FINAL REPORT

Review of AusNet's electricity maximum demand forecasting methodology

Prepared for
AusNet Services

17 January 2025

THE CENTRE FOR INTERNATIONAL ECONOMICS
www.TheCIE.com.au

The Centre for International Economics is a private economic research agency that provides professional, independent and timely analysis of international and domestic events and policies.

The CIE's professional staff arrange, undertake and publish commissioned economic research and analysis for industry, corporations, governments, international agencies and individuals.

CANBERRA

Centre for International Economics
Ground Floor, 11 Lancaster Place
Majura Park

Canberra ACT 2609
GPO Box 2203
Canberra ACT Australia 2601

Telephone +61 2 6245 7800
Facsimile +61 2 6245 7888
Email cie@TheCIE.com.au

Website www.TheCIE.com.au

SYDNEY

Centre for International Economics
Level 7, 8 Spring Street
Sydney NSW 2000

Telephone +61 2 9250 0800
Email ciesyd@TheCIE.com.au

Website www.TheCIE.com.au

Contents

Executive summary

The CIE has been asked by AusNet to review their electricity maximum demand forecast methodology.

The review has considered:

- the overall structure of the methodology, including:
  - specification of the forecasting model
  - the appropriateness of the key drivers included in the model
  - the steps in implementing demand forecasts
  - the model logic and whether forecasts are likely to be accurate and unbiased
- the input data, including:
  - the electricity demand data used
  - the demand driver data used, including considering whether the most recent and consistent inputs have been used
- the spatial disaggregation of the model and mapping for demand drivers to spatial localities
- the approach used to account for variability in weather and other demand drivers (including those which are unobserved), and
- the overall transparency and replicability of AusNet's forecasting methodology.

Note the review has focused on the methodology as opposed to its implementation, which has not been reviewed by the CIE.

AusNet's methodology

AusNet has developed their forecasting methodology based on the Monash Electricity Forecasting Model.[1] Maximum and minimum demand is estimated in seven steps.

- **Step 1:** Collect historical data, including customer numbers, half hourly operational demand data, rooftop PV capacity, modelling half-hourly solar PV generation embedded generation and weather and solar variables.
- **Step 2:** Forecast residential customer numbers using Victorian Government dwelling projections, and AEMO roof-top PV capacity projections. Non-residential customer numbers are forecast using the historical relationship with residential customers.
- **Step 3:** Model underlying half hourly demand per customer (unitised underlying demand) in two separate models:
  - average half hourly maximum (or minimum) in a given month ($\bar{y}_i$)

1 Hyndman, R. J. and Fan, S. 2015, Monash Electricity Forecasting Model, 15 June.

 – estimate an adjustment coefficient ($y^*_{t,p}$)

 Half hourly unitised underlying demand is given as:

$$y_{t,p} = \bar{y}_i \times y^*_{t,p}$$

- **Step 4:** Forecast the impact of electrification from EVs and electrification. These are applied as post modelling adjustments in step 5.
- **Step 5:** Simulate future demand by bootstrapping weather, calendar impacts and residuals using 1,000 scenarios. Solar PV generation is also simulated using weather variables. Post modelling adjustments are added at the end of this step.
- **Step 6:** Report maximum and minimum demand in terms of different probability of exceedances (PoEs), based on the probability distribution for each maximum and minimum demand from each simulation.
- **Step 7:** Validate spatial demand forecasts and include post modelling adjustment.

AusNet's approach is broadly consistent with the transmission connection point forecast, although there are some differences in how the model is implemented. Changes in demand over time are primarily driven by changes in the number of customers.

Findings

The overall structure of methodology, based on the on the Monash Electricity Forecasting Model, provides a reasonable framework to maximum (or minimum) electricity demand. However, some of the modelling assumptions are expected to overstate or understate demand somewhat. In most cases the precise magnitude of these forecasting biases cannot be determined with the data and information available.

The detailed findings of the review are summarised in table 1.

1 Summary of key findings

No.	Issue	Relevant step	Discussion	Materiality/impact on forecast
1	Adjusting forecast for embedded generation	Forecasting maximum and minimum demand	Embedded generation is not subtracted from forecasts of underlying demand	This will materially overstate the level of maximum and minimum demand forecasts but may not affect the growth rate where future embedded generation is accounted for as part of post modelling adjustments.
2	Missing demand drivers	Demand models	Electricity prices are not incorporated into demand models	Likely to understate demand based on AEMO price forecasts, however the impact on maximum and minimum demand is unclear.
3	Missing demand drivers	Demand models	Energy efficiency is not incorporated into demand models	Whilst energy efficiency is likely to materially impact average demand (consumption), the impact on maximum and minimum demand is unclear.
4	Missing demand drivers	Demand models	Behind the meter batteries are not incorporated into demand models	Expect to: ▪ not have a material impact on the maximum demand forecasts compared to AEMO's ESOO 2024 forecast (overstate maximum demand by around 1 - 2 per cent over the regulatory period).

No.	Issue	Relevant step	Discussion	Materiality/impact on forecast
				– AEMO only includes exiting and committed VPP programs in their central forecasts. Any uptake in excess of existing committed VPP programs is likely to result in similar forecast errors for AusNet's forecast as for AEMOs ESOO 2024 projections. ▪ have a moderate impact on minimum demand forecasts (understate minimum demand by around 4 per cent in 2030-31)
4	Missing demand drivers	Demand models	Tariff structure is not incorporated into demand models	The evidence around the impact of tariff structure on minimum and maximum demand is mixed. Further information is required to assess its materiality.
5	Accounting for COVID	Model estimation	Not clear how the impact of COVID has been accounted for in parameter estimation (if relevant), or if impacts will persist	Unclear
6	Potential improvement	Validation	Peak/minimum demand-to-average ratio is not allowed to vary overtime	▪ If the peak to average ratio is increasing, fixing this relationship would understate demand. ▪ Further analysis of AusNet forecast results would be required to assess materiality.
7	Potential improvement	Reconciliation	Customer numbers at the feeder level are reconciled to substation level forecasts. Demand forecasts are not reconciled and may be inconsistent depending on the level of aggregation.	Unclear

Source: CIE.

1 Scope of the review

The CIE has been asked by AusNet to review their electricity maximum demand forecasts. The review has considered:

- the overall structure of the methodology. This includes consideration of the specification of forecasting models (i.e. the variables included and how they enter the model) as well as the steps in implementing demand forecasts
- the input data, which includes the electricity demand data and the input demand drivers which are used to explain variation in demand over time
- the spatial disaggregation of the model. Forecasts of demand at the connection point level will often rely upon demand drivers forecast at the state or LGA level; how these forecasts are attributed to connection points can have an impact on the validity of the forecasts
- simulation of weather and residuals. Observed demand reflects, underlying demand drivers (e.g. prices and population), weather outcomes and a residual. To forecast maximum demand, the weather process and residuals should be accounted for in the methodology, and
- the overall presentation and clarity of AusNet's forecasting methodology documentation.

Coverage of review

We have been provided with the following documents for review.

- Demand Forecasting Methodology – Electricity Distribution Network, 20 June 2024
- "Future Networks Sub-Panel #3 _Meeting Pack – May 2023.pptx".
- "Data from, demand forecasting_July 2024.pptx"
- "Tariffs and Pricing Meeting #4 _30 October 2023_FINAL.pptx"
- The R code used to implement the methodology

This review is primarily based on the demand forecasting methodology document, as of 20 June 2024, as well as personal correspondence and consultations with AusNet.

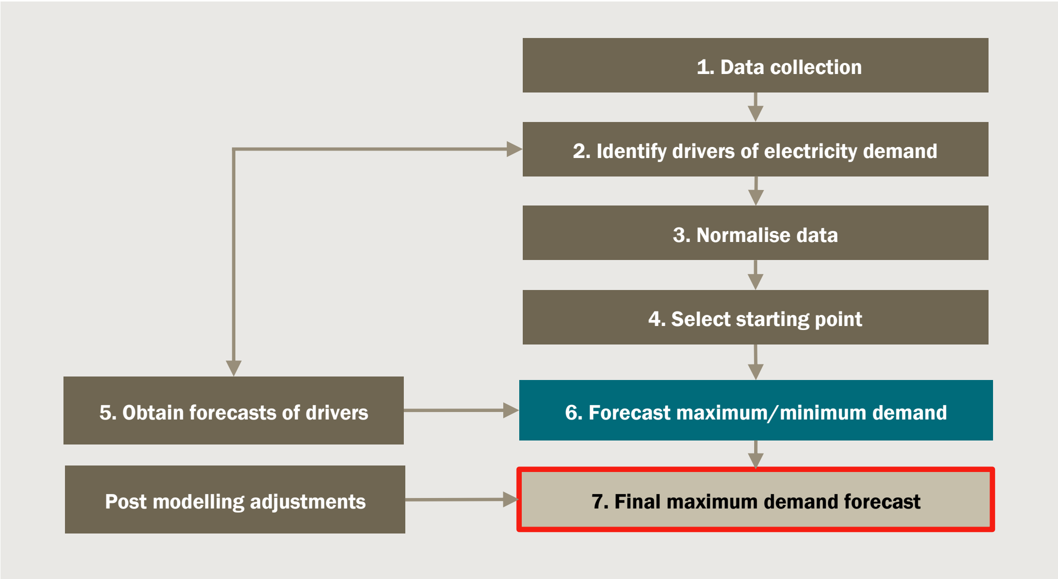
Note we have not reviewed the implementation of the model in terms of auditing the code against the methodology reviewing forecast outputs. Hence, we can only verify our understanding of the methodology, rather than that this is faithfully implemented.

Overview of typical maximum/minimum demand forecast

The structure of a typical demand forecasting process is outlined in chart 1.1 and consists of:[2]

1 Data collection, where the relevant electricity, weather and demand driver information is collected and mapped to substations or connection points
2 Identifying relevant drivers of electricity demand to be included in the model
3 Normalising data by estimating relationships with demand drivers, which allows consideration of demand under normalised weather conditions
4 Selecting the starting point for the forecast
5 Obtaining forecasts of drivers
6 Forecasting maximum and minimum demand from the chosen starting point
7 Producing final forecasts including post modelling adjustments.

1.1 Forecasting steps



Data source: CIE based on ACIL Allen and AEMO.

Principles of forecasting

Forecasting is an inherently imprecise science. In arriving at demand forecasts for a regulatory determination:

- it is important that forecasts are unbiased. That is, projections do not systematically understate or overstate demand, and

2 Based on ACIL Allen Consulting 2013, "Connection Point Forecasting: A nationally consistent methodology for forecasting maximum electricity demand", prepared for AEMO and AEMO 2021, Transmission Connection Point Forecasting Methodology: Maximum and minimum demand.

- it is important that forecasts are as accurate as is possible. The less accurate the forecast the greater the risks to the regulated business.

Forecasts can be inaccurate but unbiased if over a sufficiently long period of time the forecast error is zero or in expectation the forecast error is zero. This would be the case for climatic conditions for example which are inherently uncertain.

There are many possible areas where forecast errors can arise. They have been detailed in technical terms by Hendry and Clements 2001 (shown in table 1.2). In plain English, the main areas of forecast error in electricity forecasting are likely to be:

- uncertainty around drivers of peak/minimum demand, such as
  - climatic conditions
  - population
- uncertainty around the impact that past drivers of electricity demand will have in the future, such as:
  - weather impacts remaining similar to those experienced in the past
  - trends in demand uptake rates remaining similar to those experienced in the past
  - the ratio of commercial demand to residential demand remaining similar to the past
- impacts of additional policies or factors, such the increased uptake for rooftop solar PV, electric vehicles or batteries.

1.2 Forecast error taxonomy

1 Shifts in the coefficients of deterministic terms	2 Shifts in the coefficients of stochastic terms
3 Misspecification of deterministic trends	4 Misspecification of stochastic terms
5 Misestimation of the coefficients of deterministic terms	6 Misestimation of the coefficients of stochastic terms
7 Mismeasurement of the data	8 Changes in the variances of the errors
9 Errors cumulating over the forecast horizon	

Source: Hendry, D. and M. Clements (2001), "Economic forecasting: some lessons from recent research", *Economic modelling*, vol. 20(2), (March, pp. 301–29).

The AER sets out the principles of best practice demand forecasting which they assess demand forecasts against. These are summarised in table 1.3.

1.3 AER demand forecast assessment principles

Demand forecast assessment principle	Description
Accuracy and unbiasedness	A Network Service Provider (NSP) should ensure its demand forecasting approaches produce demand forecasts that are unbiased and meet minimum accuracy requirements.
Transparency and repeatability	Demand forecasting approaches should be transparent and reproducible by independent sources.

Demand forecast assessment principle	Description
Incorporation of key drivers	A best practice forecasting approach should incorporate all key drivers either directly or indirectly, and should rest on a sound theoretical base.
Weather normalisation	Correcting historical loads for abnormal weather conditions is an important aspect of demand forecasting.
Model validation and testing	NSPs should validate and test the models they use to produce demand forecasts
Use of the most recent input information	NSPs should use the most recent input information to derive their demand forecast.
Spatial (bottom up) forecasts validated by independent system level (top down) forecasts	NSPs should prepare their spatial forecasts and system level forecasts independently of each other.
Adjusting for temporary transfers	Before determining historical trends, NSPs must correct actual maximum demands at the spatial level to system normal conditions by adjusting for the impact of temporary and permanent network transfers arising from peak load sharing and maintenance.
Adjustment for discrete block loads	NSPs should account for large new developments in their forecasts.
Incorporation of maturity profile of service area in spatial time series	NSPs should recognise the phase of growth of each service area
Use of load research	NSPs' demand forecasting approach should incorporate the findings of research on the characteristics of the load on their networks.
Regular review of demand forecasting approaches	NSPs should review their demand forecasting approaches on a regular basis.

Source: AER 2013, (AER) in its 'Better Regulation Explanatory Statement- Expenditure Forecast Assessment Guideline'

In the remainder of this document, we set out and review Ausnet's maximum and minimum demand forecasting methodology.

For this review, we have drawn on AEMO's connection point and demand forecasting methodologies as well as AER's approach to evaluate forecast which are documented in:

- AEMO 2024, "Forecasting Approach – Electricity Demand Forecasting Methodology"
- AEMO 2021, "Transmission Connection Point Forecasting Methodology: Maximum and minimum demand"
- AER 2013, "Better Regulation Explanatory Statement- Expenditure Forecast Assessment Guideline".

2 Overview of the AusNet methodology

AusNet has developed their forecasting methodology based on the Monash Electricity Forecasting Model.[3] Maximum and minimum demand is estimated in seven steps.

- **Step 1:** Collect historical data, including customer numbers, half hourly operational demand data, rooftop PV capacity, EV numbers, embedded generation and weather and solar variables.
  - Embedded generation and solar PV generation are added to operational demand to give underlying demand (used in step 3 onwards).
- **Step 2:** Forecast residential customer numbers using Victorian Government dwelling projections, and AEMO roof-top PV capacity projections. Non-residential customer numbers are forecast using the historical relationship with residential customers.
- **Step 3:** Model underlying half hourly demand per customer (unitised underlying demand) in two separate models:
  - average of maximum (or minimum) demand for each given half hour period in each month ($\bar{y}_i$, where i denotes the month)
  - estimate an adjustment coefficient ($y^*_{t,p}$), which measures the relationship between maximum (or minimum) half hourly demand at time t (measured in half hourly intervals) and period p ($p = 1, \dots, 48$) and demand drivers, such as weather. On average this will be equal to 1 for the respective maximum and minimum demand models.

  Unitised underlying half hourly demand is given as:

  $$y_{t,p} = \bar{y}_i \times y^*_{t,p}$$
- **Step 4:** Forecast the impact of electrification from EVs and electrification. These are applied as post modelling adjustments in step 5.
- **Step 5:** Simulate future demand by bootstrapping weather, calendar impacts and residuals using 1,000 scenarios. Solar PV generation is also simulated using weather variables. Once the simulation is complete the forecasts are processed as follows:
  - operational demand is recovered by subtracting simulated solar PV generation from forecast underlying demand (note we understand embedded generators are not subtracted).
  - other post modelling adjustments are applied.
  - determine maximum and minimum demands for each simulation by year and season.
- **Step 6:** Report maximum and minimum demand in terms of different probability of exceedances (PoEs), based on the probability distribution for each maximum and minimum demand from each simulation.

3 Hyndman, R. J. and Fan, S. 2015, Monash Electricity Forecasting Model, 15 June.

- **Step 7:** Validate spatial demand forecasts and include post modelling adjustment.

- **AusNet's approach is based on a well established methodology, but differs in terms of the demand drivers included.**
- **Average maximum (or minimum) demand is modelled as one block, and is not broken down by different times of day. This approach is appropriate as it does not include drivers which would have different impacts on average demand depending on the time of day. If additional drivers were included, such as energy efficiency, then this specification would need to be modified.**
- **During step 5, we understand that the methodology does not subtract embedded generation from forecasts of underlying demand. This is likely to overstate the level of maximum and minimum demand forecasts, but may not affect the growth rate where future embedded generation is accounted for as part of post modelling adjustments.**

3 Data

Electricity data

The AusNet methodology uses half hourly maximum (minimum) interval operational data for residential, commercial and industrial customers. Data is collected from the following sources:

- Customer numbers are extracted by asset and customer type from the tariff database and spatial asset database. This includes:
  - Customer classification based on tariff type
  - Feeder and zone substation supplying the customer
  - Whether the customer has solar PV installed.

  Customers are allocated to different assets based on customer allocations as at historical maximums. This is intended to account for changes in network configuration overtime.
- Maximum (or minimum) operational demand is based on SCADA sensor data on network elements such as feeders and substations. This data describes the maximum (or minimum) demand within each half hourly period as opposed to consumption over this period, which means the model estimates instantaneous maximum (or minimum) demand as opposed to half-hourly maximum (or minimum) demand.
- Embedded generators data is extracted from advanced metering infrastructure interval database.

The type of data used for AusNet's forecasts is consistent with best practice approaches which focus on forecasting demand at the connection point level. While this data allows for the disaggregation of customers, operational demand is not split by type (as distinct from customer level data has in the past been used to estimate maximum demand). This means, like AEMO's approach, that the relationship between demand and demand divers cannot be tailored for specific customer types (such as for residential, commercial and industrial customers, or of new or existing customers).

Several adjustments are also made at the terminal station level to account for: planned and unplanned feeder reconfigurations (corrections are made to remove step changes in demand due to reconfiguration of the network); and large embedded generators (generation exports are added back to terminal station demand data).

- **The data used to measure electricity demand and customer numbers are consistent with best practice approaches to estimate maximum and minimum demand.**
- **Demand is adjusted to account for changes in network configuration.**

Demand drivers

The AusNet Methodology estimates demand separately in terms of customer numbers, unitised average demand and adjustment coefficient (half hourly demand). Multiplying these three elements together gives the estimate of total half hourly demand.

The drivers of **customer numbers** are:

- dwelling projections from the Victorian Government mapped to substations, which are used to project the number of residential customers by substation in year. This process is repeated for feeders. Victorian Government Projections are provided at 5 year intervals (i.e. 2021, 2026 etc.) to 2036. Where projections do not reflect actual growth, (based on network planning engineers experience with recent connections and information from developers), these projections are adjusted.
- commercial and industrial customer growth is projected based on residential customer numbers. The historical ratio between residential and commercial/industrial customers is estimated. This trend is projected into the future and multiplied by residential customer numbers to forecast commercial and industrial customers for each feeder.
  - Adjustments are made to commercial and industrial forecasts where information on upcoming connections is available.
  - Large commercial and industrial customers are accounted for in block load adjustments

The drivers of **average unitised maximum (or minimum) demand** are:

- temperature data which is used to calculate Heating Degree Days (HDDs) and Colling Degree Days (CDDs). Postcode level data form Weather Zone is mapped to feeders and zone substations. The analysis uses the same critical temperature of 18.5°C for both CDDs and HDDs in line with documentation for the Monash Electricity Model.[4] For Victoria, AEMO recommends critical temperatures of 16.5 °C for HDD and 18.0°C.[5]

The drivers of the half hourly **adjustment coefficient** are:

- weather data including temperature, wind speed and humidity. Post code level data from Weather Zone is mapped to feeders and zone substations.
- calendar effects, such as seasonality, public holidays, day of week and month, holidays and school holidays.

In addition, the analysis takes into account the following drivers outside of the estimated models:

- solar PV update and half hourly generation, which is estimated, and large embedded generation, which is data, are added to operational demand to give underlying demand, which is estimated by AEMO's methodology. The impact of these over time

4 Hyndman, R. J. and Fan, S. 2015, Monash Electricity Forecasting Model, 15 June.

5 AEMO 2024, "Forecasting Approach – Electricity Demand Forecasting Methodology", Appendix A2.

on operational demand can be subtracted from forecast underlying demand to forecast operational demand

- gas electrification, which is included as a post model adjustment
- EV uptake and charging profile, which is included as a post modelling adjustment, and
- block load adjustments.

No other drivers are directly included in the model. Drivers which are often included in models, but are not incorporated into AusNet's forecasts include:[6]

- **Economic growth**. Dwelling growth reflects population growth, a key driver of economic growth. However, it doesn't consider other factors like productivity, which can influence economic activity per capita. This can affect electricity demand because as economies grow, businesses and industries produce more goods and services, often requiring more electricity. When economic growth per capita is positive, AusNet's approach is likely to underestimate demand. This impact however is likely to be small and is not likely to impact the geographical distribution of demand growth given the limited economic growth forecasts available. Reliable forecasts for Gross State Product (GSP) are only available at the state level so do not allow differences in growth for AusNet's service area to be determined. Because regional variation is likely to be important, focusing on dwellings, which can more effectively be forecast at the local level, may reduce forecasting errors compared to also incorporating economic growth.
  - The AEMO connection point forecast methodology does not directly include economic growth in PoE estimates, but rather reconciles connection point forecasts to operational demand forecasts which include population growth, economic and demographic outlook, electricity prices, energy efficiency and performance, and small-scale embedded technologies.[7]
- **Electricity prices**. Models of demand typically include an electricity price variable, consistent with economic theory that lower prices lead to higher consumption and higher prices lead to lower consumption. AEMO's residential annual consumption forecasts use a price elasticity -0.1 for residential heating and cooling load, -0.1 for all business load which means a 10 per cent increase in prices results in a 1 per cent decrease in demand.[8] Note that AEMO also assumes that residential baseload appliances are inelastic or do not respond to changes in prices – using AEMO's elasticities, the price impacts would therefore depend on share of electricity use across different customers and appliances. Higher elasticities have been estimated in the economic demand literature and used by AEMO in the past; but there is uncertainty

[6] See for example: AEMO 2024, "Forecasting Approach – Electricity Demand Forecasting Methodology", p. 7-8. and ACIL Allen Consulting 2013, "Connection Point Forecasting: A nationally consistent methodology for forecasting maximum electricity demand", prepared for AEMO.

[7] AEMO 2021, "Transmission Connection Point Forecasting Methodology: Maximum and minimum demand", p. 26 and AEMO 2024, "Forecasting Approach – Electricity Demand Forecasting Methodology", p. 52.

[8] AEMO 2023, "2023 Inputs, Assumptions and Scenarios Report", p. 85.

around the appropriate elasticity to use and whether they are significantly different from zero during peak periods.

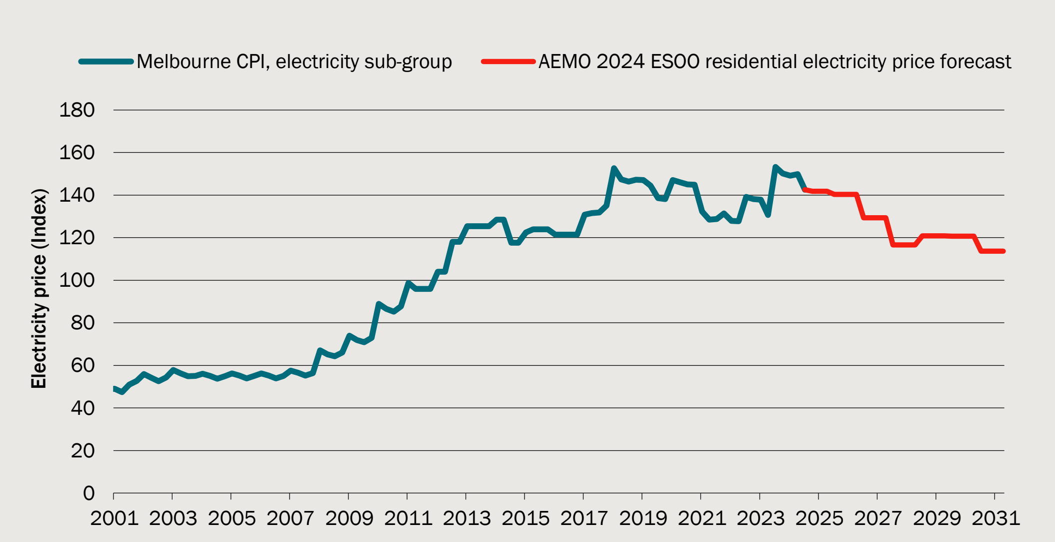
- AusNet has previously provided evidence that elasticities during peak periods were close to zero in a trial of customer rebates.[9] Similar evidence is not available for minimum demand periods. While we expect that the result could be different if the price change was an increase in price as opposed to a rebate, this indicates that elasticities during maximum and minimum demand periods may vary from the average demand elasticities estimated and used by AEMO. The AEMO connection point forecast methodology does not directly include electricity prices in its half hourly model used to generate PoE estimates, but rather reconciles these forecasts to operational demand forecasts which do include electricity prices.[10] This implicitly assumes that the maximum/minimum to average ratio of demand remains constant in prices – to allow demand during maximums (or minimums) to be less elastic would require the maximum/minimum to average ratio of demand may change as prices change.
  - Note AusNet's methodology does not estimate average demand, but rather average unitised maximum (or minimum) demand
- Noting the uncertainty around the around elasticities at maximum (or minimum) demand, not including prices in as a demand driver AusNet's approach would broadly be expected to (chart 3.1):
  - overstate demand from 2000 through to 2018, as prices were generally increasing
  - understate demand from 2018 through to 2023, as price generally fell (although there was a considerable spike in prices in the September quarter 2023)
  - understate demand over the forecast horizon as prices are expected to fall in real terms
- The materiality of excluding prices could be tested by estimating PoE for maximum and minimum demand for previous years. If prices are an important driver, we would expect forecast PoEs to lie above actual maximums/minimums prior to 2018, and below actual maximums/minimums between 2018 and 2023.

---

9 CIE 2019, "Review of AusNet's electricity demand forecasting methodology".

10 AEMO 2021, "Transmission Connection Point Forecasting Methodology: Maximum and minimum demand", p. 26.

3.1 Electricity price index



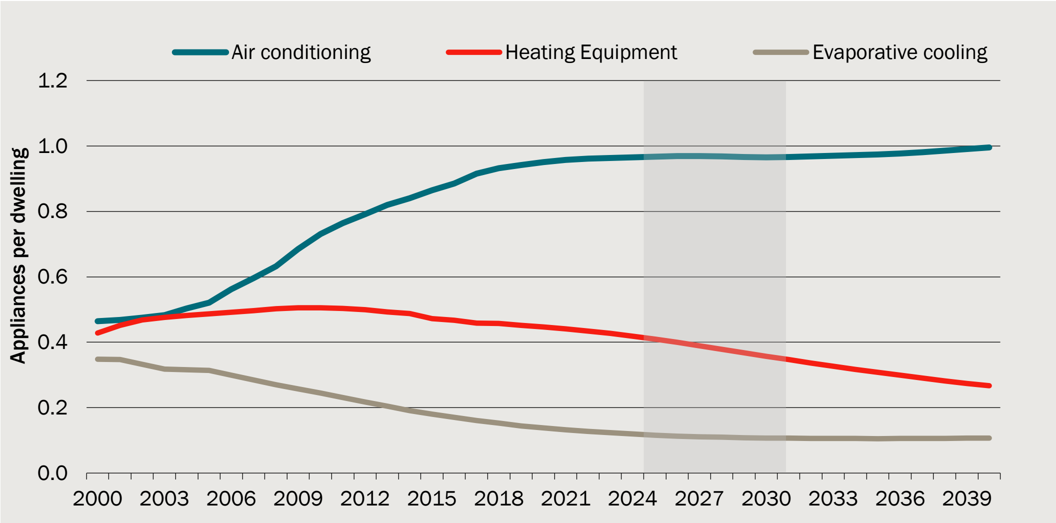
Data source: AEMO ESOO 2024, ABS 6401.0 Consumer price Index, Australia September quarter 2024, CIE.

- **Energy efficiency**. Energy efficiency or consumption per customer may change over time because of:
  - appliance replacement – in general this would be expected to reduce demand
  - differences in energy efficiency between existing and new dwellings – we would expect this to reduce demand due to energy efficiency standards for new dwellings
  - changes in the types of dwelling constructed – higher density dwellings, such as apartments tend to consume less electricity than detached dwellings. As the share of higher density dwellings in completions increase, the energy consumption would be expected to fall.

  Energy efficiency has the potential to impact on electricity consumption as well as maximum and minimum operational demand. AEMO's ESOO reports future energy efficiency and shows that in 2024-25 in Victoria, the energy efficiency adjustment is around 1 per cent of annual operational consumption, while in 2030-31 is it 8 per cent of annual operational consumption.[11] It is not clear, however, how energy efficiency impacts on consumption correspond to impacts on maximum or minimum demand.
- **Growth in the number of appliances**, namely the number of air conditioning systems and heating systems. This is expected to have a limited impact on demand forecasts as uptake of air conditioning is expected to slow as due to market saturation (chart 3.2). Electrification of appliances (from gas) is accounted for in gas switching post modelling adjustments.

11 AEMO 2024, "2024 Electricity Statement of Opportunities", forecasts accessed from: https://aemo.com.au/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-and-planning-data/electricity-forecasting-data-portal

3.2 Ratio of heating and cooling appliances to dwellings, Victoria



Data source:

- **Residential battery uptake** is not accounted for in the demand forecasts. Note AusNet's methodology adjusts for the impact of larger embedded generators, such as windfarms and large-scale batteries, from network data to identify underlying network demand.

  AusNet has indicated that residential batteries were not modelled because their current numbers are relatively small, and their impact on maximum demand remains limited.

  – AusNet provided data on forecasts prepared in 2023 which projected around 28,500 residential batteries by July 2026 in the AusNet's service area and around 62,000 by July 2031. This implies around 11 per cent and 19 per cent of households with solar PV would also have a battery in 2026 and 2031 respectively.

  – The impact of batteries on maximum demand depends on the installed battery capacity, as well as whether the installed batteries are uncoordinated or coordinated (part of a Virtual Power Plant or VPP). Coordinated batteries as part of a VPP are likely to have a larger impact on lowering peak demand compared to a negligible impact of uncoordinated batteries. In developing their forecasts for the 2024 ESOO:

  "AEMO assumed only batteries in existing or committed VPP programs will be available to provide a coordinated response at times of maximum demand for the purposes of the ESOO Central scenario. All new batteries were assumed to be optimised for minimising the household's purchases from the grid only."[12] [13]

  … AEMOs central projection expects batteries to reduce maximum underlying demand by less than 1 per cent in Victoria by 2033-34, excluding the impact of

[12] AEMO 2024, "2024 Electricity Statement of Opportunities: A 10-year outlook of investment requirements to maintain reliability in the National Electricity Market", p. 37.

[13] Note that AEMO report results with and without VPP growth.

VPPs.[14]. However, this is a somewhat incomplete picture, as batteries in VPPs are modelled as supply and their impact cannot be identified from the forecasts reported as part of the 2024 ESOO. Using the impact of VPPs reported in the 2022 ESOO (see box 3.3), we estimate that assuming no growth in VPPs (i.e. assuming the impact is fixed at the 2024/25 level) would be associated with a 0.8 per cent reduction in maximum demand. If VPP capacity were allowed to increase, this would increase to 6 per cent by 2030/31.

– The impact of batteries on minimum demand also depends on battery capacity and the extent of coordination. Daytime charging of batteries can use excess energy generated by solar PV. Coordination has a significant impact on how these technologies affect minimum demand.[15]
  … AEMOs central projection expects batteries to increase minimum underlying demand by around 4 per cent in Victoria by 2033-34.[16] However like the maximum demand impact this is a somewhat incomplete picture, as batteries in VPPs are modelled as supply and their impact cannot be identified from the forecasts reported as part of the 2024 ESOO. AEMO has not previously published sensitivity analyses which report the impact of batteries in VPPs on minimum demand.

Based on the available evidence excluding batteries is unlikely to have a material impact on AusNet's maximum demand forecast compared to AEMO ESOO 2024 projections, which only assume existing or committed VPP programs. Any additional uptake compared to existing committed VPP programs is likely to result in similar forecast errors for AusNet's maximum demand forecast as for AEMOs ESOO 2024 projections.

In contrast, the impact on minimum demand is expected to be material compared to AEMO ESOO 2024 projections, which only assume existing or committed VPP programs. The impact on minimum demand from higher rates from additional update of VPP programs has not previously been reported by AEMO and is uncertain. However, we would expect additional VPP programs would further increase minimum demand.

---

14 AEMO 2024, "2024 Electricity Statement of Opportunities", forecasts accessed from: https://aemo.com.au/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-and-planning-data/electricity-forecasting-data-portal. This is calculated based as the share of battery in underlying demand.

15 AEMO 2024, "2024 Electricity Statement of Opportunities: A 10-year outlook of investment requirements to maintain reliability in the National Electricity Market", p. 40.

16 AEMO 2024, "2024 Electricity Statement of Opportunities", forecasts accessed from: https://aemo.com.au/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-and-planning-data/electricity-forecasting-data-portal. This is calculated based as the share of battery in underlying demand.

3.3 The impact of VPPs on maximum demand

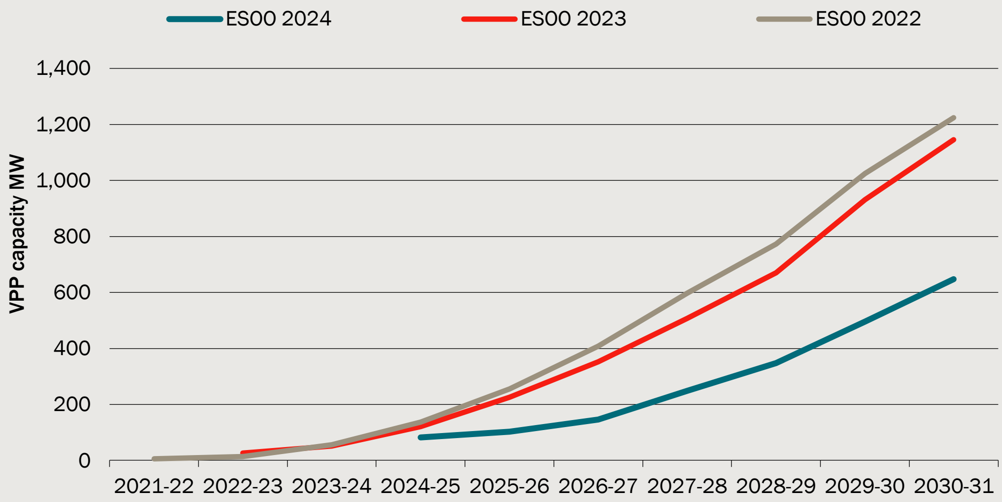
The impact on maximum and minimum demand depends on the installed battery capacity, as well as whether the installed batteries are uncoordinated or coordinated (part of a Virtual Power Plant or VPP). In recent ESOOs AEMO has not reported the impact of coordination on maximum demand.

This impact was most recently reported in 2022: coordinated residential batteries could be expected to reduce maximum demand by 13 per cent in Victoria in 2031-32.

If we assume that the impact on maximum demand and capacity of batteries in VPPs is linear, we can use this data point to infer the maximum demand impact for different levels of VPP capacity. This would imply that for each GW of capacity, maximum demand for Victoria falls by 9 percentage points.

Chart 3.4 shows VPP capacity over the past three ESOOs, which has progressively been revised lower.

3.4 VPP capacity – Step Change Scenario



Data source: AEMO

Applying the ratio between percentage impact on maximum demand and VPP capacity suggests a VPP impact on maximum demand of:

- 0.8 per cent in 2024/25 based on the 2024 ESOO projections
- 6.0 per cent in 2030/31 based on the 2024 ESOO projections.

- **In the absence of spatial economic activity projections, it is reasonable to assume that commercial and industrial demand will be linked to dwelling growth.**
- **Economic growth is not incorporated into demand forecasts, but is unlikely to material affect forecasts. Much of the impact of economic growth will already be accounted for by dwelling and population growth. Also, economic activity is**

difficult to forecast at the feeder or terminal station level, such that excluding it may reduce forecast errors.

- **Electricity prices are not incorporated into demand forecasts. Not including prices as a demand driver (and assuming a negative elasticity significantly different from zero) AusNet's approach would broadly be expected understate demand based on AEMO price forecasts.**
  - **Note the impact of prices at maximum and minimum demand periods is uncertain.**
- **The future impact of energy efficiency is not included in the model. Whilst energy efficiency has a clear impact on average demand (consumption),[17] it is unclear whether it would similarly bias maximum and minimum demand.**
- **Appliance uptake, namely air conditioners are not included in the forecast. This does not have a material impact on forecasts due to market saturation.**
- **Behind the meter batteries are not included in the forecasts. This is expected to:**
  - **not have a material impact on the maximum demand forecasts compared to AEMO's ESOO 2024 forecast (overstate maximum demand by around 1 - 2 per cent over the regulatory period). AEMO only includes exiting and committed VPP programs in their central forecasts. Any uptake in excess of existing committed VPP programs is likely to result in similar forecast errors for AusNet's forecast as for AEMOs ESOO 2024 projections.**
  - **have a moderate impact on minimum demand forecasts (understate minimum demand by around 4 per cent in 2030-31)**

Data and sources

The sources of demand drivers are summarised in table 3.5.

3.5 Demand driver data sources

Data	Sources	CIE comment
Dwelling projections	▪ Victorian Government dwelling projections	VIF is the standard data sources for spatially disaggregated dwelling projections. Where there is evidence of VIF projections not reflecting actual growth, the VIF forecasts are adjusted based on recent trends and an assessment of local conditions.
Weather data including temperature, wind and solar irradiation	Weather Zone	We understand this data is based on data from Bureau of Meteorology weather stations as well as Weather Zone's satellite data.

Source: CIE.

17 AusNet's consumption forecast model was outside the scope of this engagement.

- **AusNet has used standard data sources for dwelling projections (with adjustments made by AusNet to reflect observed differences from VIF forecasts), temperature and solar irradiance.**

Half hourly temperature data

AusNet uses standard temperature data, however the documentation does not specify whether this is a dry bulb measurement, consistent with the data used in AEMO's forecasts. [18]

From this CDD and HDD are calculated as follows:

$$CDD = \max(0, Average\ daily\ temp - CT_{sum})$$

$$HDD = \max(0, CT_{win} - Average\ daily\ temp)$$

Where T is the temperature for a given half hour and CT_{sum} = 21°C is the temperature cut-off for summer and CT_{win} = 18°C. This is the same as the calculation used by AEMO[19], although AusNet's summer and winter critical temperatures are greater than that that those used for Victoria by AEMO (18°C and 16.5°C respectively).[20] These small differences are not likely to have a material impact on results. Temperature data is collected for a 10-year period.

Specific weather stations are mapped to substations based on proximity.

- **AusNet use standard data sources and formula to calculate CDD. The difference in temperature thresholds compared to AEMO are unlikely affect results.**

Solar PV generation

Solar PV generation is estimated on half-hourly basis using the following relationship:

$$Solar\ PV\ generation = PV\ power\ \times PV\ capacity\ \times Efficiency\ Factor$$

The efficiency factor is set as 0.85. The data sources of other inputs are summarised in the table 3.6.

3.6 Data sources of inputs of rooftop PV generation

Input	Data source
PV power	Historical PV power is collected from Solcast. This data set is from 2021 and includes 2,014 observations.

[18] AEMO 2019, "Electricity demand forecasting Methodology Information Paper", p. 35-36.

[19] Note CDD is incorrectly defined in AEMO 2019, "Electricity demand forecasting Methodology Information Paper", p. 44.

[20] AEMO 2019, "Electricity demand forecasting Methodology Information Paper", p. 44.

Input	Data source
Solar Irradiance	Three solar irradiance variables are considered: Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI). Data is collected from Weather Zone.
PV capacity	The number of PV customers and the amount of PV capacity sourced are AusNet internal database

Source: CIE based on AusNet.

PV power

The relationship between PV power and solar variables is estimated using a Generalized Additive Model (GAM). Power data is at 30-minute intervals for 2021, with a total of 2,014 observations used for model estimation. Solar irradiance data is collected from Weather Zone.

Once the model is trained, it is used to generate PV power forecasts with the simulated solar variables for the forecast period. AusNet notes that the relationship between PV power and the solar variables remains stable over time, making it unnecessary to retrain the model frequently during the forecast period.

PV capacity

PV capacity is forecast based on PV growth rates from AEMO ESOO, as well as observed trend growth.

- Trends in PV capacity per customer are calculated for each region.
- These trends are used to scale PV forecast for each region by the PV growth rate assumption for VIC provided in the AEMO 2024 Inputs, Assumptions and Scenarios.

This allows PV capacity growth to vary across transmission stations based on historical trends.

- **AusNet use appropriate data and methods to estimate rooftop PV generation.**

Post modelling adjustment

The methodology allows post modelling adjustments for:

- Electric vehicles
- Gas switching
- Block loads

Uptake of electric vehicles

The half-hourly electric vehicle (EV) load for a type of customer is estimated by:

$$EV\ load\ (KW) = EV\ count\ \times the\ share\ of\ the\ customer\ type \\ \times average\ load\ per\ EV\ of\ the\ customer\ type$$

Historical data for EVs is collected from Victorian Department of Transport and Planning, which is mapped from postcode to feeder and substation. Future EV uptake is forecast using the growth rate from the AEMO's ESOO. This is then reconciled to ensure EV uptake forecast for the AusNet service area is consistent with AEMO's forecast for all of Victoria.

The average load per EV is derived from the EV charging profiles that provide indicative load values for each half-hour interval according to the AEMO's ESOO electric vehicle workbook. This requires assuming the number of different vehicle types and charging profiles, which we expect are based on AEMO.

To avoid double counting, when subsequently applying block loads, AusNet removes block loads related to commercial fast chargers.

The application of Victorian forecasts for the AusNet service area introduces an inconsistency, as the method assumes that public charging (which includes fast chargers) occurs in the same area (i.e. supplied by the same feeder or substation) as where a given EV is registered. In practice EVs which are not charged at home, may generate additional demand across many different feeders. This inconsistency is unlikely to be material as almost all charging occurs at home during the regulatory period.

- **AusNet uses standard data sources and formulas to estimate EV charging loads. Given data gaps, this approach requires the use of several assumptions, primarily that AusNet EV owners have similar characteristics as for all Victoria EV owners in Victoria and that all charging occurs in same feeder or substation where the vehicle is registered.**
- **AusNet avoids double counting of commercial fast chargers, by removing these from block loads.**

Gas switching

The gas electrification load for a network asset is the product of the following factors:

- Gas penetration rate – the percentage of customers with gas connection,
  - The effect of the gas phase-out policy on new gas connection is reflected by the reduction in the number of future gas customers.
- Electrification rate – the percentage of customers swapping from gas to electricity,
  - AEMO 2024 GSOO gas connection forecasts are used to estimate the electrification rate. This is based on a tops down view of changes in usage that would achieve emissions targets. We understand the GSOO reports the electrification rate in terms of 'effective' gas connections that is determined from total gas demand divided by historical levels of consumption per connection.[21]

[21] AEMO 2024, "Gas Statement of Opportunities: For Australia's East Coast Gas Market", p. 24.

  This suggests that this rate reflects customers disconnecting, switching appliances, getting more energy efficient appliances or using appliances less.

- Average impact on electricity consumption for each season and each half-hour interval.
  – This is derived from an internal AusNet impact study, which quantifies the relationship between the change in electricity demand per residential customer and predictors such as temperature, gas penetration rate, and the month of a year.
- The base electricity consumption for each season and each half-hour interval
  – For customers switching from gas to electricity, it is assumed that their total underlying demand is equivalent to that of existing electricity customers.

- **AusNet uses standard data sources and formulas to estimate the impact of gas switching in the residential sector.**

Industrial loads

Adjustments are made for factors such as large customer connections (block loads), the impact of ongoing network projects, and inconsistencies in AMI data.

For block loads, a post-model adjustment is applied by evaluating advanced connection requests above 1 MVA, considering factors like project probability, customer type, and load uptake. If block loads exceed forecasted demand growth, adjustments are made to avoid double-counting, incorporating only the additional load.

Note block loads associated with EV charging infrastructure are excluded to avoid double counting with the adjustments made for the uptake of electric vehicles.

Tariff structure

The methodology does not make any post modelling adjustments for the tariff structure (i.e. higher prices during peak periods).

AusNet has provided evidence that between October 2021 and October 2022 customers without solar had an almost identical evening peak regardless of whether they are on a Time of Use (TOU) or single rate tariff.[22] This suggests this tariff structure may have a limited impact on maximum demand.

In contrast, evidence from other trials has suggested that tariff structure may be material for both minimum and maximum demand for particular customers. For example, a trial of an off-peak EV charging incentive increased charging outside of peak periods increased from 70 per cent during baseline periods to 90 per cent off-peak.[23]

---

22 AusNet 2023, "Tariffs and Pricing Meeting #4 _30 October 2023_FINAL.pptx".

23 Origin 2022, "Origin EV Smart Charging Trial: Lessons Learnt Report", accessed on 9 December 2024, https://arena.gov.au/assets/2022/05/origin-energy-electric-vehicles-smart-charging-trial-lessons-learnt-2.pdf.

AusNet is currently undertaking several trials to consider the impact of tariff structure on demand, which will create an evidence base around the importance of incorporating tariff structure into maximum and minimum demand forecasts.[24]

- **The evidence around the impact of tariff structure on minimum and maximum demand is mixed. Further information is required to assess its materiality.**

24 AusNet 2023, "Tariffs and Pricing Meeting #4 _30 October 2023_FINAL.pptx".

4 Estimation of relationship with demand drivers

Customer numbers

Customer numbers are a critical driver of future electricity demand. Customer numbers are forecast using the Victorian Government's dwelling projections as outlined in the Victoria in Future (VIF) projection. The relationship between customers and dwelling numbers is not estimated, rather growth rates for dwelling at the SA2 level are used to grow customer numbers. This is because there will be close to a one for one relationship between new dwellings and new electricity customers.

Growth in commercial and industrial customers is proportional to residential forecasts, as the Victorian Government does not prepare projections for commercial or industrial growth. It is implemented by applying the trend in the ratio of residential to commercial/industrial customers on each feeder to residential customer projections. This assumes consistency in local planning regulations, and allows trends in residential-to-commercial customer ratio over time to continue.

Reconciliation

A reconciliation process for customer number forecasts is performed between feeder and zone substation. This is implemented to ensure that customers numbers at different levels of aggregation are internally consistent. Once forecasts are prepared the reconciliation is implemented in the following steps:

- Compare the sum of feeder customers (for a given substation) to the substation level customer forecast (following reconciliation these should be consistent).
- Modify each feeder's customer forecast by multiplying its original forecast by the ratio corresponding to the associated zone substation.
- Recalculate the zone substation's forecast by summing the modified forecasts of its feeders.
- Calculate the terminal station's forecast by summing the modified forecasts of its zone substations.

- **AusNet uses standard data sources and approach for customer number forecasts.**

Estimating average unitised maximum (or minimum) demand

The monthly average unitised maximum (or minimum demand) per customer $(\bar{y}_i)$ is estimated using weather and calendar variables through a linear regression model as follows:

$$\bar{y}_i = \beta_1 + \beta_2 n_{CDD} + \beta_3 n_{HDD} + \sum_i \beta_i d_i + e$$

where:

- β_1 is a constant
- n_{CDD} represents the number of cooling degree days (CDD) in the month,
- n_{HDD} represents the number of heating degree days (HDD) in the month,
- d_i represents the dummy variable of the month i of the year.

The average demand, as estimated above, reflects the change in electricity consumption in response to medium- to long-term weather and calendar variables.

It is not clear over what period the model is estimated, and how it controls for COVID-19 (if relevant) and associated changes in electricity consumption patterns (namely the shift to work from home during and following the pandemic).

The model is not estimated for different time of day, which assumes a constant relationship between drivers and unitised maximum demand for different half hourly blocks. This is not likely to bias forecasts as the model is primarily driven by weather drivers; any weather adjustment not captured in the average unitised maximum (or minimum) demand component will be captured by the half hourly adjustment coefficient, which accounts for the different relationships between demand and weather depending on the time of day.

- **The model of estimating unitised average demand does not capture price effects, other economic factors, energy efficiency or allow for a trend in average demand.**
- **The period over which the model is estimated is not specified.**
- **It is not clear how (if relevant) the model accounts for the impact of COVID-19 and the subsequent shift in work-from-home behaviours during and after the pandemic.**

Estimating half hourly adjustment coefficient

The half hourly maximum (or minimum) demand (y) is estimated by combining the average maximum (or minimum) demand in the corresponding month, multiplied by an adjustment coefficient (y^*) which accounts for half hourly fluctuations in demand as follows:

$$y_{t,p} = \bar{y}_i \times y^*_{t,p}$$

The next step is to estimate the drivers of the half-hourly fluctuations. Before estimating the relationship of half-hourly fluctuations against the short-term drivers using historical data, the half hourly fluctuations are defined as normalised half-hourly demand as follows:

$$\ln\left(y^*_{t,p}\right) = \ln\left(\frac{y_{t,p}}{\bar{y}_i}\right)$$

The log of the half hourly fluctuation, or the log of normalised half hourly demand, is then calibrated against a range of short-term drivers including:

- Wind speed
- Humidity
- Current temperature
- Past temperatures at 1, 2 and 3 hour ago, as well as 1, 2 and 3 days ago
- Daily extremum and average temperatures of the day,
- Day of the week, and
- Whether the day is a school holiday or a public holiday.

The precise combination and specification of drivers included in the model is determined by estimating larger number of specifications (1,407 combinations of short-term weather drivers are tested) in linear models. The Mean Absolute Error (MAE) is used to identify the optimal set of predictors which best fit drivers to half hourly fluctuations in demand.

This process is undertaken for three periods each season:

- Morning: 6am to 2pm
- Afternoon: 2pm to 10pm
- Evening: 10pm to 6am

This gives the specification which is then estimated for each half hour (i.e. all morning half hours will share the same specification but have different parameters).

Next, a generalized additive model (GAM) is used to estimate non-linear relationships between the drivers and the response variable, allowing for the saturation effect at high temperatures. The resulting coefficients are then used in simulation to convert the forecasted average demand into half-hourly underlying maximum (or minimum) demand ($y_{t,p}$).

We understand the specification does not include a time trend or drivers which deterministically change overtime. This implies the ratio between average maximum (or minimum) and peak/minimum demand is fixed overtime. For maximums this suggests demand is not allowed to become "peakier" overtime. The sort of factors which could make demand peakier include:

- Higher uptake of solar PV, which reduces average maximum demand across all half hours in day, but doesn't have that much of an impact at peak times.
  - This is likely to also be important for minimum demand which is likely to be driven by periods when solar PV generation is largest.
- Energy efficiency improvements, which reduce average maximum demand , but may not have as much of an impact during peak times.
- Changes in temperature responsiveness, i.e. from higher air conditioner penetration or changing behaviours because of work-from-home.

- In the other direction, EV uptake could make demand less peaky where charging occurs overnight, as this would increase average maximum demand across all half hours, but would not have much of an impact at peak times.

Where demand is becoming peakier, this may understate maximum demand. This could be examined further by considering trends in historical peak/minimum demand to average demand ratios overtime.

It is not clear over what period the model is estimated, and how it controls for COVID-19 (if relevant) and associated changes in electricity consumption patterns (namely the shift to work from home during and following the pandemic).

- **The methodology robust accounting for the main drivers of half-hourly demand., including accounting for demand saturation.**
- **Peak/minimum demand and average minimum (or average demand) demand ratio is fixed overtime. This may understate (overstate) maximum (minimum) demand if demand is becoming peakier.**
- **It is not clear how (if relevant) the model accounts for the impact of COVID-19 and the subsequent shift in work-from-home behaviours during and after the pandemic.**

5 Forecasting maximum and minimum demand

Starting point

The simulation is applied to the modelled average maximum (or minimum) demand and the half hourly adjustment coefficient.

This is known as starting the forecast off the line (taking weather corrected PoE values for the modelled outcome as the starting point). This places equal weight on all historical data as best indicator of maximum demand. The alternative, of starting the forecast 'off the point, gives weight to the final observed year and discards previous years.

Forecast simulation of maximum and minimum demand

Maximum and minimum demand are forecast by:

- The estimated relationships between underlying electricity demand and demand drivers (explained in chapter 4),
- Simulating underlying demand by bootstrapping observed weather variables, calendar variables, and residuals from half hourly demand model
- Simulating solar PV generation by bootstrapping observed solar irradiance
- Subtracting simulated Solar PV generation from simulated underlying demand and adding in post modelling adjustments to recover operational demand
- Determining maximum and minimum demand from operational demand.

Bootstrapping weather values

All the weather data included in the adjustment coefficient or half-hourly demand model, must be simulated. This includes

- wind speed
- humidity, and
- temperature.

10 years of historical half-hourly data is used to simulate future demand.

Weather data are simulated using a double seasonal bootstrap method.[25] The output of bootstrapping involves randomly sampled data based on historical data. Before resampling, the historical data is divided into blocks. For temperature, calendar and solar variables, variable block lengths are used to account for seasonal variability, with four

[25] R Hyndman and Fan 2015, "Monash Electricity Forecasting Model".

distinct block lengths corresponding to the following time periods – November to March, April to May, June to August, and September to October.

During each simulation iteration, one historical demand year is randomly selected for each block. For these four groups of seasons, explanatory variables such as temperature, calendar effects, and solar data are randomly drawn from different historical demand years for each half-hour interval. This process generates 200 unique sets of explanatory variables at half-hour intervals. These sets are then used to estimate half-hourly maximum or minimum underlying demand based on the model developed in the previous step.

Bootstrapping temperature values

As part of the bootstrapping process, simulated temperatures are adjusted by adding noise to better match the distribution of daily maximum temperatures observed since 1900, as described in the Monash Model documentation; however, this is not documented in AusNet's methodology, but it is apparent in the model code. This noise term follows a normal distribution with a mean of zero and a standard deviation of 0.3 if the maximum temperature in a block is below 42°C. For blocks with a maximum temperature above 42°C, additional noise is introduced to further adjust the distribution. The climate change is also allowed by modifying the noise term that is added to the bootstrap samples to have a positive mean and a larger standard deviation.

Bootstrapping residual values

To simulate the residuals (i.e., the errors from the half hourly demand model estimated in the previous chapter), a single seasonal bootstrap is applied with a block length of one-month. Four random residual time series are generated from this bootstrapping process.

Forecasts based on bootstrapped values

The best model corresponding to a specific half-hour interval (as explained in the previous chapter) is retrieved and applied to the bootstrapped weather values to predict the fitted values. These fitted values are then combined with the bootstrapped residuals to have the final simulated values. Simulated values are then exponentiated to return them to their original scale and multiplied by the customer count to calculate total simulated underlying demand. This value is further adjusted to derive the total stimulated operational demand by subtracting the PV generation estimates and adding post modelling adjustments (EV charging, gas electrification and block loads).

The methodology does not subtract embedded generation from forecasts of underlying demand. This is likely to overstate the level of maximum and minimum demand forecasts, but may not affect the growth rate where future embedded generation is accounted for as part of post modelling adjustments.

There are 1,000 stimulated demand traces for each block. For each stimulated demand trace, the maximum (or minimum) is calculated. To understand the variability of the predicted maximum (or minimum) demand, the following quantiles are computed to present different probabilities of exceedance for planning purposes:

- 10% Quantile (PoE90) – The 10th percentile of the predicted maximum (or minimum) demand, with a 90 per cent probability that maximum (or minimum) demand will exceed this value.
- 50% Quantile (PoE50) – The 50th percentile of the predicted maximum (or minimum)
- 90% Quantile (PoE10) – The 90th percentile of the predicted maximum (or minimum) demand, with a 10 per cent probability that maximum (or minimum) demand will exceed this value.

- **The simulation methodology aligns with the Monash Electricity Forecasting Model, with different block lengths selected in the AusNet simulation.**
- **The methodology does not subtract embedded generation from forecasts of underlying demand. This is likely to overstate the level of maximum and minimum demand forecasts, but may not affect the growth rate where future embedded generation is accounted for as part of post modelling adjustments.**

THE CENTRE FOR INTERNATIONAL ECONOMICS
www.TheCIE.com.au