ELECTRICITY DEMAND FORECAST METHODOLOGY

FINAL REPORT AND DETERMINATION

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EXECUTIVE SUMMARY

The publication of this Final Report and Determination (Final Determination) concludes the Forecasting Best Practice Guidelines consultation process conducted by AEMO to formalise the Electricity Demand Forecasting Methodology (the Methodology) Document component of its Forecasting Approach.

AEMO's Issues paper asked stakeholders whether various forecasting components listed in the Methodology are fit for use in AEMO's Electricity Statement of Opportunities (ESOO) and other medium- to longer-term reliability assessments and system planning purposes, including the Integrated System Plan (ISP).

The Draft Determination responded to concerns identified in submissions to the Issues Paper regarding:

- The purpose of Electricity Demand Forecasts.
- Granularity of data used.
- Economic measures.
- Forecasting new technologies.
- Incorporating probabilistic forecasts, weather and climate.
- Differing methodologies for segmented demand.
- External review of AEMO's Methodology.

In response to a stakeholder submission on hydrogen, and in light of stakeholder interest in the matter in the Forecasting Reference Group (FRG) and ISP, AEMO added the Hydrogen Sector as a component of the Methodology.

Submissions to the Draft Determination and the Draft Methodology closed on 15 April 2021.

AEMO received one general submission to the Draft Determination, supporting a change made in the Draft Determination, and providing a further recommendation regarding forecasting new technologies. No further changes were made to the Methodology.

AEMO's determination, following consideration of the submissions received, is to publish the Electricity Demand Forecast Methodology Document in the form published with this Final Determination.

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1. STAKEHOLDER CONSULTATION PROCESS

As required by Section 2.1 of the Australian Energy Regulator's (AER's) Forecasting Best Practice Guidelines[1] (FBPG), AEMO has consulted on its Electricity Demand Forecasting Methodology in accordance with the FBPG consultation process in Appendix A.

While the FBPG is only applicable to AEMO's National Electricity Market (NEM) forecasting function, AEMO intends to apply a consistent forecast approach across the NEM and Western Australia's Wholesale Electricity Market (WEM) wherever possible. So, with the exception of references to the FBPG and where noted otherwise, this Final Determination and the Methodology apply to both.

AEMO's timeline for this consultation is outlined below.

Deliverable	Indicative date
Notice of first stage consultation [and Issues Paper] published	18 December 2020
First stage submissions closed	21 January 2021
Meeting held with Queensland Energy Users Network (QEUN) on request	16 February 2021
Draft Report and Notice of Second Stage Consultation published	16 March 2021
Submissions due on Draft Report	15 April 2021
Final Report published	27 May 2021

The publication of this Final Determination marks the completion of the second stage of consultation.

Note that there is a glossary of terms used in this Draft Report at **Appendix A**.

2. BACKGROUND

2.1. Context for this consultation

Section 2.1 of the FBPG requires AEMO to consult on each component of its Forecasting Approach[2] at least once every four years. AEMO has not previously formally consulted on this Methodology prior to the introduction of the FBPG, although it was historically updated and published annually.

AEMO invited comment from stakeholders on any matter contained in the Methodology. To aid stakeholders in providing feedback, several questions were posed throughout the Methodology.

2.2. First stage consultation

AEMO issued a Notice of First Stage Consultation[3] on 18 December 2020. The issues Paper[3] outlined changes to the document since it was previously published and requested stakeholder feedback on whether various forecasting components listed in the Methodology are fit for use in AEMO's Electricity Statement of Opportunities (ESOO) and other medium to longer-term reliability assessments and system planning purposes, including the Integrated System Plan (ISP).

AEMO received five written submissions in the first stage of consultation from CitiPower, ERM Power, Deloitte, Queensland Energy Users Network (QEUN), and Major Energy Users (MEU).

Copies of all written submissions and minutes of meetings have been published on AEMO's website[3].

[1] See: https://www.aer.gov.au/system/files/AER%20-%20Forecasting%20best%20practice%20guidelines%20-%2025%20August%20 2020.pdf

[2] See: https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/ forecasting-approach

[3] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/electricity-demand-forecasting-methodology

2.3. Second stage consultation

AEMO issued a Draft Determination[3] on 16 March 2021 alongside an amended version of the Methodology. In response, AEMO received one written submission from CitiPower, referred to in Section 4.3.1. The submission did not result in further changes to the Methodology.

3. SUMMARY OF MATERIAL ISSUES

The key material issues arising from the proposal and raised by Consulted Persons are summarised in Section 4:

- Section 4.1 discusses the scope of the Methodology.
- Section 4.2 discusses issues raised about the granularity of data used in AEMO's forecasts.
- Section 4.3 explores emerging technologies topics raised including distributed photovoltaics (PV), electric vehicles (EVs), hydrogen, and storage.
- Section 4.4 discusses economic related issues including elasticity and economic measures used.
- Section 4.5 discusses an external review of AEMO's Methodology.
- Section 4.6 discusses issues regarding the nature of probabilistic forecasts, including weather.
- Section 4.7 discusses specific segments forecast: Large Industrial Loads (LIL), Business Mass Market (BMM) and residential.
- Section 4.8 discusses other matters raised.

4. DISCUSSION OF MATERIAL ISSUES

4.1. Purpose and applicability of Electricity Demand Forecast

4.1.1. Issue summary and submissions

The electricity demand forecasts produced following the Methodology is fundamental to a number of planning and reliability forecasting processes, and is designed for and suited to those purposes. CitiPower's submission expressed concern that forecasts arising from the Methodology may be used for purposes that they are less suited to:

> We remain concerned with the tendency for regulators and policy makers to routinely apply AEMO's terminal station forecasts[4] (which are derived from the state-wide forecasting methodology) for the purposes of distribution network planning. This occurs through the regulatory reset process or as part of the Regulatory Investment Tests for Distribution (RIT-D). Like other distributors, we do not use AEMO's forecasts.

CitiPower noted that its own forecasts are suitable for network loads, but that "many policy makers and regulators seek to take AEMO's terminal station level forecasts and equally apportion them across all zone substations and feeders". CitiPower's submission requested that AEMO provide guidance to regulators and policy makers on the inappropriateness of using the demand forecasts produced using the Methodology for distribution network planning purposes. Elsewhere in its submission, CitiPower put forward its view that:

> AEMO's electricity demand forecasts, particularly as drivers of the ISP, must be reliable, consistent, and transparent to provide investment certainty at a time of need for investment in capacity, renewables, and new technologies.

[4] CitiPower apparently uses 'terminal station' to mean what AEMO defines as transmission connection points.

4.1.2. AEMO's assessment

AEMO has a separate process for Transmission Connection Point (TCP) forecasting, which differs from the regional approach consulted on in this document. The TCP forecast takes into account spatial drivers, including Distribution Network Service Provider (DNSP) feedback on locational specific changes, for example new block loads or load shifting. The TCP forecasting methodology can be found on AEMO's website[5].

For these TCP forecasts, it should be noted that:

- The coincident maximum demand forecast for a region is calculated based on a reconciliation with the regional forecast, applying diversity factors to match up the two forecasts.
- Non-coincident peak forecasts are not driven by the regional forecast, though a number of input drivers to the TCP forecasts and regional forecasts will be consistent (such as distributed PV uptake and population growth).
- AEMO does not currently have information that allows it to project load growth specific to a finer spatial resolution, such as at zone-substation level.

Overall, the TCP forecasts, which are published separately to the ISP and ESOO, provide a greater level of spatial detail than the regional forecasts, and they support DNSPs in making efficient network investment and guide the regulator's review of related proposals.

CitiPower makes a valid point that forecast changes in demand at TCP level are not necessarily shared evenly across lower levels of the distribution networks, and AEMO acknowledges that application of TCP forecasts to zone substations and feeders requires detailed information about the distribution networks to be accurate.

AEMO disagrees with CitiPower's view that demand forecasts 'must' provide investment certainty. AEMO's forecasts are intended to be as accurate as possible, but they cannot provide certainty where the uncertainty is outside AEMO's control. The existence and definitions of high-level uncertainties is consulted on extensively through AEMO's draft Inputs, Assumptions and Scenarios Report (IASR)[6] , and the resulting scenarios are transparently described. Finer grain uncertainties associated with various drivers are recognised throughout forecasting components, with forecast uncertainty bands indicating the expected range of variance. Finally, as addressed in Section 4.3 of this report, new technologies are inherently difficult to forecast, and from time to time may result in corrections as the underlying drivers are revealed.

AEMO notes that CitiPower and any other stakeholders can provide feedback to AEMO on any assumptions and draft component forecasts (for example distributed PV) though the consultation on AEMO's draft IASR noted above and the subsequent engagement with stakeholders through the Forecasting Reference Group (FRG)[7].

Furthermore, AEMO annually publishes its Forecast Accuracy Report, which assesses the accuracy of the forecast components. The corresponding Forecast Improvement Plan proposes improvement initiatives where possible, and is subject to consultation, allowing stakeholders to provide input on how forecast performance can be enhanced.

[5] See: https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-and-planning-data/transmission-connection-point-forecasting.

[6] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/2021-planning-and-forecasting-consultation-on-inputs-assumptions-and-scenarios

[7] See FRG Consultations at: https://aemo.com.au/en/consultations/industry-forums-and-working-groups/list-of-industry-forums-and-working-groups/forecasting-reference-group-frg

4.1.3. AEMO's conclusion

When AEMO updates its TCP forecast methodology, it will include a 'purpose and application' section that describes the limitations of the forecast for purposes outside its core application. In particular, it is inappropriate to apply AEMO's TCP forecast to lower level network demand by evenly assigning it across zone substations without sufficient information to support this as a valid approximation. AEMO has added a similar section to the Methodology to clarify its purpose and reference its TCP forecasts and methodology as supplementary material to increase awareness of the more spatial forecasts available.

4.2. Model granularity, definitions and data

4.2.1. The value of granularity in forecasts

Issue summary

AEMO's forecasting process models various components of electricity demand, with each modelled to a level of detail that balances its criticality with the needs for accuracy, explainability, and efficiency.

Numerous submissions made reference to increasing granularity, suggesting that such granularity increases forecasting accuracy. This was most explicitly stated by MEU: "MEU is of the view that greater segregation of residential consumer demand will enhance forecast accuracy". Related quotes show a theme among submissions:

- MEU stated that "further granularity is needed to reflect the reality there are quite distinct subgroups within [BMM and residential cohorts]". It provided the example of houses and units, where houses may or may not have solar, and are occupied by owners or renters. Elsewhere, it noted differing energy uses by day or week
- ERM Power stated: "In the model all connections are considered to be equal and no analysis of the type of residential housing stock is defined to determine more granular values for different types of housing such as high density apartments, medium density units or detached housing. In predicting future consumption, the model relies solely on the forecast number of new and existing connection points. Should the shares of individual types of future residential connections deviate from the current shares, then considerable time may elapse prior to the model applying a degree of self-correction to the defined values for baseload, heating and cooling consumption."
- ERM Power stated: "We recommend that AEMO request assistance from DNSPs to improve the granularity of load classification on a National Market Identifier (NMI) on the basis of differentiation of network tariff structure to better identify business consumption types."

QEUN, in its verbal submission, requested that AEMO segment BMM in its forecast, perhaps separating small and medium. It went on to further request that AEMO work with the AER to consolidate definitions of small, medium and large customers to make it consistent among states and energy data users Australia-wide.

In terms of the delivery of greater granularity, stakeholders referenced a wide range of data sources they considered relevant:

- MEU listed retailers, DNSPs and transmission NSPs (TNSPs) as having good data about end user usage patterns, and flagged the smart meter data as particularly relevant.
- ERM Power questioned whether the Essential Services Commission and AER's retailer-supplied solar tariff data would provide a more accurate value for forecasting distributed PV numbers.

AEMO's assessment

In modern management, greater granularity is associated with insights at a segment level, and is particularly appropriate where there is an expectation that different actions can be directed towards different segments. Importantly, however, increasing forecast granularity does not necessarily provide more accurate forecasting results than an aggregated forecast. Appendix B describes the considerations for segment definition and increasing forecast granularity, along with a worked "EDFM Draft Determination Example Spreadsheet[8]" to demonstrate various scenarios in which forecast accuracy is not improved as a result of increasing forecast granularity.

AEMO considers the appropriate level of granularity when performing Exploratory Data Analysis (EDA) during model development. Depending on the problem attempting to be solved, increasing forecast granularity is also considered during a forecast accuracy review. Typically, AEMO sees the merits of increased forecast granularity as supporting comparison with external data or expectations at the segment level, which may enhance stakeholder confidence. As described in Appendix B, increasing the forecast granularity is not required in order to incorporate a relevant variable into a model, and this option may deliver sought forecast accuracy improvements and some degree of insights.

ERM Power's statement that "in the model all connections are considered to be equal" is incorrect. A forecasting model, such as AEMO's connection model, can validly model the average of a heterogenous group without considering or assuming that the heterogenous elements are equal. In AEMO's connection model, the additional energy consumption forecast due to a single additional connection should be understood according to the statistical term 'expected value', rather than a deterministic prediction. As the number of additional connections increases, the additional electricity consumption per connection tends towards the average consumption, according to the statistical law of large numbers.

ERM Power's statement that "should the shares of individual types of future residential connections deviate … then considerable time may elapse prior to the model applying a degree of self-correction…" implies that the connections model requires a number of residual values to significantly influence a parameter reflecting housing mix. This would be true for a typical regression model, however AEMO uses the single most recent annual data point of the current proportion of dwelling types as a basis from which to grow the consumption forecast according to the other variables described in the Methodology. AEMO's Energy Efficiency model already utilises a forward view of connections by dwelling type, which AEMO can present as background information for stakeholder consideration when presenting draft forecasts in the future.

Regarding QEUN's suggestion of AEMO working with the AER to consolidate definitions of small, medium and large customers, AEMO notes that the existing range of definitions has already been widely deployed into various IT systems of market participants, and change could be substantial and costly without a clear quantification of the benefits or improvements to the forecasts. AEMO considers that a tool for converting between the various definitions employed is likely to be a more tractable solution than a large scale initiative to harmonise definitions. AEMO proposes to work with interested stakeholders to identify options for such a solution.

AEMO notes that few of the submissions' recommended data sources were organisations acting across the NEM; most were state-based or DNSP-based. In designing the Methodology, AEMO carefully considers the reporting burden on NEM participants, and where possible, requests data from a single NEM-level source rather than individual DNSPs. However, AEMO is working with DNSPs to identify new loads and understand new technology uptake in the distribution networks. Also, AEMO is using smart meter data to drive insights, for example around technology use and residential vs. business usage trends.

[8] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/electricity-demand-forecasting-methodology

AEMO's conclusion

The assessment has shown that increasing forecast granularity is not a panacea for forecast accuracy, particularly where costs must be managed, more assumptions need to be made about future trends and/or historical data is not available to measure the more granular forecast's performance. The complexity increase associated with increased granularity needs to be justified based on materiality to the forecast. It is unclear whether stakeholders' recommendations would lead to material improvements.

In that light, AEMO looks forward to working with stakeholders to clarify their goals in recommending increased forecast granularity:

- Where the goal is to increase forecast accuracy, AEMO considers a variety of options alongside increasing forecast granularity, including incorporation of additional drivers to the forecast model.
- Where the goal is to increase confidence in the forecast, AEMO will deliver this through its annual Forecast Accuracy Report (FAR), noting it has previously committed to include an independent assessment of approach and potential for bias in the FAR reporting metrics at least once every four years, prior to a full FAR methodology consultation[9].
- Where the goal is to address a perception that AEMO assumes homogeneity of electricity consumers, stakeholders should note that assumption is neither required nor made by AEMO.

Similarly, AEMO considers opportunities to reduce granularity (forecast at a more aggregate level), where forecast accuracy can be maintained at a lower overall cost. Where such opportunities are identified, AEMO will seek stakeholder input through the Forecast Improvement Plan or relevant consultation.

Regarding the challenges of alternative segment definitions being used in the NEM, AEMO looks forward to working with interested stakeholders to identify a cost effective solution for conversion of key statistics between the alternative definitions.

4.2.2. Definition of business segments

Issue summary

Integral to the topic of granularity is the definition of forecasting segments.

QEUN recommended that AEMO clearly define what constitutes a small and medium size business, and noted the differing definitions within AEMO.

AEMO's assessment

AEMO agrees that segment definitions in the Methodology should be clearly defined and has attempted to make these definitions clear.

Appendix B recognises the value in electricity forecasting segment definitions matching with other definitions outside of electricity forecasting, but also identifies a number of other factors that warrant consideration.

In the case of the BMM definition used in AEMO's forecasts in particular:

- Residential electricity consumption is defined as electricity used in a place of permanent abode. This excludes, for example, hotels and boarding houses. Technically, the forecast depends on customer type in the Market Settlement and Transfer Solutions (MSATS) system as tagged by the local DNSP.

[9] See 5.1.3 in https://aemo.com.au/-/media/files/stakeholder_consultation/consultations/nem-consultations/2020/rfg/second-stage/reliability-forecast-guidelines-draft-determination.pdf

- Business electricity use is defined as all other electricity use, apart from that needed to generate and distribute electricity (generation and losses). Within business:
  - Large Industrial Loads (LIL) in the NEM are defined in Section 2.1 of the Methodology, stating that "a demand threshold of greater than 10 megawatts (MW) for greater than 10% of the latest financial year is used to identify those loads". In AEMO's demand forecasts, the LIL segment thus represents the electricity use of these very large sites.
  - Electricity used to generate hydrogen – see Section 2.2 of the Methodology "Hydrogen related demand forecasting."
  - BMM makes up all other business electricity use.

AEMO is aware that the above definition of BMM electricity use does not directly support matching with other sources such as the Australian Bureau of Statistics (ABS) or Australian Taxation Office (ATO) because it does not include employee headcount or business turnover information respectively. AEMO considers factoring in such variables in the definition to be of high cost and complexity for the benefits provided.

Similarly, AEMO's 2021 Budget[10] utilises a different definition of small business for its purpose. Rather than being instrumental to the budget itself, it is incidentally noted as background to the estimated scale of AEMO fees on households.

AEMO notes the considerations for defining segments in Appendix B are rarely all satisfied completely, and the BMM definition used in the Methodology addresses as many of the considerations as is reasonably possible. AEMO considers it the best option available for electricity forecasting.

AEMO's conclusion

AEMO has amended the Methodology's definitions for clarity. The above section, in concert with Appendix B, sets out the explanation and justification for the current BMM definition. Noting that the term Small and Medium Enterprises (SME) implies it covers specific sizes of organisation, AEMO has decided to change the term to Business Mass Market (BMM), as it better reflects all business loads but the largest. This avoids confusion that can result from various definitions of small, medium and large organisations across different industries.

4.2.3. Model granularity for maximum demand modelling

Issue summary

The MEU noted AEMO's consumption forecast segmentation differs from its maximum demand forecast segmentation. Consumption forecasts encompass LIL, BMM and residential segments, whereas maximum demand forecasts aggregate the BMM and residential segments all into one single segment. The MEU noted that maximum demand drives consumer costs more than total energy, and queried the relative segmentation levels. The MEU suggested that increased segmentation of maximum demand forecasts would better improve forecast accuracy and understanding of drivers.

AEMO's assessment

AEMO notes, as per above sections of this report and Appendix B, that greater granularity does not necessarily result in more accurate forecasts. However, there may be value to the NEM or WEM in understanding the relative contribution of different segments to demand, if this enables segment level demand management plans to be developed.

[10] https://aemo.com.au/-/media/files/about_aemo/energy_market_budget_and_fees/2020/budget-and-fees---final.pdf

Any benefits of more granular demand forecasts must be balanced against the associated costs, complexities and potential loss of accuracy. In anticipating benefits, the statistical nature of demand is a key challenge that should be recognised:

- Demand, being at a point in time rather than a cumulative value, is inherently more volatile than energy.
- A fundamental of statistical analysis is that volatility of individual segments is greater than that of their total.

These points mean that, while demand segmentation can be performed, the results tend to suffer from compounded volatility such that they are unlikely to be understandable or actionable, or more accurate than the aggregated figures.

A further challenge associated with increasing demand forecast granularity is the low numbers of business sites with interval meter data in Queensland, South Australia and Tasmania. The numbers are insufficient for developing segment level forecasts with a meaningful level of precision.

AEMO's conclusion

AEMO notes stakeholder perceptions that more detailed demand forecast segments would benefit the demand forecast, but has outlined above (and in Appendix B) this is not necessarily the case. Furthermore, even before related costs are considered, AEMO notes theoretical and practical impediments to usefully increasing granularity, such as the high resulting volatility and the limited availability of suitable data.

AEMO looks forward to ongoing engagement with stakeholders to explore the limitations inherent in statistical analysis and related forecasting techniques, and the implications of those limitations. AEMO understands that forecasting maximum demand by customer segment could help inform decision makers if there was confidence in the accuracy of those more granular forecasts.

4.3. Distributed PV and new technology forecasts

4.3.1. Performance of new technology forecasts including distributed PV

Issue summary

Distributed PV generation is a fast-growing technology which has proven difficult to forecast accurately. Table 1 illustrates this. For the forecast year 2022 (financial year ending), AEMO's consultant forecasts have kept revising up forecasts, as installations in the short term have consistently exceeded expectations. Looking at 2030, the forecasts have varied up and down, as technology cost projections and market saturation assumptions have evolved. Acknowledging the material uncertainty in distributed PV trends, AEMO engages two independent consultants to help develop the distributed PV forecasts in an effort to capture diversity of views. These forecasts are then consulted on through the FRG to test reasonableness.

Table 1 Forecast generation (in gigawatt hours [GWh]) of installed distributed PV systems across the NEM in different ESOOs

Forecast year	ESOO 2017	ESOO 2018	ESOO 2019	ESOO 2020
2022	11,871.56	13,686.34	14,134.46	15,571.60
2030	20,005.78	18,100.25	16,510.52	25,191.89

AEMO's 2020 Forecasting Accuracy Report[11] included an assessment of distributed PV forecasting. As accuracy performance was below expectations, the corresponding Forecast Improvement Plan consultation included an action on AEMO to improve the distributed PV forecast.

CitiPower in particular noted concerns with AEMO's forecast of new technologies in general, including distributed PV, EVs and batteries. Its submissions included:

> AEMO's electricity demand forecasts, particularly as drivers of the ISP, must be reliable, consistent and transparent to provide investment certainty at a time of need for investment in capacity, renewables and new technologies.

CitiPower also noted the volatility of AEMO's PV forecast (shown in Table 1) as problematic and noted that DNSPs have actual and connections data as it occurs, which AEMO should consider using to assist with the distributed PV forecast.

CitiPower went on to recommend "AEMO develop a more consistent and reliable approach to forecasting the impact of new technologies on demand. This includes the appropriateness of using post-model adjustments rather than updating the structure of the model".

CitiPower's submission on the Draft Determination re-iterated their concerns regarding significant year-on-year changes in forecasts of new technologies, i.e. rooftop solar, electric vehicles, batteries and energy efficiency, making it "difficult to refer to and validate AEMO's forecasts on a consistent basis." They suggested AEMO source and average multiple forecasts rather than relying on a single forecast, and further suggested that AEMO prioritise consistency when reviewing methodologies.

AEMO's assessment

The forecast scenarios that AEMO develops with stakeholder input lead to a forecast dispersion band for each new technology, which can be said to describe the 'known unknowns' at the time of forecasting. Thus, in a NEM with incremental changes to underlying drivers and no surprises, it would be reasonable to expect forecasts each year to be consistent with prior year forecasts. In reality, the emergence of factors (that were 'unknown unknowns' at the time of the forecast) leads to new forecasts outside the range of prior year forecasts. Unknown unknowns may include unanticipated factors such as government policies, complimentary or competing technologies, or broad societal phenomena such as the COVID-19 pandemic.

In understanding how such unknown unknowns affect the forecast, it is helpful to consider the underlying qualities of forecasts:

- Accuracy – the similarity of forecast and actual values
- Consistency – the steadiness of the subsequent forecasts with prior forecasts
- Explainability – the ability to quantitatively breakdown accuracy or consistency by drivers

Regarding CitiPower's recommendation that AEMO use more post-model adjustments, AEMO's first choice in the Methodology is to use statistical models wherever appropriate. Such data-driven models maximise objectivity and transparency and generally perform efficiently and effectively. Only where data is insufficient does AEMO utilise-post model adjustments, and AEMO typically uses specialist consultancies to inform such adjustments.

AEMO notes the strengths and weaknesses of various types of statistical models with regards to the above qualities:

- A flat line (constant) or simple time trend model typically has low accuracy, but perfect consistency

[11] See: https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/accuracy-report/forecast-accuracy-report-2020.pdf.

- A white-box model has moderate to high accuracy, and potential for excellent explainability. The level of consistency is data dependent. A regression model is an example white-box model, where beta parameters quantify the average relationship between each driver and the forecast output.
- A black-box model may be highly accurate but typically has low explainability. The level of consistency is data dependent. A neural network is an example of a black-box model. Parameter values are formed from iterative processing involving many millions of individual calculations and the resulting quantity of parameters defy human consideration.

From the above, it follows that:

- in general, forecast consistency is data dependent: as model inputs change across each iteration of the forecast, the forecast output is designed to change in some way. Only a flat line or simple time trend model ignores exogenous inputs and is consistent regardless of real world events.
- in practice, seeking higher consistency comes at the expense of accuracy.
- the explainability of consistency-focussed forecasts has limited utility, as ultimately forecasting error would be explained by reference to the desire for consistency. In contrast, explainability of accuracy-focussed forecasts succeeds in providing reasoned analysis on differences between forecasts, down to the level of detail of the underlying data if necessary.

Thus, at this point in the analysis, emphasizing consistency over accuracy and explainability appears to be a plausible preference for forecasting outcomes. However, there is a deeper logical problem in emphasizing consistency during the methodology development phase, as demonstrated via a simple thought experiment:

> Consider a new technology with 20% market penetration in a NEM region in the base year, and a forecast annual growth rate of 5% thereafter. After one year of strong growth, the new base year penetration is observed to be 28% rather than the previously forecast 25%. In the pursuit of accurate forecasts, the annual growth rate is simply adjusted in light of this and any other new data. However, if pursuing consistency, the updated annual growth rate could be:
>
> - Retained at 5% per year, for consistency with the previous forecast, or
> - Adjusted downwards in the short term, so as to achieve short term penetration values consistent with the previous forecast, or
> - Adjusted downwards beyond the short term, so as to achieve the long term technology penetration values consistent with the previous forecast

It is entirely possible that different stakeholders value different definitions of consistency. It is thus clear that stakeholders emphasizing consistency over accuracy are best served by their own analysis, rather than centrally through AEMO.

To avoid subjecting the forecast development process to conflicting consistency requirements, AEMO reserves its consideration of forecast consistency to the validation phase of an accuracy-focussed forecast. Where there are material differences between the new and previous forecasts, AEMO:

- Analyses the root cause and guards against error. To the extent the root cause of differences is unclear, it is appropriate to question whether an error has occurred in the methodology formulation or execution.
- Includes additional stakeholder engagement to ensure the reasons for differences between forecasts are clear. AEMO benefits from DNSPs and other stakeholders providing their insights of emerging issues and local knowledge. Through Energy Networks Australia, AEMO is exploring ways to better incorporate DNSPs' local knowledge of current and future technology trends in its forecasts.

CitiPower suggested the use of multiple consultant forecasts to improve consistency between forecasts.

AEMO considers the primary value of multiple consultant forecasts to be in exploring relevant factors and approaches where significant uncertainty exists. The secondary value, of averaging multiple data points, is modest and comes at a high consulting cost relative the impact of the averaging. In any case, averaging develops a central view of a forecast where all consultants are exposed to the same information. It does not address CitiPower's concern of instances where a forecast lies outside the bounds of a previous year's forecast. When unanticipated events occur, all consultants are expected to update their forecasts in light of the new information, and the averaged result may lie outside the bounds of a previous averaged result.

AEMO's recent ISP Methodology issues paper[12] noted value has been identified in DNSP and ENA input to DER forecasts. Consultation on the ISP Methodology is ongoing and AEMO look forward to submissions to this end.

AEMO's conclusion

AEMO has noted distributed PV forecast performance in the most recent Forecast Accuracy Report and consulted on initiatives to improve the performance of its forecast in the associated Forecast Improvement Plan[13]. AEMO will work with its consultants to ensure the methods applied in the future address the issues found.

New technology forecasts are more prone to 'unknown unknowns' than broader forecasts, as consumers, government, and industry respond in unanticipated ways to the drivers of the new technologies, the technologies themselves, and any side effects of the technologies. AEMO seeks input from stakeholders (and where appropriate from independent consultants) to minimise the unknown factors, so that the forecasts scenarios reflect the true uncertainty. However, the nature of the unknown factors is that some of them will be unknown to all parties at the time of a forecast.

The variety of dynamics associated with each new technology is too broad to meaningfully guide selection of a single forecasting technique across new technologies in general. Instead, AEMO's periodic forecasting methodology consultations gain stakeholder input on the most appropriate methodology for the new technology or technologies under consideration.

AEMO acknowledges that some stakeholders may value forecast-to-forecast consistency over forecast accuracy. However, for the reasons described in the assessment section above, AEMO considers it impractical to directly support the various types of consistency such stakeholders seek. Rather, AEMO emphasizes forecast accuracy and explainability, and seeks to accommodate stakeholder interest in consistency during the validation phase. To that end, draft forecast presentations compare new forecasts to previous forecasts and provide insights on the differences. This approach satisfies stakeholders seeking accuracy, whilst permitting stakeholders with a preference for consistency over accuracy to adapt AEMO's forecasts for their own needs. AEMO invites those stakeholders to consider:

- smoothing AEMO forecasts to achieve the stakeholder's desired type and degree of consistency
- averaging AEMO's forecast with the stakeholder's own forecasts, obtained either directly or via their sector's peak body
- producing plans or strategies that are resilient to the volatility inherent in new technology forecasts

As the degree and definition of consistency is stakeholder dependent, it is appropriate that the stakeholders procure relevant consultants to meet their own needs. AEMO does not see CitiPower's suggestion for AEMO to expand its use of multiple consultant forecasts as necessary or cost effective.

[12] https://www.aemo.com.au/-/media/files/stakeholder_consultation/consultations/nem-consultations/2021/isp-methodology/isp-methodology-issues-paper.pdf

[13] See p35 of https://aemo.com.au/en/consultations/current-and-closed-consultations/2020-forecast-improvement-plan-consultation

AEMO reserves the practice of obtaining forecasts from multiple consultants to occasions where, in consultation with stakeholders, it foresees uncertainty in a forecast component material enough to warrant the expense.

4.3.2. Factors affecting distributed PV output

Issue summary

The Methodology describes the incorporation of distributed PV in energy consumption and demand forecasts. Section A3.1 mentions, but does not detail, how degradation of distributed PV output is performed.

QEUN raised in its verbal submission that degradation should also consider:

- "Orphaned solar systems" – systems with worthless warranties, as they were installed by suppliers no longer in business.
- Severe weather – damage to distributed PV systems due to hailstorms.
- Under-insurance – due to rising insurance premiums, some customers (such as BMM) may be underinsuring themselves and their solar PV systems. Therefore, AEMO should discount any expected recovery from insurable events.

AEMO's assessment

The impacts of distributed PV system damage and degradation can either be captured as an adjustment to the installed capacity, or through the applied normalised generation profiles. To avoid double counting, such damage and degradation should be clearly addressed in one or the other, but not both.

AEMO accounts for the degradation of distributed PV output in the distributed PV normalised generation profiles provided by Solcast, not in installed capacity to avoid double counting of degradation. Solcast does not explicitly take the factors mentioned by QEUN into account, because the loss factors in distributed PV performance modelling are empirically derived. Consideration of such individual factors would require more detailed physical models to be developed and maintained along with assumptions on percentages insured. The reasons Solcast does not adopt a physical model approach are:

1. Data availability is insufficient and inconsistent.
2. A fully-physical loss model is prone to biases due to the various micro-assumptions required, requiring heavy calibration which in effect makes it somewhat equivalent to an empirical approach.

Solcast's distributed PV model has two steps:

- The first step determines the irradiance, which is primarily physical, and the second step determines the power which is primarily empirical. In the first step, Solcast estimates surface irradiance parameters at a suburb/town level using satellite and aerosol data. Then Solcast models each suburb/town as a series of unit distributed PV arrays and converts the irradiance to plane-of-array (that is, the angle of the installed panels is considered).
- In the second step, Solcast empirically estimates power production including a "loss factor" term. Age-related degradation is implicitly captured in its model as one of these "loss factors" (along with others, like shading, dirty panels, damaged panels and other system defects). The optimal value of the loss factor is determined empirically by running the model for a large number of actual distributed PV systems and comparing it to measured distributed PV output, and also against aggregated datasets such as from the Australian Photovoltaic Institute.

The above methodology came from the 2016-2019 Australian Renewable Energy Agency (ARENA)-funded Australian National University (ANU) research project[14] where Solcast was a partner. Since then, Solcast monitors and calibrates the loss factors. While irradiance and array geometry are found to vary regionally, no significant regional variations in loss factors are observed in the current data set. A larger body of quality-controlled data may or may not reveal significant regional variations in loss factors.

Approximately 20,000 distributed PV systems were initially used to train the performance of their model. Then over time, Solcast check the calibration of the trained model with other datasets from customers and those published by the Australian Photovoltaic Institute.

AEMO's conclusion

AEMO is satisfied with Solcast's approach to accounting for the degradation of distributed PV systems and will continue to engage with them to ensure the degradation of panels is accounted for as practically as possible.

4.3.3. Hydrogen related demand

Issue summary

AEMO is extending the Methodology to include hydrogen as an emerging technology. There is substantial uncertainty regarding the impact that the potential development of a hydrogen economy may have on electricity demand. The uncertainty stems from hydrogen production considering:

- Technology, especially electrolysis, is still maturing and the various cost projections have a wide range of uncertainty.
- The potential supply of export markets that have a highly uncertain potential demand, depending on the competitiveness of Australian produced hydrogen against international competitors. This leads to a huge uncertainty in scale as it is not bounded by Australian consumption.
- Uncertainty regarding the connection arrangements for these facilities – particularly whether they will be connected to the electricity grid or have dedicated local resources. The former is highly relevant to system analysis and therefore the Methodology, but the latter is not.

Given these uncertainties, AEMO's methodology for capturing this emerging technology is to consider the potential scale of hydrogen production as a key variable that may change between its forecasting scenarios. This is an assumption-driven approach that allows analysis of both small and large-scale hydrogen production, and informs views on whether the sector will materially impact the reliability, security, and ongoing investment needs for the NEM.

QEUN recommend AEMO consider forecasting electricity separately for:

- Green hydrogen production from NEM and WEM supplied electricity.
- Green hydrogen production from non-NEM and non-WEM supplied electricity.
- Blue hydrogen production from NEM and WEM supplied electricity.
- Blue hydrogen production from non-NEM and non-WEM supplied electricity.

AEMO's assessment

For the purpose of this response, AEMO considers:

- Blue hydrogen to be hydrogen produced from reforming or gassifying fossil fuels, where carbon capture and storage is implemented.

[14] See: https://arena.gov.au/projects/real-time-operational-pv-simulations-for-distribution-network-service-providers/

- Green hydrogen to be hydrogen produced from an electrolyser powered from renewable energy electricity generation.

AEMO is required to produce forecasts of the electricity and gas demand as well as energy sufficiency in the NEM and WEM. To do that AEMO must take a view on relevant influences that are material to the development of scenarios; hydrogen is such an influence. However, AEMO is not providing a forecast of total hydrogen production and consequently the recommendation to consider non-NEM and non-WEM hydrogen is considered out of scope[15]. The intent is to explore the potential impact of hydrogen on the NEM and WEM across potential futures.

Similarly, while blue hydrogen production may have some network electricity demand, it does not represent a sufficiently different scenario to a future without hydrogen. Blue hydrogen may be more relevant for future gas consumption forecasting.

In developing scenarios that include hydrogen, AEMO takes inputs from national forecasts and stakeholder consultation which can be scaled to represent the hydrogen production from particular electricity systems, considering the electrical efficiency of hydrogen production, and accounting for the technical operational capabilities of these facilities. The development of renewable energy resources to meet the system-wide production will be an output from AEMO's Integrated System Plan methodology, where the location of electricity and hydrogen production facilities will consider the resource quality available in each region, as well as the total system costs of managing local resources and transmission costs to deliver the electricity to the electrical loads.

AEMO's conclusion

AEMO seeks to capture the interactions between hydrogen production and the electricity system within its forecasts of electricity consumption and demand, and the location of renewable resources and other infrastructure required to provide energy for these new loads. Hydrogen forecasts are not an output of AEMO's methodology, however AEMO may assume various hydrogen production objectives as input to its scenario-analysis approach.

For clarity, AEMO will add a new section to the Methodology describing how electricity consumption and demand from hydrogen production is included in the forecast.

4.3.4. Electric vehicles

Issue summary

The Methodology describes AEMO's approach to forecasting EVs, for business and residential consumption segments.

QEUN recommended forecasting EV charging separately for:

- Homes.
- Business, commercial and industrial premises.
- Charging stations.

ERM Power noted:

- The importance of payback factor in EV uptake. To that end, movements towards kilometre-based registration charges should be included in uptake modelling

[15] If the non-network hydrogen is required as transport fuel replacement or other sector coupling vector, it will be assumed to be available at a suitable cost and would not be modelled directly.

- Residential tariff structures may change to accommodate EVs. ERM Power suggested that AEMO consult on this matter.

AEMO's assessment

Regarding QEUN's recommendation, AEMO engages a suitably qualified consultant to assist in the forecasting of electric vehicle uptake and charging. AEMO's consultant provides AEMO with a range of charging profiles[16] for different vehicle types based on international observed charging behaviour, scaled to match Australian vehicle distance travelled data, which broadly map to, or exceed, the groupings suggested by QEUN. The proportion of charging types used for each vehicle type is assumption driven, guided where possible by current experience, and specific to the individual scenarios. These assumptions are consulted on as part of AEMO's process for developing its inputs for the Inputs, Assumptions and Scenario Report[17], which includes stakeholder consultation with AEMO's FRG.

As more Australian EV charging data becomes available, the charging profiles for each vehicle type will improve as more local evidence is applied to transform those developed from international experience.

Regarding ERM Power's submission, AEMO understands there to be many potential factors driving EV purchase decisions, including:

1. Upfront purchase costs.
2. Operating costs – including fuel (petrol, diesel, electricity, hydrogen) and maintenance.
3. Salvage value.
4. Other non-price factors, such as appearance, reputation, availability of alternatives, and size.

AEMO's consultant uses a technology adoption model[18] that reflect both payback period and non-price factors. The payback period includes an operating cost component for both per kilometre registration costs, and fuel costs (which in turn reflect electricity tariffs). However, as the payback period is dominated by the high upfront costs of an EV, the impacts of registration costs and electricity tariffs[19] are relatively small.

The non-price factors are captured through the fitting of a technology adoption curve, which reflects that technology adoption will be led by an early adopter group who, despite high payback periods, are driven to invest by other motivations.

AEMO's conclusion

AEMO has reviewed the submissions and considered their merits. Overall, AEMO considers its current model structure appropriately captures the role of vehicle charging and purchasing decisions considering the influence of payback periods and electricity tariff impacts. AEMO considers the consultant's model adequately and appropriately implements costs over the EV lifecycle.

AEMO responded to stakeholder interest in EV charging by holding an FRG presentation and discussion on EV methodology (February 2021), and looks forward to informing future forecasts with further stakeholder input. No new EV methodology suggestions arose from the FRG discussion.

[16] See for example the Electric Vehicles tab in: https://www.aemo.com.au/consultations/current-and-closed-consultations/2021-planning-and-forecasting-consultation-on-inputs-assumptions-and-scenarios.

[17] See: https://www.aemo.com.au/consultations/current-and-closed-consultations/2021-planning-and-forecasting-consultation-on-inputs-assumptions-and-scenarios.

[18] See: https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/inputs-assumptions-methodologies/2020/csiro-der-forecast-report.pdf.

[19] Tariffs can however affect charging profiles and assumptions about future development of tariffs targeting EV owners inform AEMO's split between different charging profiles, with the ratio of convenience charging dropping over time being replaced with charging profiles that provide pricing stimulus to reduce peak charging. The assumed tariff uptake rates are consulted on as part of AEMO's Inputs, Assumptions and Scenario Report, and consulted with stakeholders via the FRG.

4.3.5. Batteries

Issue summary

The Methodology includes modelling of batteries. The model recognises three operating regimes:

- A solar shifting algorithm that simply diverts excess solar to the battery until fully charged, then discharges to meet household demand until fully discharged. This is the most common battery operating regime at present. While this has some benefit for peak demand, it is generally small relative to the potential peak demand reduction a battery could offer under a virtual power plant (VPP).
- Optimisation of household grid purchases under a time of use tariff. While this may contribute to consumer affordability, it has minimal benefits for managing system peak demand.
- The operation of a VPP to economically optimise sales and purchases of electricity. It's anticipated that this regime will contribute to managing system peak demand.

ERM Power noted that:

> With regards to battery charge/discharge profile used in minimum and maximum demand, we query AEMO's view that, "the effect per battery at reducing the operational demand at peak times in summer is relatively small given that battery operations are targeting residential load reductions".
>
> Whilst the effect per battery may be small, installation of 100,000, 4 kilowatt (kW) capacity batteries, (based on a Tesla Powerwall 2), could reduce system load by 400 Megawatt (MW) at peak demand times if tariff structure reform maximised the benefit for consumers to do so. Introduction of a peak period time-of-use tariff or payments for participation in a VPP scheme may facilitate a change to the charge/discharge profile of residential and commercial batteries and we recommend this be closely monitored and considered by AEMO.

AEMO's assessment

AEMO recognises that the operating regime(s) associated with batteries are critical to their effectiveness in managing system peak demand. Consequently, AEMO's current battery model estimates the evolution of the ratio between the three battery operating regimes. AEMO considers that this model structure will support:

- Evolving policy and business models,
- New opportunities enabled by technology, and
- Changing consumer preferences

The ratios assumed form part of the IASR, which is subject to consultation.

AEMO has previously conducted analysis in the WEM[20] that identified that average household demand at peak times is relatively low compared to the power rating of most residential battery systems. The battery profiles developed by AEMO's consultant support this view of low battery contribution to peak, relative to power rating. This implies that unless household batteries are capable and incentivised to discharge to the grid using the extra available capacity of the battery at peak times, the impact of the battery is relatively small.

[20] See 09. Battery peak demand modelling, in the Western Australia Electricity Consultative Forum (WAE-CF) 18 meeting pack: https://aemo.com.au/-/media/files/stakeholder_consultation/working_groups/wa_meetings/waecf/2019/wae-cf-18-meeting-pack.zip?la=en

However, AEMO's forecasts consider a growing shift towards aggregated energy storage (VPPs) to capture better optimisation of battery resources. These batteries are modelled on the supply side, as being fully available for discharge to the grid during peak demand times. The assumed proportion of aggregated batteries growing over time is scenario-dependent, and can be found in the IASR workbook.

AEMO's conclusion

AEMO agrees with ERM Power's recommendation to monitor the growth of batteries, and will continue to review the current model structure to accommodate emerging policies and changing consumer preferences.

4.4. Economic modelling

4.4.1. Choice of economic variables for business energy modelling

Issue summary and submissions

To recognise the impact of economic activity on energy use, the Methodology incorporates an economic variable. Currently AEMO uses Gross State Product (GSP) as the basis for economic activity at the regional (state) level. This variable is used in the BMM model, as the anticipated energy consumption of LILs is captured directly via LIL surveys. Economic activity is not required for residential energy use modelling.

A number of submissions commented directly on the variable used for economic modelling:

- Deloitte noted GSP's limitation is that it captures large export producing businesses, which would typically also be captured in the LIL surveys. Thus, GSP would not be entirely representative of the business segment it is used to model.
- MEU expressed a view that, in the context of energy users reducing their use of grid supplied energy, GSP is "becoming less of a guide to future growth in electricity demand of BMM". It viewed the reduced use of grid energy as supporting greater disaggregation of end user cohorts and noted that retailer data should be used for this purpose.

ERM Power recommended AEMO set out "clear criteria for selection" of the economic variable used in the Methodology. It further noted that AEMO's reference to 't' years was undefined in the Methodology, and therefore recommended that AEMO include how the 't' value is selected.

AEMO's assessment

The Methodology states that 'AEMO will periodically review and adopt the economic driver that gives the best fit with consumption and is reasonably expected to explain the changes observed'. More fully, AEMO considers the following factors for economic variables potentially used as an economic driver:

- Credibility.
- Existing acceptance – all else being equal, AEMO would use the better-known of two variables.
- Benefit to forecasting accuracy.
- Cost and availability.

With these factors in mind, AEMO has reviewed alternative variables, including Household Disposable Income (HDI), and considers GSP to perform best overall. AEMO agrees that the evolving compositional nature of the economy may change which variable most effectively models energy use, so AEMO repeats the above variable selection process periodically.

During that selection process, the timeframe 't' over which the economic variable is available and relevant is selected. The selection of the timeframe is nuanced by a broad range of technical econometric considerations, but chief among them is the selection of a timeframe that results in an accurate forecast.

While Deloitte's comment has theoretical merit, GSP has better acceptance and availability and thus is currently chosen. In any case, GSP is highly correlated with other potential economic measures.

MEU did not name any particular sectors in its comment that GSP is becoming less of a guide to electricity demand. AEMO notes evidence that the dollar per megawatt hour (MWh) economic contribution of the manufacturing sector's electricity significantly differs from other parts of the BMM cohort[21]. Additionally, AEMO notes the changing size of the manufacturing sector in Australia. These two factors (as outlined in Appendix B) warrant a customised forecast of manufacturing's electricity use. For this reason, AEMO models manufacturing's electricity use with electricity intensity data from the Australian Government's Department of Industry, Science, Energy and Resources.

Trends, including compositional changes and the changing sources of BMM energy that MEU referred to, are modelled via trend variables.

AEMO's conclusion

AEMO agrees with MEU that a range of economic predictors should be explored to improve forecast accuracy. AEMO continues to test alternative variables across varying timeframes to this end. Currently GSP remains the preferred predictor based on the four criteria requirements presented for economic variables.

AEMO's Final Determination is to continue using the GSP as the variable of economic activity. The Forecast Accuracy Report will continue to monitor the performance of the consumption forecast, and is the process by which material deficiencies in the GSP will be identified and consulted on.

4.4.2. Blending short-term and long-term business energy forecasts

Issue summary and submissions

The Methodology notes that in modelling business energy forecasts over the first four years, AEMO blends short-term forecasts with longer-term forecasts to reflect their relative strengths and purposes. In 2020, AEMO blended the short-term into the long-term forecast as follows:

- First year: weighting of 50%.
- Second year: weighting of 25%.
- Third year: weighting of 12.5%.
- Subsequently: 0%.

Deloitte's submission suggested the performance of the weightings could be tested through econometric analysis.

AEMO's assessment

AEMO's approach to blending short- and long-term forecasts is, in the absence of other information, to use a simple linear method as shown above. Anticipated improvement to the economy due to expected COVID-19 recovery is an example of a specific reason which could warrant a different blending of short- and long-term forecasts.

While AEMO agrees with Deloitte's submission that econometric analysis is generally beneficial, in the case of weightings, AEMO would have to:

[21] Table F, Australian Energy Statistics. See: https://www.energy.gov.au/government-priorities/energy-data/australian-energy-statistics

- Wait until a sufficient period has elapsed to test the performance, or
- Perform necessary data adjustments to allow back-testing to occur.

AEMO considers it more beneficial overall that the Methodology acknowledges the value of incorporating forward-looking views of 'other information' as needed, rather than seeking to optimise weightings based on analysis that is inherently historical.

AEMO's conclusion

AEMO's Final Determination is to retain the changes made to the Methodology during the Draft Determination, to reflect considerations it uses if departing from a simple linear blend of short- and long-term forecasts.

AEMO notes the weightings constitute part of the forecast reviewed in the Forecast Accuracy Report, and this can drive improvement opportunities within the Forecast Improvement Plan as required.

4.4.3. Choice of economic variables for residential energy modelling

Issue summary and submissions

AEMO's Methodology describes the blending of short-term NMI counts with long-term ABS household projections to form the connections forecast. This new approach follows a previous approach of exclusively using Housing Industry Association (HIA) housing completions.

Deloitte suggested incorporating an economic forecast of connections rather than the trended NMI for the entire forecast. It wrote:

> Using the NMI data (and a depreciation assumption) to estimate the historical dwelling stock sounds sensible but I'd suggest incorporating an economic forecast of connections rather than the trended NMI for the entire forecast. Dwelling completions vary significantly from year to year in accordance with the dwelling cycle which in turn is connected to key economic drivers such as interest rates, the unemployment rate and net migration. I suspect the NMI trend forecast fails to take this into account.

AEMO's assessment

First, it should be noted that the Methodology currently uses a NMI trend for only a limited timeframe, and to a diminishing extent over that timeframe[22].

AEMO notes that the historical HIA housing completion time series enjoys reasonable correlation with electricity use, even when factors such as vacancy make the relationship imperfect. However, AEMO's experience with the housing completion time series prior to 2020 was that electricity forecasting did not improve because of the challenges in forecasting housing completions. For example, the HIA forecast anticipated a 40% reduction in construction completions due to COVID-19, however this drop did not eventuate.

AEMO's conclusion

AEMO views the current approach of blending short-term and long-term connection forecasts provides greater stability and higher forecast performance than using housing completions. AEMO's Final Determination is to continue with this approach and monitor its performance in the Forecast Accuracy Report.

[22] See page 60 of the Methodology

4.4.4. Tariff reform

Issue summary and submissions

AEMO outlined its considerations of retail electricity prices in Appendix A1 of the Methodology.

MEU made the following submission

> Tariff arrangements also have a great impact on the impact of price sensitivity and the MEU is aware there is considerable discussion about tariff reform especially targeted at residential and small businesses. In the recent network revenue resets, there has been considerable pressure to make changes to network tariffs which will, in turn, impact retail tariffs. The MEU considers that AEMO needs to closely monitor these tariff changes and incorporate the effects of these in their forecasts. As this tariff reform will continue, it is important that AEMO look to moderate their forecasts to reflect the expected changes that will occur over time, rather than basing their forecasts on recent trends and traces.

AEMO's assessment

AEMO acknowledges that the focus of Appendix A1 of the Methodology was electricity prices.

AEMO notes that while there is broad agreement on the potential for tariff structures to influence electricity use overall and the timing of this usage, there's limited data on their impacts on electricity use and their rate of deployment (uptake). The lack of this data is an impediment to updating the Methodology with tariff considerations, though growth in tariff types that drive short term responses from consumers to price or reliability signals is implicitly built into the higher demand side participation (DSP) forecast projections[23] used in some ISP scenarios.

AEMO is currently reviewing the research regarding the effectiveness of time-of-use (ToU) tariffs as demand management under a range of circumstances. Additionally, AEMO intends to maintain its awareness of higher level trends with tariff structure deployment through the above research and ongoing engagement with stakeholders.

AEMO's conclusion

AEMO's Final Determination is to:

- Continue developing an understanding of the quantitative impacts of tariff structures, and monitor their deployment/uptake.
- Retain changes to the Methodology made during the Draft Determination which incorporate changes to electricity use as the impacts and deployment of tariff reform become clearer.

4.4.5. Price elasticity and the rebound effect

Issue summary and submissions

AEMO describes the unidirectional elasticity treatment of retail electricity prices in Appendix A1 of the Methodology, and also describes the 'rebound' effect in various sections under the Residential annual consumption heading.

MEU submitted its view that elasticity is 'not as strong as might have applied in the past' and that 'lower prices are unlikely to lead to increased usage.'

[23] The DSP forecast methodology is explained here: https://aemo.com.au/-/media/files/stakeholder_consultation/consultations/nem-consultations/2020/demand-side-participation/final/demand-side-participation-forecast-methodology.pdf.

ERM Power submitted that the unidirectional elasticity treatment was 'somewhat contradicted' by the rebound effect. In related content elsewhere in its submission, ERM Power noted that:

- "Whilst it is reasonable that base load could potentially be impacted by this rebound effect, it is less clear that heating and cooling load would be significantly impacted.
- A replacement new appliance whilst larger than the replaced appliance may have higher energy efficiency and may potentially use less energy than the replaced appliance. We recommend AEMO detail in the Methodology how variance in energy consumption is calculated for replacement as opposed to new appliance uptake."

In its verbal submission, QEUN submitted that, based on its 2018 survey[24], it considered electricity price reductions to exhibit strong elasticity – BMM stated an intention to hire more staff, produce more, and thus consume more electricity. When AEMO noted that some BMM have the ability to hedge against electricity price increases through the installation of distributed PV, QEUN responded that BMM were more concerned with daily profitability and breaking even in the short term than with investing in longer-term cost savings. QEUN also recommended that, when selecting consultants for retail price forecasts, AEMO consider those consultants with a favourable track record of forecast accuracy.

AEMO's assessment

AEMO notes that society's response to the evolving energy market is rich and complex, incorporating:

- Electricity price and tariff structure changes, and market awareness of them.
- Behavioural changes, both rational according to economic principles and otherwise.
- Ongoing changes to standards of living and income levels, noting that it varies widely between demographics.
- The purchase and use of newer and more energy efficient appliances, with the use of older less energy efficient appliances not necessarily being discontinued.
- The availability and uptake of DER, including distributed PV and batteries.

In the absence of detailed and ongoing data on the above factors and their interactions, AEMO simplifies them into three higher level observations:

- Rising electricity retail prices alone tend to moderate energy use.
- Falling electricity retail prices alone tend to have little effect on energy use.
- Academic research supports the 'rebound effect' whereby there is a degree of non-realisation of expected energy efficiency savings. AEMO assumes that investments in distributed PV systems to lower customer electricity bills similarly will result in a rebound effect.

AEMO considers that, without fully explaining the complex underlying factors and their interactions, these three observations can be pragmatically modelled as:

- A unidirectional elasticity.
- A rebound effect encompassing DER (inclusive of distributed PV) and energy efficiency.

AEMO does not consider these two modelling elements of the Methodology contradictory, and emphasises these elements seek to model, rather than fully explain, observations from a complex set of human behaviours that are unlikely to be understood in detail. While it would be interesting to conduct a fuller analysis of how the rebound effect might differ by heating, cooling and base load, AEMO considers

[24] See: https://www.qeun.com.au/pdf/BusinessSurvey/J2998V3_OverallResults_RegionalQld_ImpactHigherElectricityPrices.pdf

that its assumption of equal rebound effect (ie. a constant percentage) across base, heating and cooling loads to be a sound position prior to such analysis.

Regarding QEUN's submission, AEMO notes that while surveys are valuable in highlighting concerns that require further exploration and research, surveyed intentions do not necessarily reflect practice, so overall AEMO places more weight on historical actual data than surveyed intentions. Furthermore, question 10a of the survey, regarding BMM intentions in the event of an electricity price reduction, is not structured so as to directly inform a quantitative electricity forecasts. For example, it is unclear if the 35% who 'would consider upgrading' their equipment and machinery would do so on the basis of greater capacity (and therefore energy use), or on efficiency (lower electricity use) or on non-energy features. For the 33% who 'would consider' employing more staff or increasing staff hours, the mapping to energy use is unclear. For example, if a café owner were to have staff cover a dinner shift rather than themselves, this may have no impact on energy use.

AEMO consults on prioritised improvements in the Forecast Improvement Plan, which may include longer-term investigations and research needs. AEMO proposes that stakeholders share their view on the relative importance of various improvements, including any suggested by themselves, being guided by the scale of likely impact on the forecasts, and the likely cost and complexity of each initiative.

AEMO already consider consultants' forecast performance track records in the selection process.

AEMO's conclusion

AEMO has clarified the relevant parts of the Methodology to document the relationship between unidirectional elasticity and the rebound effect. AEMO will specifically seek stakeholder input on the prioritisation of research activity in future Forecast Improvement Plans.

4.4.6. Demand destruction

Issue summary and submissions

AEMO outlined its economic modelling of business loads in the Methodology.

ERM Power submitted:

> We are also concerned that the Methodology fails to clearly detail how "demand destruction" is adequately considered in the model. Our observation is that once BMM or commercial and light industrial (C&I) departs due to high price outcomes, it is many years, if ever, before an alternative consumption source makes up for the load which has exited. We recommend AEMO provide additional clarity in these areas of the Methodology to remove any contradictory interpretation.

AEMO's assessment

AEMO acknowledges the phenomenon that ERM Power described, and notes that, rather than being covered by a specific 'demand destruction' parameter in the model, it is reflected:

- For the BMM segment,
  - in the economic forecasts, and
  - in the unidirectional price elasticity applied.
- For the LIL segment, in the economic narratives of the scenarios.

Stakeholders were consulted on both of the above features of the Methodology. Most recently, the Slow Change scenario included descriptions of some large load closures due to unfavourable conditions and prices. The scenario outcomes, when available, inform stakeholders on the significance of demand destruction to the NEM.

AEMO's conclusion

AEMO considers that its current method of catering for demand destruction is appropriate. AEMO's Final Determination is to retain updates to the Methodology introduced in the Draft Determination which describe the means of modelling demand destruction.

Incorporation of EV charging profiles into half hourly forecast Issue summary and submissions

AEMO's Methodology describes various indices applied to half-hourly demand, including population growth, economic factors and price.

In response, ERM Power queried how such a process would allow for EV charging and discharging profiles. Specifically, it wrote:

> It is unclear to us how this process would allow for structured charging, and potentially discharging of electric vehicles when an annual growth index is applied to all half hours. We recommend that AEMO considered if individual growth index values should be applied to different half hour periods.

AEMO's assessment

AEMO accounts for EV charging forecasts within the half-hourly simulation process, adding half-hourly EV charging profiles for a range of vehicle types and charging regimes[25] to the simulated underlying demand, which excludes EV charging load[26]. The charging profiles are scaled to match the forecast EV uptake at the given time. This results in an internally consistent forecast because:

- As described in Section 5.6 of the Methodology, the simulation process incorporates one or more scenario-dependent indices to account for growth drivers in the consumption forecast (such as population growth, prices, economy, and housing stock). The indices exclude weather and climate impacts (as the half-hourly simulation captures this directly when sampling the weather years), LILs (which are modelled separately), and any impacts of DER technologies, including EVs.
- As described in Section A4 of the Methodology, the consultant's EV model incorporates various EV growth factors such as relative pricing with alternatives, payback, ride sharing, vehicle purchase trends, technology improvements, limiting factors, and decarbonisation targets. Although not explicitly mentioned, the Methodology applies such factors consistent with the standard scenario-specific forecasts for (for example) population growth, prices, economy, and housing stock.

Thus, both the simulation process and the scaled EV charging profiles include consistent growth drivers, allowing them to be added together without duplication or omission of the indices[27].

The above is straightforward when EV charging is following set profiles. The Methodology captures this well. As noted in the Methodology Appendix A4.1.2, EV charging can also be coordinated (structured), that is, optimised towards system conditions. This type of charging includes coordinated EV charging, where charging is optimised to happen at time of low system demand, and vehicle to grid (V2G) type operation, which charging/discharging can be dispatched within the dispatch modelling / supply modelling.

The impact of the coordinated charging is excluded from the initial maximum/minimum demand simulation and instead estimated subsequently when making the half hourly traces. The published demand forecasts include the impacts of this type of charging at time of minimum and (if any) maximum demand, and the Methodology will be updated to make this clear.

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[25] See for example the Electric Vehicles tab in: https://www.aemo.com.au/consultations/current-and-closed-consultations/2021-planning-and-forecasting-consultation-on-inputs-assumptions-and-scenarios.

[26] In this process, profiles for rooftop PV and battery charging are applied as well to convert from underlying to operational demand.

[27] Note that the above EV references make this response relevant to the specific question, but the same process applies to all forms of DER. For a battery, for example, all references to 'charging' above should be read to mean 'charging or discharging'.

AEMO's conclusion

AEMO thanks ERM Power for identifying an opportunity to improve the description of EV inclusion, and updated the Methodology during the Draft Determination.

AEMO's Final Determination is to retain the current approach for EV charging within AEMO's maximum and minimum demand simulation methodology.

4.5. External review

4.5.1. Issue summary and submissions

In light of the complexity of electricity forecasting and the importance of robust reporting on forecast performance, AEMO commissioned the University of Adelaide to review the Forecast Accuracy Report methodology (2019).

In its submission on the Methodology, ERM Power noted the complexity of scaling half-hourly demands and that no framework for independent analysis or audit of the process was described. AEMO responds to the matter of half hourly demand traces in Section 4.6.3 and this section addresses the general point regarding external review.

4.5.2. AEMO's assessment

To the extent the forecast forms part of a Reliability Forecast that requires AEMO to request AER to make a reliability instrument, the AER audits the execution of the Reliability Forecast according to agreed inputs, assumptions, scenarios and methodology. For a recent example, see https://www.aer.gov.au/node/65588.

AEMO notes requests for independent reviews in both the Reliability Forecast Guidelines[28] (RFG) and the 2020 Forecast Improvement Plan[29] consultations. Due to the costs involved, AEMO has prioritised an independent assessment of approach and potential for bias at least once every four years, prior to a full FAR methodology consultation. The FAR assessment is the key vehicle for identifying, and where required, rectifying forecast issues.

4.5.3. AEMO's conclusion

AEMO reiterates its commitment to an independent assessment of approach and potential for bias at least once every four years.

4.6. Probabilistic forecasts, weather and climate

4.6.1. Incorporation of Climate Change into models

Issue summary and submissions

AEMO uses the Representative Climate Pathway (RCP) adopted by the Intergovernmental Panel on Climate Change (IPCC) as a basis for modelling future probabilistic weather years in the Methodology.

CitiPower supported AEMO's incorporation of climate change impacts on the grid and noted it was critical that AEMO continue to do so.

ERM Power noted their interpretation and concern that the Methodology's various references to climate change calculations meant the Methodology duplicated allowances for climate change.

[28] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/reliability-forecast-guidelines
[29] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/2020-forecast-improvement-plan-consultation

AEMO's assessment

AEMO notes that it uses many power system component and demand component models to achieve its forecasting objectives. As such, the physical impacts of climate must also be modelled per component. In this case, the physical impacts of climate change are considered in both the operational energy consumption forecasts and the extreme demand forecasts. While energy forecasts are a key input to the extreme demand forecast trajectories, the effects of climate change are removed for this purpose, specifically to avoid duplication of impacts.

AEMO's conclusion

AEMO agrees on the importance of understanding climate change impacts on the grid, but notes that due to AEMO's higher-level focus, DNSPs should consider undertaking more specialised research for the impacts at distribution levels.

AEMO amended the Methodology during the Draft Determination to clarify how climate change adjustments for electricity consumption and extreme demand are considered, free from duplication. AEMO's Final Determination is to retain this change.

4.6.2. Probabilistic demand forecasts

Issue summary and submissions

The Methodology includes a description of probabilistic demand forecasts.

In response, ERM Power noted:

- Actual maximum demand in the Victorian region has not exceeded AEMO's 10% probability of exceedance (POE) demand forecast, yet demand has fallen below the 90% POE forecast for 25% of years.
- Its concern that actual demand outcomes result in recalibration of baseline data and the 50% and 10% POE benchmarks. It believed that more detailed analysis and consultation on prevailing factors that led to the 10% POE forecast being exceeded is warranted when such an event occurs, prior to any decision by AEMO to make significant adjustments to baseline and 50% and 10% POE benchmark data. ERM Power considers that this has not been the case to date, with significant adjustments made with inadequate consultation.

ERM Power concluded with a recommendation that "AEMO provide additional transparency in the regional forecast maximum demand values as an appendix in the Forecast Accuracy Report, by including in tabular form the full range (0 to 100% POE) of regional forecast maximum demand values derived from their modelling process. This should be displayed in at least 21 blocks, each of 5 percentile increments".

In another part of its submission, ERM Power requested that AEMO provide further details regarding the relationship between the generalised extreme value (GEV) model and the half-hourly model.

AEMO's assessment

Due to limited supporting data with the submission, AEMO was an unable to verify the basis for ERM Power's statement that "actual maximum demand in the Victorian region has not exceeded the market operators 10% POE demand forecast, yet demand has fallen below the 90% POE forecast for 25% of years". AEMO provides data of this nature on a yearly basis to monitor the performance of the forecasts; this can be seen in Figure 14 of the 2019 Forecast Accuracy Report. Figure 14 shows that actual demand in Victoria has twice exceeded the one-step ahead 10% POE forecast in the last 14 years, and twice equalled it.

More broadly, AEMO examined the performance of the probability forecast in the 2019 Forecast Accuracy Report[30], and found no cause for concern, while noting that the limited history made definitive conclusions difficult.

ERM Power's second point implies that recalibration occurs as a result of an 'event'. In contrast, AEMO's recalibration results from the available history of NEM data growing by one year each year; recalibration occurs annually to take into account the most recent year of data. The half-hourly demand model is trained on 5-10 years of data, and the GEV model is trained on 18 years of data. Following the recalibration, AEMO's model outputs are assessed for reasonableness rather than expectations of a specific output.

AEMO does not have any principle-based objections to presenting a full range of forecast demand values. However, practically, accurate estimation of either end of the distribution, such as 5% POE, is problematic because the combination of low frequency and high variance requires a large number of simulations. Such an increase in computer resources comes at a non-trivial cost and seems unwarranted.

Regarding the relationship between the GEV model and the half-hourly model, each of the models has their own strengths and limitations. The role of each model is:

- GEV model – at a seasonal and monthly time basis within the first year only, estimates the distribution of extreme values
- Half-hourly model – accounts for the impact of distributed PV (and new technology generally), the economy, and other drivers on short-term patterns (day profile and across the week). Longer-term climatological changes are also applied within the half-hourly model.

To combine their respective foci, the method uses the GEV distribution as the starting point or 'base year' distribution of minimum and maximum demand while the half-hourly model drives the transition of that distribution to future states.

AEMO's conclusion

AEMO sees no new issues raised or data provided in ERM Power's submission, and refers the reader to AEMO's responses to previous submissions on this topic[31,32].

During the Draft Determination, AEMO updated the Methodology's description of the integration of the GEV and half-hourly models to form the demand forecast. AEMO's Final Determination is to retain this update.

4.6.3. Probability of exceedance demand traces

Issue summary and submissions

The last step in AEMO's demand forecasting process is the development of half-hourly demand traces. The demand traces are used in a number of AEMO's reliability and planning processes, including the Medium-Term Projected Assessment of System Adequacy (MT PASA) and the ESOO.

In its submission, ERM Power noted the recent MT PASA rule change that provides information regarding the range of daily maximum demand outcomes post scaling to both the 50% and 10% POE annual maximum demand forecasts. It referred to observations across the regions that, post-scaling to the

[30] Page 28 of the report found at https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/accuracy-report/forecast_accuracy_report_2019.pdf?la=en

[31] See Section 2.2 of the Forecasting Accuracy Report Methodology Final Determination, available at: https://aemo.com.au/-/media/files/stakeholder_consultation/consultations/nem-consultations/2020/forecast-accuracy-report-methodology/forecast-accuracy-reporting-methodology-final-determination.pdf

[32] See Section 5.6 of the Forecast Improvement Plan Submission Response Document, available at: https://aemo.com.au/-/media/files/stakeholder_consultation/consultations/nem-consultations/2020/forecast-improvement-plan/submission-response-document.pdf

maximum annual demand, the maximum of the daily range of daily peak demand outcomes for demand traces scaled to the 50% POE annual maximum demand forecast were higher than the maximum of the daily range of daily peak demand outcomes for demand scaled to the 10% POE forecast, approximately 70% of days. ERM Power questioned how a daily 50% POE forecast could be higher than the 10% POE forecast.

AEMO's assessment

The demand traces used in the reliability assessment of the MT PASA do not target daily 50% POE forecasts or daily 10% POE forecasts. The daily 50% POE and 10% POE forecasts required to be reported as part of the MT PASA process continue to be estimated outside the reliability assessment and reported separately. The new information now reported as part of the MT PASA rule change aims to increase transparency of the daily demands across the range of demand traces used in the reliability assessment.

The Methodology explains the process of creating the half-hourly demand traces. AEMO's trace development process aims at creating realistic half-hourly demand traces that preserve the shape of historical traces as much as possible, but are stretched and grown as required to meet the following criteria for each region and POE:

- The highest half-hourly demand during summer must match the forecast summer maximum demand.
- The highest half-hourly demand during winter must match the forecast winter maximum demand.
- The lowest half-hourly demand during the year must match the forecast annual minimum demand.
- The annual consumption (sum of the half-hourly demand across the year) must match the forecast annual consumption.

A historical demand trace that is stretched and grown to meet a 10% POE targets for maximum and minimum demand will therefore have the same annual consumption as the same trace grown to 50% POE targets. As some periods have been lifted more in the 10% POE case than the 50% POE case, others need to be relatively lower for the annual consumption to be similar. To minimise distortion of the days outside the periods that have been selected to be grown to maximum or minimum targets, all other periods are scaled with the same factor, which include daily peaks outside those grown to seasonal peaks or minimum demand target.

To further aid understanding of this process, AEMO have developed a simplified spreadsheet example titled 'trace growing example' in the attached EDFM Draft Determination Examples spreadsheet.

In this simplified example, the year contains only four periods, instead of 365x48=17,520 half hours. Accordingly, this example simply defines energy as the sum of all demand periods, rather than MWh. Minimum demand is not considered in this example.

The starting point is a "reference year", which total consumption is 950 units (sum across the four periods) and its peak demand of 500 units occurs in period 3. The period of maximum demand is highlighted for easy reference.

The reference year is now grown to both the 50% and 10% POE targets:

Step 1 – the reference year profile has a maximum demand value of 500 units, however, the 50% POE demand target value is 450 units. Because Period 3 is sufficiently above the other periods, its value of 500 can simply be replaced with the target value of 450 for the 50% POE trace, and still remain as the maximum demand value. Similarly, its value of 500 is simply changed to 550 to reflect the 10% POE trace. Periods 1,2 and 4, that did not have their values changed, are referred to as 'ungrown'.

Step 2 – the energy (sum of all demand) must also be adjusted to meet the energy target, while maintaining the recently maximum demand value. The 50% POE trace must have its total energy increased from 950 units to 1,100 units. This is done by sharing the 150 units proportionally amongst the periods that won't affect the target demand value. In this case, 150 units of energy are proportionally allocated across Period 1 (100->130), Period 2 (200->260) and Period 4 (200->260). Period 3 is unchanged as adjusting it would impact the achievement of the demand target. Similarly, the 10% POE trace has adjustments from 1,050 (after adjusting Period 3 to its target demand) to 1,100 units: Period 1 (100->110), Period 2 (200->220) and Period 4 (200->220).

This demonstrates that the size of the target demand value in Step 1 influences the volume of energy allocation in Step 2:

- 10% POE has a higher demand value to grow Period 3 to, leaving a smaller remaining energy target to meet with the ungrown periods 1, 2 and 4.
- 50% POE has a lower demand value to grow Period 3 to, leaving a greater remaining energy target to meet with the ungrown periods 1, 2 and 4.

Note that the effect shown in the 4 load block example is exaggerated. When the calculation is done across over 17000 periods, such adjustments are minor. However, AEMO will continue to consider whether there are other approaches that can improve trace development and reduce this effect. Note that the effect shown in the 4 load block example is exaggerated. When the calculation is done across over 17000 periods, such adjustments are minor. However, AEMO will continue to consider whether there are other approaches that can improve trace development and reduce this effect.

AEMO's conclusion

AEMO's Final Determination is to retain its trace growing process, as the traces are fit for their intended purpose of:

- calculating expected USE in accordance with the Reliability Standard Implementation Guidelines[33], and,
- guiding outage planning through the use of multiple reference years. The reference years maintain natural variability of seasonal and weather driven daily demand outcomes with minimal distortion to the daily load shapes.

4.6.4. Weather simulation – volatility

Issue summary and submissions

The Methodology describes AEMO's use of weather simulation and the application of stochastic volatility therein.

In response, ERM Power questioned "given the significant array of weather sensitive input assumptions already applied in the model, which are already varied over time, why an additional stochastic volatility factor is required."

AEMO's assessment

Often, statistical models are utilised for their ability to capture the mean value of a phenomenon. For example, when AEMO forecast an energy consumption of x gigawatt hours (GWh), the statistical statement is that 'AEMO's model forecasts a mean value of x GWh'. Such models incorporate explanatory variables such as weather, each of which has its own statistical distribution (variance). For the given value of the

[33] See: https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-and-reliability/reliability-standard-implementation-guidelines

explanatory variables such as temperature, humidity, public holidays, the average energy consumption is X GWh. Mathematically this can be described as the conditional mean $E(Y|X)=f(x)$.

In the case of the probabilistic electricity demand forecasts, AEMO seeks to produce an interval forecast of demand, therefore AEMO needs to understand both the conditional mean, given the explanatory variables, and the variance around that mean. For example, two days that are very similar in terms of explanatory variables (temperature, season, weekday) may exhibit non-trivial differences in their electricity demand. This difference in demand could also be termed volatility or variance around the mean or 'line of best fit'.

AEMO has reconsidered the use of the term 'stochastic volatility' to describe the above and now proposes the technical term 'residual' instead. It is critical that non-technical readers understand the technical term 'residual' describes an inherent feature of any statistical model, and it does not refer to an omission on AEMO's part in explaining model performance.

AEMO's conclusion

AEMO, in order to achieve an accurate forecast, seeks to reflect sources of variation including those due to explanatory variables and those inherent in the demand for electricity. AEMO considers the current model structures fulfil that purpose. AEMO updated the Methodology during the Draft Determination to clarify the matter.

AEMO's final determination is to retain the Methodology changes made during the Draft Determination.

4.6.5. Weather simulation – climate futures and synthetic weather years

Issue summary and submissions

The Methodology describes AEMO's use of 3,000 synthetic weather years and their basis in the 20 years of available high quality weather data. The Methodology also describes technical details of incorporation of climate change in Appendix A2.3

In response, ERM Power noted it was unclear how this would ensure the "historically observed normal pattern of rolling within season of weather outcomes are maintained across the entire 3,000 simulated synthetic weather years".

The submission also sought clarification as to how, since all 20 historical years are warmed to meet a possible future climate conditions, a 'natural range of historical outcomes' will be achieved. The submission then stated: "We consider these years should maintain the normal spread of reasonably possible weather outcomes as opposed to a central forecast view of future outcomes."

AEMO's assessment

As a forward looking forecast, the Methodology utilises the IPCC's view of future climates rather than a backward looking 'natural range of historical outcomes'. The IPCC provides a number of RCPs to reflect possible climate change rates and mitigation outcomes.

The Australian Government states[34]: 'The climate modelling community has developed RCP to explore credible future options'. Its description goes onto provide specific guidance on the application of the RCPs: 'These scenarios span the range of plausible global warming scenarios. They provide a range of options for the world's governments and other institutions for decision making.'

The forecasting scenarios developed with stakeholder input in the IASR describe climate narratives, and AEMO's modelling uses the corresponding RCP. Thus, AEMO does utilise a spread of 'reasonably possible weather outcomes as opposed to a central forecast view of forecast outcomes'.

[34] See: https://www.climatechangeinaustralia.gov.au/en/climate-campus/modelling-and-projections/projecting-future-climate/greenhouse-gas-scenarios/

To aid understanding of the synthetic weather simulation process, AEMO provides below an alternative description of synthetic weather year generation as a two-step process:

> **Step 1 – Generating climate adjusted weather sets**
>
> AEMO selects 20 weather years of high-quality historical weather data as the input data. Typically, these are the last 20 years, except if a data quality issue exists. These 20 historical weather years are warmed based on how long ago they occurred relative to the year being generated.
>
> For example, the process will warm the 2000 historical weather year more than the 2020 historical weather year to represent, for instance, a 2035 climate .
>
> **Step 2 – Simulating future weather from climate adjusted weather sets**
>
> A synthetic weather year is constructed fortnight-by-fortnight through the year, by randomly selecting from the pool of corresponding fortnights in the climate adjusted weather set. This results in a synthetic weather year that follows seasonal patterns and also preserves temperature patterns within the two-week sampled period. This is repeated so as to create a set of 3,000 synthetic weather years. Within this set, the warmed version of a historical temperature event will appear with the same frequency by design. For example, if 43ºC is the top 1% of temperatures over the last 20 years, the warmed version of 43ºC will also occur in the top 1% of the 3,000 synthetic weather years.

In response to the submission that the simulate should preserve the 'historically observed normal pattern of rolling within season of weather outcomes'. The simulation process achieves this by constructing each synthetic weather year a fortnight at a time. It assigns the first fortnight randomly selected from all the first fortnights of history then assigning the second fortnight etc. An effective set of synthetic weather years reflects the full breadth of outcomes in their expected proportions, that is, the mid-January day is warmer than the mid-June day in the majority of cases.

AEMO's conclusion

AEMO's commitment to accurate forecasts requires it to use credible climate futures, and stakeholder involvement in defining forecasting scenarios ensures the climate futures modelled are of relevance to industry and stakeholders. The above description of the Methodology's technical process of weather simulation hopefully provides confidence to stakeholders that the weather simulation process is fit for purpose.

AEMO made minor clarifications to the Methodology during the Draft Determination

AEMO's final determination is that no change to the method is required, and to retain the clarifications made during the Draft Determination

4.6.6. NSIG deviation from weather

Issue summary and submissions

AEMO documented the modelling of non-scheduled intermittent generation (NSIG) in the Methodology.

In response, ERM Power submitted that given the large capacity of NSIG in the NEM, it is important that the Methodology describe how NSIG output is applied to minimum and maximum demand forecasts. Its submission stated:

> It is unclear if output from NSIG is applied based on:
>
> - individual year historical weather aligned outcomes,
> - the average output across all years or

- the minimum output across all years at the time of maximum and the maximum output at times of minimum demand.

AEMO's assessment

The NSIG output is not incorporated into the demand forecast via any of the suggested mechanisms in ERM's submission. Instead, AEMO incorporates distributed PV NSIG into each of the 3,000 simulation outcomes based on the weather in each unique simulation. The probabilistic demand forecast is the statistical distribution resulting from the simulations.

Non-scheduled wind (<30 MW) is incorporated via typical contribution at time of minimum and maximum demand, but solar is explicitly considered in forming the simulation outcomes and the solar value used reflects the weather, season and time of day.

AEMO's conclusion

AEMO agree that NSIG output must be modelled accurately for the benefit of an accurate forecast, and consider its current method is effective in doing so. AEMO's Final Determination is to retain this method.

AEMO also determines to retain changes to the Methodology made during the Draft Determination which clarify the incorporation of NSIG output in demand forecasts.

4.7. Segment specific methodologies

4.7.1. Large Industrial Loads

Issue summary and submissions

AEMO described the use of LIL surveys in the Methodology.

ERM Power raised two points[35], noting that:

- The Methodology did not mention whether deviations between actual and forecast electricity usage were discussed with LIL survey participants. ERM Power went on to recommend that discussions regarding deviations between forecast and actual consumption are included as a clear discussion point in the Methodology.
- There are no benchmark criteria for the inclusion of new LILs in the NEM. ERM Power recommends the Methodology specify inclusion criteria, and notes the criteria for inclusion in the WEM forecast. This would apply both to the current LIL definition (which is supported by ERM Power) and for a suggested group of loads with a half-hourly demand in the 2 MW to 10 MW range.

AEMO's assessment

Regarding discussions with LILs on their deviations to forecast, AEMO thanks ERM Power for identifying an element that was inadvertently omitted from the Methodology.

Regarding the documentation of criteria used to determining the inclusion of new LILs in AEMO scenarios, AEMO agrees this should be listed for the NEM as it is for the WEM.

The introduction of an additional segment of 2-10 MW sized loads was discussed along with other suggestions for increased granularity in Section 4.2. In general, the statistical distribution of loads is log normal, meaning that any inclusion of loads under the existing 10 MW threshold will vastly increase the number of affected loads, however, the scale of those loads is small relative to the original selection.

[35] A further comment to the LIL forecast from ERM Power, suggesting AEMO to move to forecast loads with a half hourly demand in the 2 MW to 10 MW range separately from the remaining BMM loads, is discussed in Section 4.2.

As AEMO notes in Section 4.2, additional segmentation may not improve forecast quality, but does increase forecasting cost. AEMO considers that ERM Power's recommendation would:

- Drive significant administrative costs within AEMO, by applying the criteria to a large number of prospective connections in the NEM
- Invalidate the use of economic forecasts and thus increase forecast error. Economic forecasts by their nature include incremental growth and decline of individual businesses, and the emergence and elimination of whole businesses. The recommended criteria, operating in parallel to the economic forecast, would duplicate the emergence (but not elimination) of businesses with over 2 MW demand, and thus can be expected to introduce upward bias and increase forecast error.

AEMO's conclusion

AEMO made a number of updates to the Methodology for the Draft Determination:

- clarified that atypical electricity use deviations are discussed with the LIL survey participant.
- added criteria for inclusion of new LILs in the NEM.

AEMO's Final Determination is not to introduce NEM entry criteria for loads below the existing 10 MW threshold, and to retain the above changes introduced from the Draft Determination

4.7.2. BMM – sub-regional seasonality

Issue summary and submissions

AEMO describes the forecasting process for BMM, including the use of seasonality.

ERM Power queried how AEMO's seasonality component "differentiates between loads that have a seasonality component and loads that do not". The submission then described an example of "BMM loads in holiday resort areas would have very high seasonality impacts whereas BMM loads in a metropolitan location may not".

AEMO's assessment

AEMO agrees that various BMM customers have different seasonal loadings. However, the Methodology does not attempt to differentiate between them in this manner, because at a regional (state) level, the seasonality factor applied is the weighted average of all BMM in that region.

AEMO's conclusion

AEMO's Final Determination is to continue using the current application of BMM seasonality at a regional (state) level.

4.7.3. BMM – uncertainty adjustment

Issue summary and submissions

The Methodology describes AEMO's reflection of BMM forecast uncertainty through the use of a dispersion around the central scenario.

ERM Power noted that the Forecast Accuracy Report contains no details regarding the accuracy of the BMM forecast, so there appears to be no justification for the level of dispersion employed. The submission recommended that the level of dispersion be justified through improved analysis of actual electricity usage.

AEMO's assessment

AEMO notes there are multiple techniques for estimating current forecast dispersions and the submission appears to have assumed that historical forecast accuracy is required to do so.

In fact, AEMO utilises a standard statistical technique of estimating the forecast dispersion from the standard deviation of the difference between actual and fitted values of the current BMM forecasting model. This takes into account all years of actual data that go into training the current model, and thus provides the best possible dispersion estimate of the current forecasting model. Using this technique, the performance of historical forecasts (which are likely to have had different model parameter values and even different model structures) is irrelevant to the forecast dispersion of the current model.

AEMO regards the above technique as superior to the submission's recommendation, because it directly addresses the primary purpose of describing forward looking accuracy. The chosen technique best reflects the likely benefits of ongoing model improvement and the benefit of increasing data history.

AEMO's forecast dispersion is a 95% confidence interval, meaning, that in the long run, 95% of actual values are within the forecast confidence interval.

AEMO's conclusion

AEMO updated the Methodology during the Draft Determination to describe the basis for the dispersion estimate.

AEMO's final determination is to retain its current technique of estimating dispersion, and the updated description in the Methodology

4.8. Other matters

4.8.1. Consumer advocate funding

Issue summary and submissions

The Methodology contains a volume of detailed content.

QEUN submitted that reviewing such consultation documents is a burden for consumer advocates, and that consumer advocates need funding in order to contribute to represent their consumer base.

AEMO's assessment

This matter has been addressed in Section 4.2.2 "Funding for consumer representatives" of the Reliability Forecast Guidelines Final Determination[36].

AEMO's conclusion

When seeking feedback on the Methodology from QEUN, AEMO conducted a telephone call to help QEUN use its time efficiently. AEMO's position regarding funding is described in the above-noted section of the RFG.

4.8.2. Conservatism

Issue summary and submissions

AEMO targets the production of an accurate and unbiased forecast.

ERM submitted:

[36] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/reliability-forecast-guidelines

> ERM Power acknowledges the ongoing work by AEMO to attempt to improve the veracity of the Methodology in the areas of annual consumption and maximum and minimum demand outcomes. However, we remain concerned that AEMO maintains an overly conservative methodology with regards to the forecasting of regional maximum demand outcomes. This is highlighted by historical outcomes vs forecasts, in particular for the Victorian region. In December 2019 new temperature records were set at numerous weather stations in the Victoria region, however actual operational demand fell well below the 10% POE forecast for the month of December. Similarly, in January 2020 when daily maximum temperature outcomes during the last week of January were well above historical 95th percentile outcomes and very close to historical maximums at numerous weather stations in the Victorian region, adjusted demand remained below AEMO's Summer and January monthly 10% POE forecasts.
>
> We also note that in the history of the National Electricity Market (NEM), actual maximum demand in the Victorian region, following any required adjustments for defined load interruption, has not exceeded the market operators 10% POE demand forecast, yet demand has fallen below the 90% POE forecast for 25% of years.
>
> In addition, we are also concerned with what we consider are reactive responses by AEMO, where actual demand outcomes, whilst remaining within the range of outcomes derived from the forecasting process, result in recalibration of baseline data and the 50 and 10% POE benchmarks. AEMO's regional maximum demand forecasts are derived from a set of 3,000 synthetic weather years, these potential weather outcomes which include for a wide range of weather variability is used to calculate a range of potential summer and winter maximum daily demand outcomes ranging from 0 to 100% POE. As set out in the Methodology, significant tail values exist in the distribution of outcomes between the 0 to 10 and 90 to 100% POE values. We consider that it is entirely possible and also that it should be expected, that at some point in time actual demand could exceed a 5% POE (1 in 20 years) or even a 2% POE, (1 in 50 years) outcome which following an actual occurrence should not automatically justify significant adjustment to the 10% POE forecasts. We believe that more detailed analysis and consultation on prevailing factors that led to the 10% POE forecast being exceeded is warranted when such an event occurs, prior to any decision by AEMO to make significant adjustments to baseline and 50 and 10% POE benchmark data. This has not been the case to date, with significant adjustments made with what we believe has been inadequate consultation.
>
> We recommend that AEMO provide additional transparency in the regional forecast maximum demand values as an appendix in the Forecast Accuracy Report, by including in tabular form the full range (0 to 100% POE) of regional forecast maximum demand values derived from their modelling process. This should be displayed in at least 21 blocks, each of 5 percentile increments.
>
> We also urge AEMO to seek assistance from the regulators with respect to using performance data provided by participants to the Essential Services Commission (ESC) and the AER on a quarterly basis. Some of this data, such as monthly feed in tariff customer numbers by jurisdiction, monthly smart meter installation by metering type and number of customers with smart meters by tariff type (controlled load, time of use) may be useful as a reference source for trend analysis.

MEU submitted:

> As a general observation, the MEU recognises that AEMO is continually seeking to enhance its practices and so improve the quality of its forecasts. Equally, the MEU is concerned that AEMO forecasting still exhibits considerable conservatism in its assessments of future of peak demand (10%PoE). The MEU accepts that some limited conservatism is appropriate but stresses that with recent changes (eg the Retailer Reliability Obligation) and expected new changes (eg from the Energy Security Board post 2025 review) in the market rules, the impact of excessive conservatism in forecasts will lead to significant but unnecessary costs for end users that are already expressing

considerable concern at the costs of delivered electricity. In this regard it is worth highlighting end users have clearly expressed a view that they do not want increased reliability of supply if that increases costs and lower costs for electricity supplies are essential. The MEU considers that AEMO needs to improve their forecasting practices ensure that they do not exhibit excessive conservatism.

AEMO's assessment

Regarding the submission's references to December 2019 and January 2020, as explained in the Reliability Standard Implementation Guidelines (RSIG) consultation, comparing individual months to probabilistic forecasts is not statistically valid. All probabilistic forecasts are 'in the long run' (law of large numbers) and referring to two monthly data points does not constitute evidence that the demand forecast is materially biased. Refer to University of Adelaide's expert report on demand forecast accuracy reporting.

Section 4.6.2 of this report addresses the comments regarding actual maximum demand in the Victorian region over the history of the NEM. The section also addresses ERM Power's perception that an actual occurrence automatically justifies "significant adjustment to the 10% POE forecasts".

Section 4.6.2 also addresses ERM Power's recommendation of tabulating the full range of regional forecast maximum demand values. The suggestion regarding ESC and AER data is addressed more generally in Section 4.2.

MEU did not provide new information or evidence of conservatism, and AEMO has previously refuted the claim of conservatism in the Reliability Forecast Guidelines Final Determination[37].

AEMO's conclusion

This matter has been addressed in Section 5 "Identifying and addressing conservatism and bias" of the Reliability Forecast Guidelines Final Determination[37].

5. FINAL DETERMINATION

Having considered the matters raised in submissions, AEMO's Final Determination is to amend the Electricity Demand Forecasting Methodology[38], available under AEMO's Forecasting Approach[39].

[37] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/reliability-forecast-guidelines
[38] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/electricity-demand-forecasting-methodology
[39] Available at: https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-approach

APPENDIX A. GLOSSARY

Term or acronym	Meaning
AEMO	Australian Energy Market Operator
AER	Australian Energy Regulator
BMM	Business Mass Market
DNSP	Distribution Network Service Provider
ESOO	Electricity Statement of Opportunities
EV	Electric Vehicle
FBPG	Forecasting Best Practice Guidelines
FRG	Forecasting Reference Group
GEV	Generalised Extreme Value
GSP	Gross State Product
IPCC	Intergovernmental Panel on Climate Change
ISP	Integrated System Plan
NEM	National Electricity Market
NER	National Electricity Rules
NMI	National Meter Identifier
POE	Probability of exceedance
RCP	Representative Climate Pathway

APPENDIX B. FORECAST GRANULARITY

Definition of granularity

Forecast granularity describes the level of detail at which calculations occur and results are presented, and may refer to time increments (annual, monthly, daily, hourly etc) or segmentation by customer type or geography. Examples of possible segmentation applied to an energy forecast include:

- Customer type: residential, BMM, industrial.
- Geography: NEM region (effectively state borders).
- Hybrid: geographical and customer type: for each NEM region – residential, BMM, industrial.

The granularity chosen should reflect the intent of the forecast, stakeholder needs and what is practically achievable.

Correctly defining segments

As time and geographical segmentations are rarely confusing, this section will focus on the definition of customer type segments. The definitions of customer type segments should:

- Be collectively exhaustive; for example, there should be no consumption outside residential, BMM and industrial.
- Be mutually exclusive. Care should be taken with customer types that could be (or perceived to be) double counted. For example, given the co-location of home based businesses with residences, a fully defined residential segment definition would recognise this limitation.
- Share definitions with the primary data source(s) – for example, defining BMM by annual sales turnover is inappropriate if the forecasting IT systems do not include an annual sales turnover field.
- As much as possible, reflect both:
  - Common usage of the segment name.
  - Definitions in external data sources that would provide related insights. For example, organisations such as the ABS publish data that helps inform debate and strategic decisions in various Australian contexts. Such organisations define their terms by considering their own stakeholders and data availability. For example, the ABS definition of 'small and medium business' is businesses employing less than 200 people. In contrast, the ATO, with its own needs and purposes, define Small businesses as an entity with a turnover less than $10 million[40], and a Large/Medium company based on an annual total income of more than $10 million[41]. Subject to the other factors above, the segment definition should match with the external definition most likely to be useful.

Increasing forecast granularity

A generic example is used to illustrate what's involved in increasing forecast granularity.

An organisation initially forecasts average residential energy use over time. Its statistical model is that average residential energy use is a function of:

- A base level amount, plus
- A trend amount that changes over time, plus

[40] See: https://www.ato.gov.au/business/small-business-entity-concessions/eligibility/

[41] See: https://www.ato.gov.au/Tax-professionals/Prepare-and-lodge/Tax-agent-lodgment-program/Tax-returns-by-client-type/Large/medium-taxpayers/

- An economic driver, plus
- A residual term that reflects statistical uncertainty.

A decision is made to increase the granularity of the forecast, meaning that:

- Segment definitions are developed as per the heading further above, which in this simplified example are houses and units (in practice the definitions would be more complex).
- A separate forecast is required for both houses and units. Thus, the above elements of the average residential energy use model are now required for each segment.

Note that the above change to forecast granularity is conceptually different to including the ratio of houses to total residences (or units to total residences) into the former average residential energy model. In such a case, the ratio is a driver of the average residential energy use forecast, but this does not deliver independent forecasts of average energy use for houses and units. The value of the driver is data-driven, and may provide useful insights as to its importance.

Costs associated with increasing granularity

Costs associated with increasing granularity include:

- Up-front identification of a trusted and cost-effective data source(s) of suitable frequency, for each segment level variable, and both historical and forecast values of the drivers of the segment level variable.
- Development of relevant data ingress, storage and quality validation processes.
- Development, validation and communication of segment level forecasts.
- Updates to reporting systems and processes, including the Forecast Accuracy Report.

Benefits of increased granularity

Aggregated models are surprisingly effective and, strictly mathematically, increasing the granularity alone does not result in increased accuracy. The attached "EDFM Draft Determination Examples Spreadsheet[42]" illustrates three different hypothetical worlds of residential energy forecasting.

Table 2 Combined v segmented example

EDFM DD Example Spreadsheet	Annual consumption amount	Numbers of houses and units
Example 1 – Constant growth and size	Constant for houses, and constant for units	Housing and unit counts both trending at 0.25% per month
Example 2 – Different growth, constant size	Constant for houses, and constant for units	Housing trending at 0.1% Units trending at 0.25%
Example 3 – Different growth, changing size	Changing over time for houses, and over time for units, at different rates	Housing trending at 0.1% Units trending at 0.25%

It should be noted that the spreadsheet is intended to illustrate a general point regarding the sufficiency of aggregated models, and not reflect AEMO's exact method for residential energy consumption forecasting.

The examples demonstrate the aggregated model captures the net result of the trends occurring within the segments, because in all three cases the aggregate model produces the same result as the segment level model.

[42] Available at: https://aemo.com.au/en/consultations/current-and-closed-consultations/electricity-demand-forecasting-methodology

Increased granularity can improve forecast accuracy if the future value of one segment's drivers and their impacts are better known than for the aggregated forecast, and the relative size of the segments are unknown. For example, if new laws were to take effect regarding residential unit construction, an aggregated residential dwelling forecast could be disaggregated to support application of the new laws to units only. However, for this to result in a forecast accuracy improvement, the estimated impact of the new law on units would need to be more accurate than the accuracy of the aggregated forecast in general.

Increased forecast granularity can result in lower forecast accuracy when:

- the more granular data is of lower accuracy than the aggregated alternative. For example, moving to forecasting half-hourly residential and business demand separately would rely on the data qualities of these respective segments. Operational demand at half-hourly intervals is accurately measured at a regional level through metering of generation output and interconnector flows. As not all business load is metered half-hourly and even less residential is metered at that level, any split of demand into these two groups will rely on estimation with inherent error. Such segment level forecasting models would be less accurate than the aggregated alternative.
- more assumptions are required - to the extent the additional assumptions are incorrect, the accuracy suffers
- forecasts are sensitive to the additional volatility of granular year-on-year outcomes

Other than the limited circumstances in which forecast accuracy is technically improved, the benefit of increased forecast granularity is in the provision of:

- Insights to stakeholders and forecasters, although the direct value of such insights is questionable in a demand forecasting context because, in general, a MW of peak demand from customer segment A is equivalent to a MW of peak demand from customer segment B at the same time, in the same forecasting geography. Only when considering secondary effects, such as the extent to which customer segment B has greater opportunity for demand management, do segment level forecasts provide actionable insights.
- Ability to compare segment forecasts with external data or expectations at the segment level (assuming they exist). Satisfactory results from such comparisons may enhance stakeholder confidence in the forecasts.

Summary of forecast granularity

The above content explains that a given level of forecast granularity requires careful development of segment definitions. Increasing forecast granularity is non-trivial and only in limited circumstances directly results in an accuracy improvement. For these reasons, the intent behind proposals to increase forecast granularity need to be well understood. If the intention is to increase forecast accuracy, then a broader set of options, such as including a relevant driver in the aggregated model, should be considered.