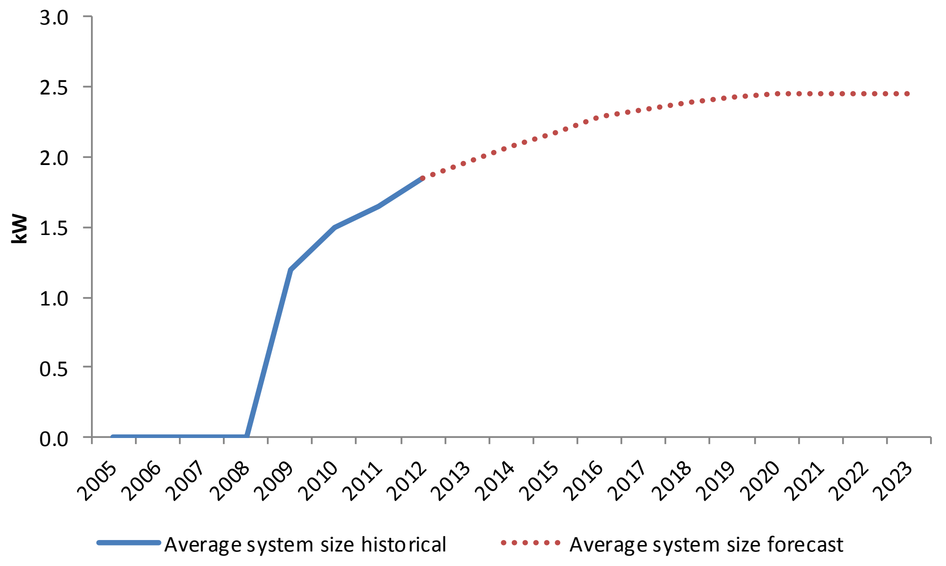
Figure 14 **Solar PV systems – installed capacity, SWIS, 2005 to 2023**



Data source :NIEIR

Intuitively this may seem to be too rapid given the removal of the larger feed in payments. However, to the extent that data are available, they appear to indicate that the rate of installation of solar PV systems has not abated following the closure of the generous feed-in tariff scheme. In addition, the capacity figures shown in Figure 14 reflect an assumed increase in the average system size installed of slightly more than 30 per cent, from less than 2 kW per system to approximately 2.5 kW (see Figure 15).

Figure 15 **Solar PV systems, average system size (incremental), SWIS, 2005 to 2023**



Data source: NIEIR

As the IMO states in the 2012 SOO, a wide range of outcomes are possible for solar PV systems. The upfront cost of these systems has been substantially reduced by Government intervention through the Small scale Renewable Energy Scheme (SRES). The level of subsidy is likely to continue to fall with time in line with existing Government policy, with the Solar Credits multiplier reducing and the effective upfront cost of solar PV systems increasing (assuming all else is constant).

However, the recent strength of the Australian dollar is likely to offset this decline, at least to some extent in the short to medium term[15].

Demand for solar PV systems is also influenced by activity in the new housing sector. Solar PV systems can be used to attain improved energy efficiency ratings under certain circumstances. Therefore the move towards 6 star energy efficiency requirements for new homes is likely to support demand for solar PV systems. In this way, the cost of solar PV systems forms part of the larger cost of building an energy compliant new home or carrying out a substantial renovation. In this context, it can be traded off against the cost, and contribution to energy efficiency ratings, of appliances such as air conditioning units.

In our view NIEIR's projected growth in installed capacity of solar PV systems in the SWIS is not unreasonable though we note that there is significant uncertainty regarding what that take up rate will turn out to be.

Projected energy output

The amount of electricity generated by a solar PV system depends on its size and a range of variables relating to where and how it is installed. At the detailed level, factors including the angle at which the solar panel(s) face the sun, shading and ambient temperature are all relevant to the actual output of an individual system.

However, for forecasting purposes, it would be impractical to take account of all of these factors. NIEIR's 2012 report does not go into detail about the process by which it estimates the total energy output of solar PV systems but we note, as summarised in Figure 16, that the average output ranges between 0.8 in 2010 and approximately 1.65 in the later years of the projection.

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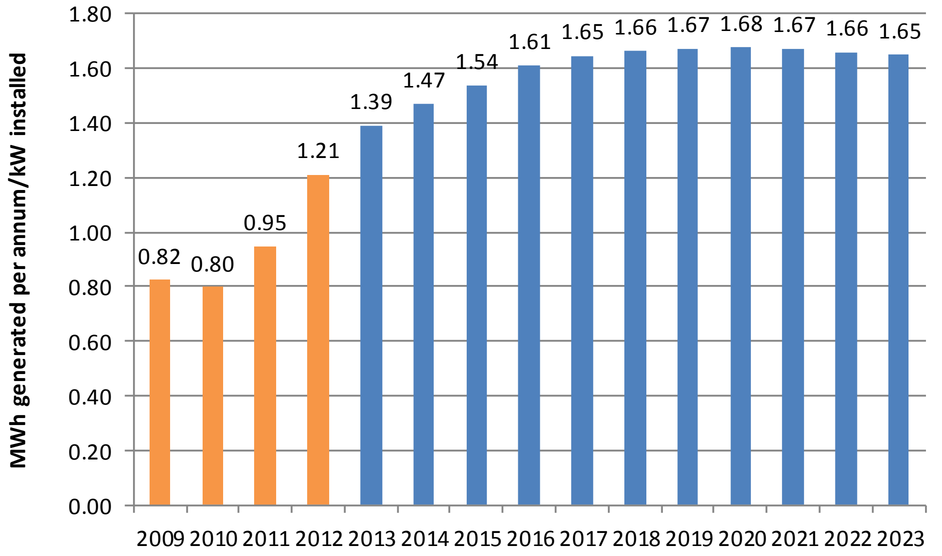
15 In the longer term, ACIL Tasman expects the exchange rate to decline to longer term averages (say between $0.60 and $0.80 USD) as commodity prices return to a reflection of long run marginal costs and in combination the terms of trade also declines.

Figure 16 **Average electrical output of solar PV systems, SWIS, historical and projected**



Data source: NIEIR

The ramp up of the average electrical output between 2010 and 2013 can be explained largely by the progressive installation of solar PV systems throughout the year, in combination with a very small number of pre-existing installations in those years. As a result, the total output in these years is dominated by new installations which are distributed throughout the year and do not operate for a full year. Over time, the stock of systems comes to be dominated by existing systems which operate over an entire year, hence the average electrical output of solar systems begins to stabilise at around 1.65 after 2017.

We have compared NIEIR's projected output of about 1.65 with the rate at which the Office of the Renewable Energy Regulator (ORER)[16] deems the output for a solar PV system. This is based on postcode zones. Every Australian postcode is assigned to one of four zones and, thereby, assigned a rating. That rating is multiplied by the system size to estimate the total electrical output of the system in a typical year and this forms the basis of allocating renewable energy certificates, which can be sold through the SRES scheme.

The ORER ratings are shown in Table 15.

[16] The Office of the Renewable Energy Regulator (ORER) was amalgamated into the Clean Energy Regulator on April 2, 2012.

Table 15 **ORER Zone ratings for small-scale solar panels**

Zone	Rating
1	1.622
2	1.536
3	1.382
4	1.185

Data source: ORER

Most Western Australian postcodes are in ORER zone 3, with a smaller number in zones 1, 2 and 4. The zone 3 rating is significantly lower than the corresponding value as implied by NIEIR's projection and shown in Figure 16. In fact, NIEIR's medium to long term average is higher than even ORER's zone 1 rating.

This suggests that NIEIR's projection of the electrical output of solar PV systems may be too high. ACIL Tasman recommends that further analysis be conducted to assess the appropriateness of the output rating used by NIEIR for the forecasts against those suggested by alternative sources such as ORER.

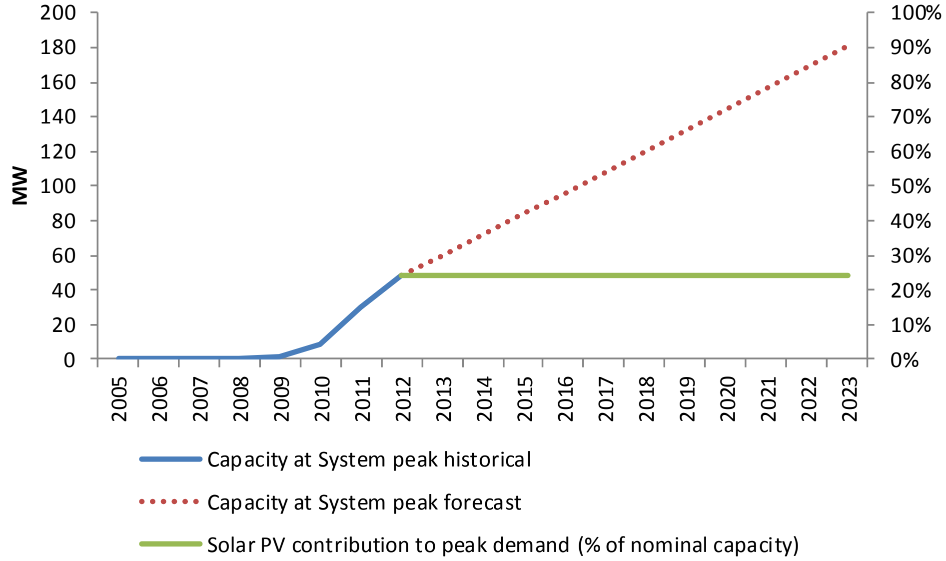
Solar PV systems contribution to peak demand

As noted above the amount of electricity generated by solar PV systems at any given time depends on a range of factors including the angle of the sun. Typically, peak demand in Western Australia occurs in the late afternoon or early evening in summer, when the sun is low in the sky. This tends to reduce the electrical output of roof mounted Solar PV systems, which are typically oriented upwards to catch the day time sun when it is at maximum intensity[17]. As a result, the contribution Solar PV systems make to peak demand is less than their nominal capacity.

As Figure 17 shows, NIEIR projects that Solar PV systems will make an increasing contribution to maximum demand. However, this is driven by the increased uptake of PV systems. The figure also shows that NIEIR projects that, on average, solar PV systems will be operating at approximately 25 per cent of their nominal capacity during peak demand events.

[17] Small-scale rooftop solar PV are usually installed in a fixed frame – the cost of installing a rotating frame to track the sun is very expensive relative to the cost of a standard small-scale solar PV installation and is not justified.

Figure 17 **Solar PV systems, contribution to peak demand, SWIS, 2005 to 2023**



Data source: NIEIR

As with the uptake rate of Solar PV systems, this is a difficult quantity to forecast. In our view the key issue is to ensure that the expected impact of Solar PV systems on maximum demand is less than their nominal capacity for the reasons explained above. Despite the difficulties assessing this without access to NIEIR's 2012 report, NIEIR appears to have has taken this into account.

Beyond this, we note that NIEIR projects that solar PV systems will have a total impact on maximum demand ranging between 100 and 200 MW over the forecast period. Over the same period, projected maximum demand ranges from almost 4,500 MW to almost 6000 MW. In this context, the impact of solar PV systems on peak demand is relatively minor, approximately 2 to 3 per cent. Any error in the solar PV forecast is likely to be trivial from a system maximum demand perspective, compared to the case of energy consumption where solar PV makes a larger contribution to the total

6.7 Model validation and testing

6.7.1 Back-casting

NIEIR have stated that, from time to time, it assesses its models ability to explain the historical behaviour in electricity sales and maximum demand for the SWIS at a high level. ACIL Tasman considers that this is the very minimum that NIEIR should undertake in terms of assessing model validity and performance.

If the models show significant within sample errors then these need to be examined and accounted for. It could be that large errors are the result of one or more significant exogenous events that were unpredictable.

However, increasing in sample errors could also arise because of faulty assumptions made in the modelling process. For example, NIEIR identified in 2011 an error in its air conditioning methodology whereby it discovered that the replacement rate of air conditioning systems was higher than it previously had assumed. As a consequence it was overstating the total air conditioning load on the SWIS and producing forecasts of maximum demand that were higher than they should have been.

This is a concrete example of how constant re-evaluation of models is necessary to identify errors, poor specifications and faulty assumptions.

6.7.2 Out of sample testing

ACIL Tasman considers that a much better test of a model is its out of sample performance. It is possible for some models to have poorer in sample explanatory power while possessing features which enable them to out-perform in out of sample testing.

There is currently a significant difficulty with conducting a credible out of sample analysis of the maximum demand and electricity consumption forecasts.

Unfortunately, there is only a relatively short time series of historical data from which a 10 year forecast horizon is generated. It is therefore not possible to test the out of sample performance of the forecasting methodology more than a few years into the future.

ACIL Tasman recognises that there are problems associated with an out of sample testing exercise in this case. However, as more data is accumulated, it will become increasingly feasible to calibrate the models using a subset of the full time series, and then test the out of sample accuracy of the models using the remainder of the full time series.

ACIL Tasman also considers, that the models be assessed against alternative models as a means for identifying any performance issues with the existing methodology (we provided several examples of how this might be done using relatively naïve models throughout our assessment).

6.7.3 Ex-post evaluation of forecast performance

It is ACIL Tasman's view that ex-post evaluation of the previous year's forecasts be conducted to evaluate its performance and assess the reasons for any deviations from actual outcomes.

This process is important for the constant re-evaluation and improvement of the modelling process. Without it, it is more difficult to identify ways of improving the process.

ACIL Tasman considers that this process should be undertaken every year between NIEIR and the IMO, with a detailed analysis of what factors played a role in causing deviations from actual outcomes. This approach should focus on:

- Errors in forecasting the models inputs such as GSP, population and household formation
- Structural issues with the models ability to generate accurate forecasts arising because of incorrect relationships between model variables
- Identification of factors that the models failed to capture- such as new policy changes, technological and behavioural trends

ACIL Tasman does not consider this task to be too large or difficult, especially with respect to the first and third points listed above. The ex-post evaluation does become more difficult if there is reason to believe that there are structural issues associated with NIEIRs models. This then entails looking into the workings of the model itself which may become time consuming. ACIL Tasman however, does not envisage structural problems associated with the models to arise every year.

ACIL Tasman considers that this requirement for an annual ex-post evaluation of the performance of the forecasts could be made explicit within the Market Rules.

6.7.4 Models not calibrated every year in forecasting process

Based on a meeting with NIEIR, ACIL Tasman understands that NIEIR does not necessarily recalibrate its models every year for the purposes of producing forecasts for the SWIS.

NIEIR claims that due to the potential for data to be revised later[18], that there is some trade-off between timeliness and parameter stability in the models. ACIL Tasman does have some sympathy for this view and recognises that if

[18] The problem of regular revisions to historical data is largely associated with the Australian Bureau of Statistics estimates of WA GSP and to a lesser extent Australian GDP.

new data is considered to be unstable or unreliable then there may be some justification in excluding it from the calibration. However it is difficult to know before the fact which data points are going to be revised and which are not.

ACIL Tasman considers that there is considerable risk in this approach, especially since the time series available for the purposes of the modelling is quite short. If relationships between variables are dynamic, then failure to recalibrate the models when additional data becomes available can lead to errors as the historical relationships between variables change. While this will not be a significant issue for relationships that are relatively stable, ACIL Tasman considers that the use of more information is preferable to less, and that the recalibrated models based on additional data will be likely to have more validity.

It is ACIL Tasman's recommendation that NIEIR should recalibrate its models to incorporate the latest data and information whenever generating the latest set of peak demand and electricity sales forecasts for the SWIS. Its forecast reports should be clear as to when parameters were estimated and upon which data they were based.

6.8 Quality assurance of data inputs

Any process of quality assurance should aim for datasets that are accurate, reliable, complete and timely. During the course of this review it became evident to ACIL Tasman that there is a need to formally assess and validate the datasets that are used as the basis for the forecasting process.

From discussions with the IMO, it is evident that there are sometimes inconsistencies between the market sent out data from the IMO and total generation data provided by System Management. ACIL Tasman considers that a formal process should be established where the datasets are checked and assessed as being free from errors and fit to use in the forecast process. This process should take place within Western Power and the IMO, prior to the datasets being provided to NIEIR for use in their forecasting methodology.

As a consequence of producing the IMOs forecasts since 2006, NIEIR has been able to develop a detailed database containing the data required to produce the necessary forecasts. By assembling a data base with continuous time series, NIEIR is able to identify any inconsistencies or errors which may be missed by the IMO prior to being provided to NIEIR.

ACIL Tasman considers that while this offers some protection against erroneous data being used in the forecasting process, that a quality assurance process should be formulated and implemented. This is likely to require greater co-operation between Western Power and the IMO. ACIL Tasman considers that there is scope to greater enhance the level of co-operation between Western Power and the IMO, particularly in this area.

ACIL Tasman also recommends that given the importance of timely acquisition of data from other agencies in facilitating the generation of the forecasts that an adjustment be made to the Market Procedures to require such timely delivery of data if a request is made.

6.8.1 Lack of transparency

In 2008 when the last review of NIEIR's forecasting methodology was conducted, Frontier expressed the concern that NIEIR's methodology could benefit from increased transparency.

At present, NIEIR provides some information on the input assumptions made, such as the rate of economic and population growth implied by its models, and also assumptions and about other factors such as the uptake of solar photovoltaic cells. ACIL Tasman considers this to be acceptable.

However, it is difficult to make an assessment of the methodology between the input assumptions and the outputs that are generated. NIEIR have expressed the opinion that they are unwilling to provide this level of detail in order to protect their intellectual property. NIEIR made some general comments about its modelling approach, but declined to provide meaningful detail about the methodology and data sources used in the specific case of the forecasts provided to the IMO. For example, NIEIR indicates that, as a general proposition, it estimates key parameters such as output elasticity of demand for energy from either observed data provided by the business for which it is preparing forecasts or alternative sources such as ABARE. However, it declined to specify which source of data was used in preparing the IMO's forecasts on any given occasion.

While we understand NIEIR's desire to protect its intellectual property, we consider that it would be reasonable for NIEIR to provide considerably more information on the process between the input assumptions and the generated outputs without compromising the sensitivity of the process. This increased level of transparency is important for generators and consumers of electricity that ultimately provide and pay for the level of reliability that is in part determined by the energy and demand forecasts.

In the absence of this information, a significant measure of reliance must be placed on NIEIR's judgement. This judgement appears to be a routine part of a forecasting model. NIEIR does not appear to rely on a purely mechanistic, statistical approach. Instead, it exercises judgement as to whether a particular forecast is credible. This judgement is based both on its own expertise and that of other agencies and experts.

ACIL Tasman considers that the use of judgement in the forecasting process is an important factor. However, it is preferable that the use of such judgements be set out explicitly, with the forecaster summarising the relevant and particular judgements and underlying analysis associated with a particular forecast. This enables the user of the forecasts to form their own view as to whether the forecasts are conservative or otherwise and whether they are suitable for a given purpose.

6.9 New Block loads

The possibility of large new loads has the potential to cause a significant shift in maximum demand and energy in the SWIS. In order to estimate the size and timing of new large loads, the IMO discusses the requirements for capacity with potential new mines and other large industrial enterprises. The IMO also consults with Western Power with whom the developers have lodged applications for network access, as well as with other government agencies such as the Department of State Development. After the consultation process, the IMO makes a final estimate of the size and timing of any new loads. These forecasts are then provided to NIEIR who then add them to the NIEIR base forecasts.

In 2011, the IMO estimated new block loads from a number of sources:

- Boddington Gold[19]
- De-salination plant
- Extension Hill mine
- Gindalbie
- Grange-Southdown mine
- Simcoa aluminium smelter and
- Oakajee Port.

ACIL Tasman generally agrees with the approach of adding relevant projected new large loads onto NIEIR's base forecasts. However, the approach to calculating the size of the block loads should consider a number of issues including:

- Whether the block load is large enough to move the system wide forecast

[19] Technically not a new load, but rather an increase in predicted load compared to the previous summer

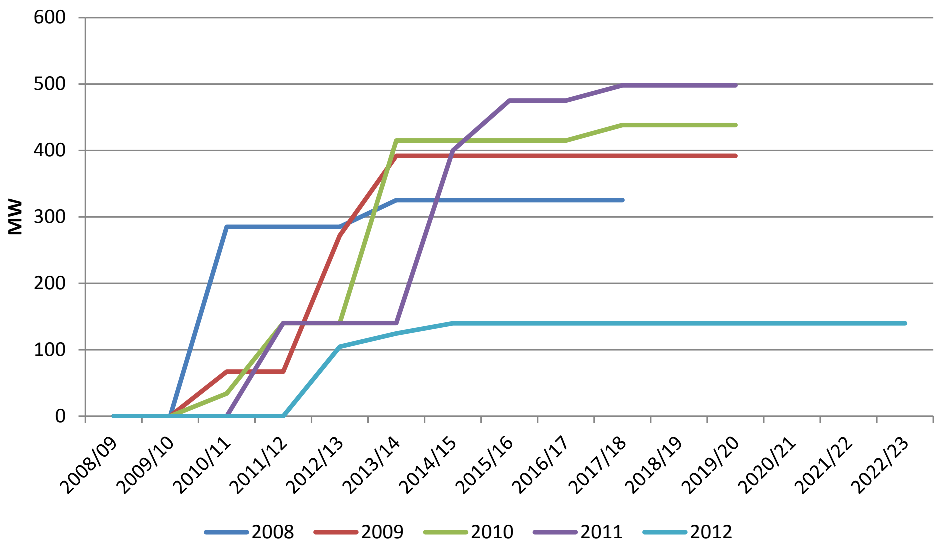
  - For this purpose an appropriate threshold should be developed and applied
- Whether the block load is unique enough so that it is not captured by the econometric specification that relates maximum demand to its underlying drivers such as GSP
- The probability of the block load being committed and commissioned.

The current approach taken by the IMO to estimate the size and timing of any block loads is to specifically ask the prospective users, as well as Western Power and other government agencies. We note that there is a natural tendency for the developers of large new mining projects to overestimate both the size and the likelihood of their specific project going ahead. This is in part to ensure that the infrastructure is established to support their requirements without delay but also because of the natural psychological tendency to overconfidence and optimism within project developers which is usually driven by large incentives linked to the project proceeding. ACIL Tasman recommends that the IMO should be making adjustments to the estimated block loads to account for this bias.

ACIL Tasman notes that the IMO has recognised that it has significantly overestimated by the size and timing of new large loads in previous years and has made a significant downward revision to the block loads to be included in the 2012 forecasts. This is consistent with ACIL Tasman's view that large new loads be adjusted for over optimism.

Figure 18 shows the evolution of the IMOs base case forecasts for new large loads over time. Each coloured line represents a set of forecasts for a given year. The figure shows that the number and magnitude of new block loads that were forecast generally increased over time from 2008 to 2011, before being reduced substantially in 2012. This reduction involved cutting both the size and timing of new loads, with some of the projected loads forecast in 2011 removed altogether. This reduction was made in response to the systematic over estimation of forecasts block loads from 2008 onwards. ACIL Tasman considers that this re-assessment is an appropriate response to the bias in the block load forecasts.

Figure 18 **Evolution of IMOs base case block load forecasts, MW**



Data source: IMO

The IMO applies a threshold of 20 MW to any prospective block load before it can be considered. ACIL Tasman considers this to be an appropriate threshold that is large enough to ensure that the new load can be considered unique.

At present, the IMO does not apply probability weights to its block loads. ACIL Tasman recommends that the IMO should apply a conservative approach to probability weighting new large projects as they have the capacity to move the system level forecast considerably due to their size. ACIL Tasman suggests that only those forecasts that have a very high chance of proceeding be included. Those new loads that are not expected to come online after 3 years or more should be heavily discounted or possibly ignored altogether.

Based on experience, it is ACIL Tasman's view that new large loads projected to come online after 3 years have a strong likelihood of not eventuating. ACIL Tasman notes that the IMOs latest block load forecasts for 2012 do not include any loads after 3 years into the forecast period. They are therefore consistent with our view.

Most of the new large loads projected for the SWIS are mining related loads. The prospects of a new mine going ahead is affected by a large number of uncertainties. These uncertainties should be analysed carefully and an appropriate probability weighting be applied.

ACIL Tasman notes that to the extent that these large projects will add significantly to WA GSP, there is a possibility of double counting the impact of the new loads. This can arise if GSP is used as an input into the domestic and business maximum demand and energy forecasts. The higher GSP forecast arising from the new loads will contribute to higher potential energy and maximum demand forecasts for the domestic and business sectors. This could be inappropriate if large segments of the GSP growth can be attributed to the large projects only, with no likely impact on the rest of the domestic and business sector. ACIL Tasman recognises that some caution needs to be exercised to ensure that this is not the case, and if it is found to be so, an adjustment needs to be made to the GSP forecast to remove the impact of any large new loads. We note however, that the risk of double counting in the case of the SWIS is quite low as the proposed projects are too small to impact significantly on WA GSP, despite exceeding the IMOs block load threshold of 20 MW.

The IMO in its current methodology also does not apply any coincidence factors[20] to its schedule of block loads used to adjust the peak demand forecasts. Doing so takes account of the fact that a block load can be operating below full capacity at the time of the system peak. ACIL Tasman recommends that the IMO considers the use of appropriate coincidence factors to apply to the estimated loads. The application of coincidence factors to each prospective load will improve the accuracy of the block load forecast and assist in reducing the tendency toward over prediction.

6.10 Open forecasts to annual competitive tender process

ACIL recommends that the IMOs contract to provide energy consumption and maximum demand forecasts be put to a competitive tender process at least every 3 years.

By opening up the forecasting process to competition ACIL Tasman considers that there a number of potential benefits. These include:

- Maintaining pressure on the successful tenderer to keep costs competitive
- Providing incentives to improve in certain areas such as transparency by making it a requirement under the selection criteria of the request for tender
- Allowing the IMO to gain additional knowledge of alternative methodological approaches offered by other forecasting organisations

[20] Coincidence factor measures the ratio of the size of a block load coincident with the system peak relative to its system non-coincident peak. An individual load which peaks at the time of the system peak would therefore have a coincidence factor of 1.

6.11 Future issues

This section covers issues that the IMO may wish to consider in future energy and maximum demand forecasts.

6.11.1 Electric cars

While there has not been any attempt to forecast the impact of electric vehicles on peak demand and energy use within the SWIS, ACIL Tasman considers that there may come a time when it will be necessary to account for a potentially exponential increase in electric vehicles.

ACIL Tasman considers that electric vehicles may one day grow to represent a significant market share of all vehicle sales. However, it is likely that this will take quite a few years with most of the increase taking place after 2020. The timing of significant electric vehicle penetration will depend on developments in battery technology, the future oil and carbon price and the extent to which electricity supply is decarbonised. While there may be some impact on demand during peak times, the vast majority of vehicles are likely to be charged during off-peak hours assuming sufficient pricing incentives are offered and considering the likely usage and garaging patterns of cars.

There is considerable uncertainty associated with the factors that are likely to be relevant in determining demand for electric vehicles, namely the long run behaviour in the price of oil and also the extent to which the cost of the car battery declines over time due to technological innovation. At present, the price of electric vehicles is dominated by the cost of the battery including, replacement and disposal.

Electric cars are unlikely to be competitive with conventional vehicles unless:

- Significant new subsidies to encourage the uptake of the vehicles are introduced
- Vehicular emissions are included within an emissions pricing framework, the cost of emissions rises substantially and the level of carbon implicit in electricity supply falls substantially
- The cost of the battery as a proportion of the entire vehicle cost declines substantially
- The macroeconomic environment changes such that the price of crude oil increases even further from current levels.

ACIL Tasman considers that any increase in electric vehicles effect on system maximum demand is unlikely to occur for many years and is also likely to be quite small in its initial impact. We also consider that it is appropriate for the forecasts to make no adjustment for electric vehicles at this time, although this may change in the future.

6.11.2 Time of use tariffs and smart grid

Increased uptake of energy efficiency, particularly through smart grid technology and time of use metering, has the potential to alter electricity use in the SWIS substantially in future. As summarised in the IMO's 2012 SOO, the Perth Solar City trial has shown that substantial reductions in energy use and peak demand can be made possible by smart and smart metering technologies. It is clear that, if these outcomes are repeated around the state, electricity consumption patterns in Western Australia could be quite different in future than they have been to date.

However, even if the necessary technology is rolled out more broadly, this experience will not necessarily be repeated. There are numerous reasons why trial results may not be experienced to the same extent on a broader scale, or why they may not be enduring. Appendix B provides an overview of a number of smart metering trials that have been conducted in Australia and overseas. It shows that the results can be varied and may not last beyond the first stage of the trial. This suggests that forecasting the impact of these trials will not be as simple as assuming that the Perth Solar City results will be replicated throughout the SWIS. The challenge for forecasting will be to determine what use to make of the trial results. This will inevitably include some subjective decisions based on the judgement of the forecaster.

This issue is likely to increase in importance in the future. ACIL Tasman recommends that developments in this area be monitored carefully. While there is no need to adjust the current forecasts to account for smart grid technology and time of use metering, the need to adjust forecasts in the future may be on the horizon.

7 Conclusions and recommendations

ACIL Tasman has reviewed the forecasting methodology of NIEIR against best practice forecasting principles.

The key objectives of this review as outlined in the introduction have been to:

- Assess the demand and electricity consumption forecasts and associated methodologies and determine if they are prepared according to best practice demand and energy forecasting methodologies
- Assess the accuracy of the forecasts against what would be considered to be a reasonable level of error and against alternative model specifications
- Identify and recommend improvements to the forecasting methodology to improve performance in terms of accuracy and also the robustness and defensibility of the process to external criticism
- Assess the appropriateness of the methodologies used to account for factors that are not present in the historical data and make recommendations for improvement. These include large block loads, increasing uptake of solar photovoltaic cells and energy efficiency.
- Recommend changes to the Market Rules to enable improved demand forecasting and also to better facilitate the process.

Based on information provided and statements made by NIEIR, ACIL Tasman considers that the NIEIR forecasting processes have a number of features that are a necessary and desirable part of any maximum demand and electricity consumption forecasting processes.

These are:

- NIEIRs models of maximum demand and energy appear to incorporate the key underlying drivers, both economic, demographic and weather related
- The approach appears to be based on econometric techniques which aim to establish a relationship between energy and maximum demand and their underlying drivers based on historical data which are then used as the basis for forecasting
- NIEIR apparently recognises that there are certain policy impacts that are not able to be captured within the estimated econometric relationships and so estimates these impacts outside the basic econometric framework and makes adjustments to the original forecasts accordingly
- NIEIR/IMOs methodology separately accounts and adjusts for the impact of large block loads that exceed 20 MW
- NIEIR appears to apply appropriate weather normalisation techniques to its maximum demand data given current limitations to the data

- NIEIRs forecasts of maximum demand and electricity consumption are reasonably accurate after accounting for major block loads.

NIEIRs approach to forecasting maximum demand and electricity consumption appear to be generally sound.

7.1 Key recommendations

ACIL Tasman has identified a number of areas where additional analysis and amendments to the current methodologies could lead to greater accuracy and more robust and improved methodologies.

These are:

- That NIEIR analyses the tendency for its models to under-predict WA GSP and population growth and seek to identify methodological improvements that remove this downward bias
- That NIEIR adopts the use of simulation based weather normalisation methods as the basis for the maximum demand forecasts as soon as it is suitable to do so
- That NIEIR and the IMO consider producing electricity consumption forecasts conditional on different weather scenarios in a way similar to that done for system maximum demand
- That NIEIR and the IMO conduct further analysis of the energy output of solar PV systems in the SWIS, in light of the differences between NIEIR's forecasts and alternative sources such as the ORER
- That NIEIR and the IMO undertake a detailed ex-post evaluation of forecast performance with a focus on:
  - Errors in the forecast model inputs such as GSP and population growth
  - Structural issues within the models which may lead to less accurate forecasts
  - Identifying factors which the models may be failing to capture such as new behavioural or technological trends and policy changes
- That this ex-post forecast evaluation be conducted annually and that it be required under the Market Rules
- That NIEIR recalibrate its models every year using the latest available information
- That a process of data quality assurance be implemented to ensure that any data used in the forecasting process is free from errors, reliable, complete and timely
- That the Market Procedures be altered to require the timely acquisition of data requested from other agencies or organisations to facilitate the generation of the forecasts

- That NIEIR takes additional steps to improve the transparency of its processes, both of its models calculations between the input assumptions and the generated outputs and any judgements made during the forecasting processes and the underlying rationale behind them
- That the IMO adopt a more critical stance in evaluating new block loads by
  - Applying probability weights to its block load forecasts
  - Heavily discounting or excluding altogether those loads that are expected to come online after 3 years of more
  - That careful consideration be given to the degree of uncertainty associated with new mining loads and that these be reflected in the probability weights
  - That some adjustment be made for the level of coincidence at the time of the system peak and an appropriate coincidence factor be applied to the forecasts block loads
- That the IMO puts its contract to provide energy consumption and maximum demand forecasts out to competitive tender at least every 3 years.

A 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.

A.1 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.

A.2 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.

A.3 MAE

As the name suggests, 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.

A.4 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:

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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.

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

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

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

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

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.

A.5 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.

B Australian and overseas smart meter and smart grid trials

Most of the relevant trials identified have examined the impact of several interventions jointly, for example time of use meters together with time of use tariffs and in-home displays. This is helpful if the same combination of measures is ultimately employed in the SWIS but, if not, it may make comparing the results difficult.

For example, the cost benefit analysis prepared for the national smart meter rollout consultants to the MCE assumed that the impact on electricity sales would be between one and three per cent. Again, though, this was due to the whole package of measures, including smart meter, IHD and TOU tariff.

A brief overview of several Australian trials follows, together with some of the issues which arise in previous reviews.

B.1 Country Energy Critical Peak Pricing trial

Country Energy's trial commenced in December 2004 and ran for 18 months.[22] Smart meters and IHDs were installed in the homes of about 200 participants in Queanbeyan and Jerrabomberra. Tariff levels were as follows:

- **Off Peak:** 0.0703 cents/kWh
- **Shoulder:** 0.127 cents/kWh
- **Peak:** 0.1887 cents/kWh
- **Critical Peak:** 0.3774 cents/kWh

Critical peak events could only be called with at least two hours' notice and no more than 12 times per year. They were called when the load on the network was reaching maximum capacity or when wholesale electricity prices were high. Energy Futures Australia reports that Country Energy's experience was that electricity sales reduced during the peak periods but increased again afterwards. On one day, the peak in demand occurred later in the evening than normal, outside the critical peak period.

In terms of the impact on electricity sales in total, it has been reported that customers in the trial experienced median energy savings of 8% over a twelve

[22] Faruqui et al, "The impact of informational feedback on electricity sales – a survey of the experimental evidence", Energy Volume 35, Issue 4, April 2010, Pages 1598-1608

month period[23]. Another report was that participants in the trial reduced their energy usage by 5% on average.[24]

B.2 Energy Australia study

Energy Australia's strategic pricing study was conducted in New South Wales in 2006-07. 750 residential and 550 business customers took part. All of these had a smart meter, some with an in-house display. A public report of the results of this study is understood to be under development, although ACIL Tasman is not aware that it is yet available. The published information that is available regarding Energy Australia's review is relatively limited.

The study incorporated a control group without a smart meter and a range of groups with smart meters on different tariff structures. [25][26]

It was reported that there was a significant reduction in electricity sales of between 5% and 7% on Dynamic Peak Pricing days, which represents conservation, not load shifting. [a] These results contrasted with others which reported that the reduction in dynamic peak consumption by customers on DPP high rates and DPP medium rates was 24 and 20 per cent respectively.[27]

It is critically important to note that, at most, Energy Australia's trial enables it to call up to 12 critical peak events per year, no more than four times per month and no more than once per day.[28] Given this, while energy reductions are of the order of six to eight per cent during critical peak events, it does not follow that this is the amount by which electricity sales will be reduced throughout the year. On the contrary, using these metrics, at most the annual energy reductions would be expected to be much less than one percent.

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23 Ibid.

24 Riedy, op cit, p. 16

25 Sustainability First, "International Smart Meter Trials selected case studies smart tariffs and customer stimuli", May 2008, available at http://www.sustainabilityfirst.org.uk/publications.htm, accessed 24 March 2010.

26 Energy Market Consulting associates (EMCa), "Smart Meter Consumer Impact: Initial Analysis a report to the Ministerial Council on Energy standing committee of officials", April 2009, available online at http://www.ret.gov.au/Documents/mce/emr/smart_meters/default.html, accessed 15 March 2010.

27 Faruqui and George op cit

28 Riedy, C. op cit, p.21.

B.3 AMI study – Integral Energy

Integral Energy conducted a study in Western Sydney beginning on 1 August 2006 and running for at least two years.[29] In the trial, more than 900 residential customers, who are understood to have been volunteers, had interval meters installed. These customers were priced into one of three treatment groups and were given either a seasonal time of use tariff, or a dynamic peak price. Of the customers subject to a Dynamic peak price, some had IHDs while others did not.

The seasonal TOU (STOU) tariff was such that peak time prices were approximately triple off peak prices. Peak prices applied from 1:00pm until 8:00pm in the summer months and from 5:00pm to 7:00pm in the winter months.

The dynamic peak price was around fifteen to twenty times the off peak price and was applied on a small number of days with advance warning given either the morning of the peak day or the night before. Customers on the dynamic peak price model also paid a higher price for energy consumed between 1:00pm and 8:00pm on working days.

All customers were given access to an online mechanism to monitor their energy usage.

The results showed that the time of use tariff group used more energy in the last 18 months of the trial than the control group. Specifically, the STOU group used 2.7% more energy in peak times and 3.7% more in total. Integral Energy has noted that this group started out using 6% more energy than the control group, which implies that their energy use actually fell during the trial.[30] This observation stresses the importance of controlling for sample selection bias in conducting trials. The evidence suggests that the CPP trials were effective in reducing peak demand, although it is not clear whether this was achieved by use reduction or load switching.

B.4 Other studies

A number of other studies into the potential impact of time of use and CPP tariff structures have been conducted going as far back as the 1970s, with a

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[29] Nominally the trial ended after two years although most customers opted to stay on the ‘treatment’ tariffs.

[30] EMC[a] op cit, p.31

resurgence following the Californian power crisis of 2000/01.[31] A brief comparison of a number of these studies is set out in Table 16 below. A more detailed consideration is provided in a number of papers authored by Ahmad Faruqui of the Brattle Group, in particular Faruqui et al, 2008.

Table 16 **Summary of trials**

Study name	Tariff differential (CPP:peak:off peak, c/kWh)	Load shifting	Energy reduction
PSE&G residential (my power sense)	8.6:1.7:9	Elasticity =-0.085	Not discussed
PSE&G residential	8.6:1.7:9	Elasticity = -0.137	Not discussed
Ontario Energy Board smart price pilot	-:10:3.5	Not distinguishable from zero	6%
Anaheim critical peak pricing experiment	Rebate based		
Idaho residential pilot program – time of day pilot	8.3:4.5	Nil	Not analysed
Idaho residential pilot program – energy watch pilot			
Energy Australia network tariff reform			Slight, more in winter than in summer No effect on business customers
Illinois – Community Energy Cooperative's energy-smart pricing plan	Variable hourly up to 50 c/kWh Announced day ahead High price notification via phone or email when price > $0.10/kWh		Roughly 3 to 4%
AmerenUE CPP pilot (TOU group only)	17.3:7.5:4.8	Nil in first year, not reported in second year	
Automated Demand Response System pilot (California)			
State wide Pricing Pilot (California) (TOU group)	-:22:9	Not presented	~0.55%

[31] Faruqui, A. and S. Sergici, "Household response to dynamic pricing of electricity a survey of seventeen pricing experiments", 10 January 2009.

A number of observations can be distilled from these studies. Key among these are the observations that:

- Demand for electricity is inelastic in the short run
- There is some evidence to support a 'fatigue' effect
- Demand by business customers is less elastic than demand by residential customers
- CPP tariffs initiate a larger response than TOU tariffs.

ACIL Tasman also notes that Origin Energy recently initiated a pilot scheme of in-home-displays involving 5,000 households with the objective of learning how to provide a "new, sophisticated form of energy service" for their customers.[32]

B.5 The relevance of trials

We note that there are also some purported shortcomings of trial based studies. In a paper reviewing a number of Australian trials on behalf of the Consumer Utilities Action Centre, Dr Chris Riedy from the Institute for Sustainable Futures at the University of Technology, Sydney, made the following comments, applicable to all the trials of interval metering that have been conducted in Australia:

> First, the trials are voluntary and there are no penalties for opting out of the trial. Second, participants often receive incentive payments that offset any increases in bills. Third, some trials have excluded customers with payment difficulties so that there is no risk that these customers will experience an increase in hardship. Fourth, meters and associated equipment (including in-house displays) are provided at no cost to the customer. Finally, tariffs seem to have been set so that most customers will experience only small increases in bills even if they do not change their behaviour. [33]

In Riedy's view, these are appropriate characteristics of trials. While this may be the case, it should be noted that trials with these characteristics are likely to yield different results than would be expected in the 'real world'.

The 'real world' contains a proportion of people who see little or no net benefit in reducing their energy use. Whenever a trial is conducted using volunteers as subjects, it is unlikely that volunteers will include representatives from this group of energy users. In trials which are 'opt out', it is more likely

[32] Giles Parkinson "Origin of an energy revolution", www.climatespectator.com.au, 10 August 2011

[33] Riedy, C. "Interval Meter Technology Trials and Pricing Experiments", p.vi available at http://www.isf.uts.edu.au/publications/riedy2006intervalmeters.pdf, accessed 29 March 2010

that this group will take that option. Trials are unlikely to reflect the impact of an environmental policy on these people.

Hence trials of this kind may exaggerate the incentives applying to subjects, because trial participants are more inclined to try to reduce their energy use regardless of the trial and even more likely to do so when given the assistance that comes with the trial itself.

For these reasons, it would not be sufficient simply to assume that the experience observed in a trial will be replicated through a broad scale rollout of a new technology. The challenge for a forecaster is to determine what use to make of the trial. This will inevitably be a matter of judgement and, as such, will inevitably be subjective.