Forecasts of customer numbers, energy consumption and demand

A report for Essential Energy | 20 May 2022

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Executive Summary

Scope

Frontier Economics has developed 15 year forecasts of consumption and minimum and maximum demand

Essential Energy appointed Frontier Economics to develop 15 year forecasts of consumption and minimum and maximum demand. These forecasts will be used as part of Essential Energy's Tariff Structure Statement, 2024-29 regulatory proposal and expenditure modelling.

Frontier Economics have developed forecasts of consumption and maximum and minimum demand over the period to 2037. We do this at several different levels:

- for different types of customers across Essential Energy's network
- at each Transmission Node Identifier (TNI)
- at each Zone Substation (ZSS).

To develop these forecasts, we made assumptions about trends in new technologies, including distributed energy resources, at the total network, TNI and ZSS level. The scope of the project is summarised in **Figure 1.**

Figure 1: Our scope

Item	Scope
Customer numbers and consumption	• Forecast customer numbers and consumption by customer type (tariff type) over 15 years • Forecast consumption at TNI and ZSS over 15 years
Demand	• Summer and winter maximum and minimum demand by customer type, TNI and ZSS over 15 years
New technologies	• RFQ asked for take up for rooftop PV, battery storage, electric vehicles and embedded generation over 15 years • We have also looked at electrification

Source: Frontier Economics

Methodology

Our methodology combines traditional econometric forecasts with post-model adjustments to account for emerging technology-induced drivers of demand, consistent with best practice

The uptake of new technologies is an increasingly important component in the development of energy demand and is expected to be the main driver of energy demand trends into the future. Technology uptake will impact peak and minimum demand, as well as overall energy consumption.

Electricity consumption and demand forecasting involves separately considering:

- The **traditional drivers of demand** which are relatively predictable and can be projected forward using econometric approaches
- The **technology-induced drivers of demand** (e.g. rooftop PV, batteries, electric vehicles and electrification) are expected to have significant changes in rates of uptake and usage pattens, which mean that these need to be assessed independently and “added on” to the traditional forecast component via a post-model adjustment.

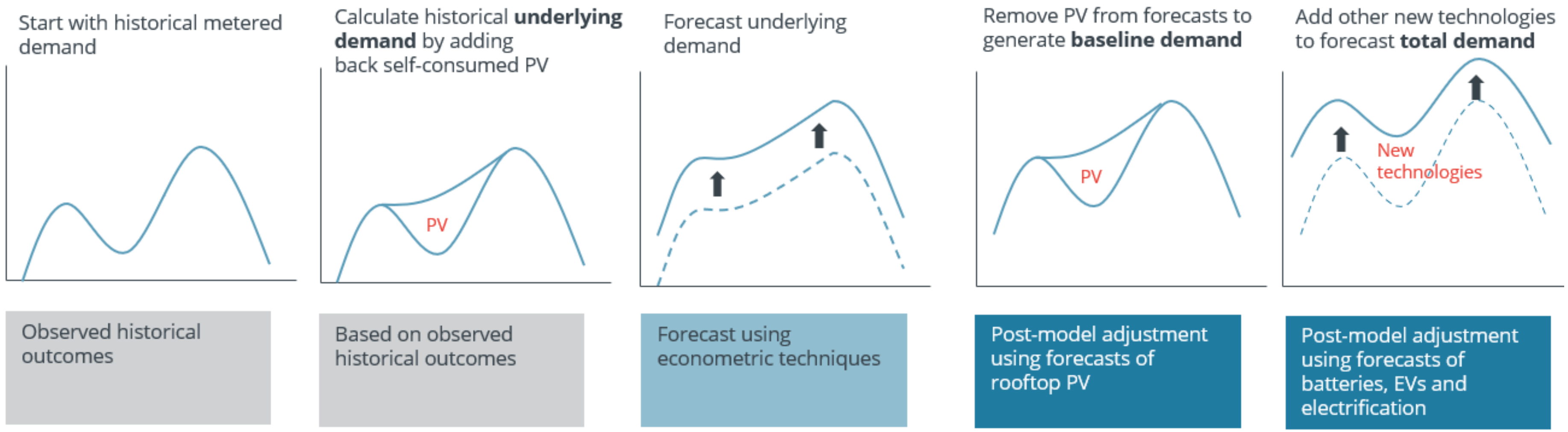
Figure 8 provides an overview of our forecasting approach, combining traditional and technology-induced drivers to forecast annual consumption and minimum and maximum demand.

Results

Consumption is forecast to grow over the longer term, reflecting the impact of new technologies on demand

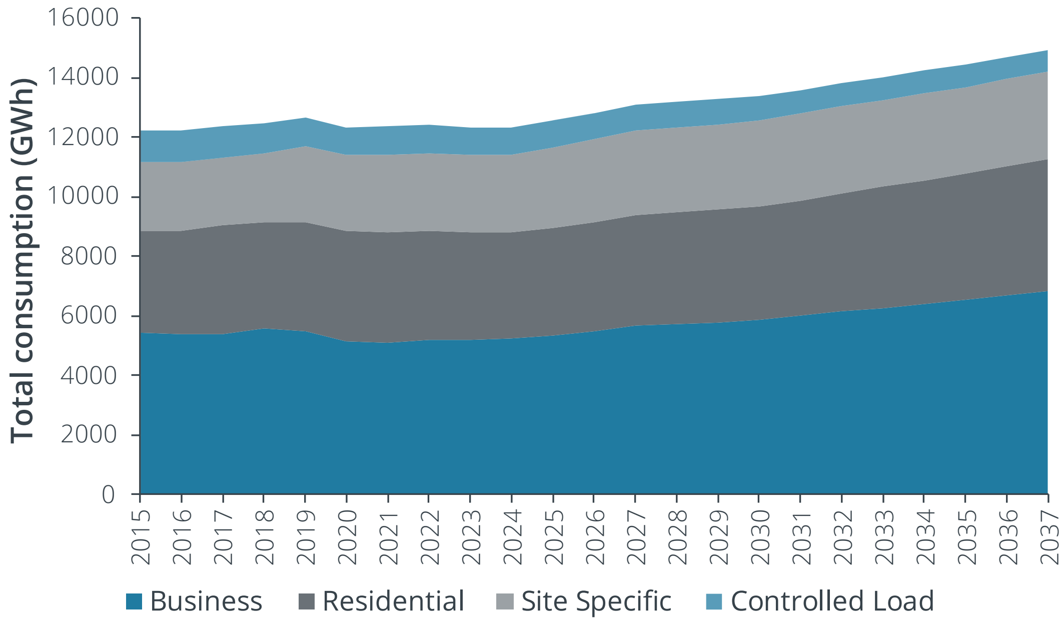
We forecast Essential Energy’s consumption to be relatively steady in the near term and increasing over the longer term, largely reflecting the impact of new technologies on demand. Baseline consumption is forecast to continue to fall, consistent with historical trends in energy efficiency and increasing rooftop PV penetration. This reduction is offset over the forecast period by increasing customer numbers and increased demand as a function of electrification and electric vehicles. **Figure 3** and **Figure 4** shows forecasted invoiced consumption by customer type and the contribution of new technologies.

Figure 2: Our approach to forecasting consumption and demand with new technologies



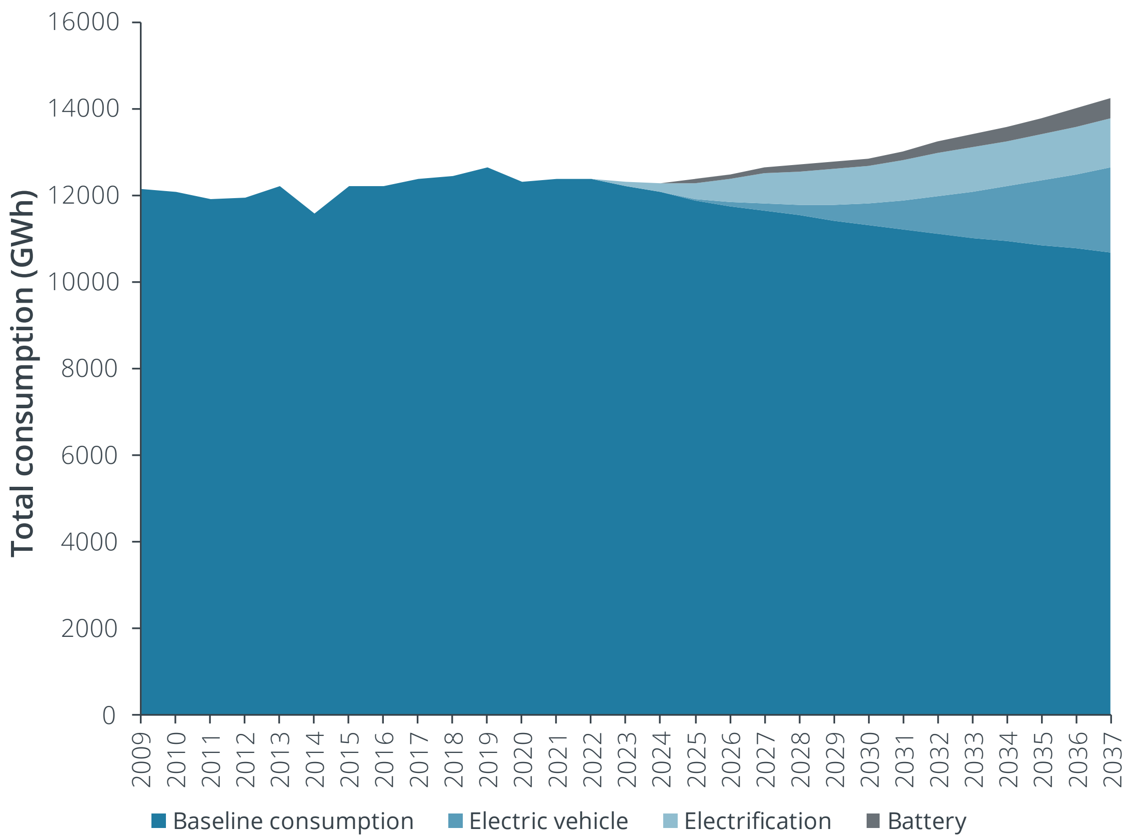
Source: Frontier Economics

Figure 3: Invoiced consumption: by customer type



Source: Frontier Economics analysis

Figure 4: Invoiced consumption: underlying demand and new technologies



Source: Frontier Economics analysis

New technologies are likely to increase maximum demand and decrease minimum demand

New technologies also have an important impact on minimum and maximum demand for Essential Energy's network. Over the period 2022-37 the maximum demand is forecast to increase towards approximately 2,500MW (See top two panels of **Figure 5**), while the minimum demand decreases towards 0MW (See bottom two panels of **Figure 5).**

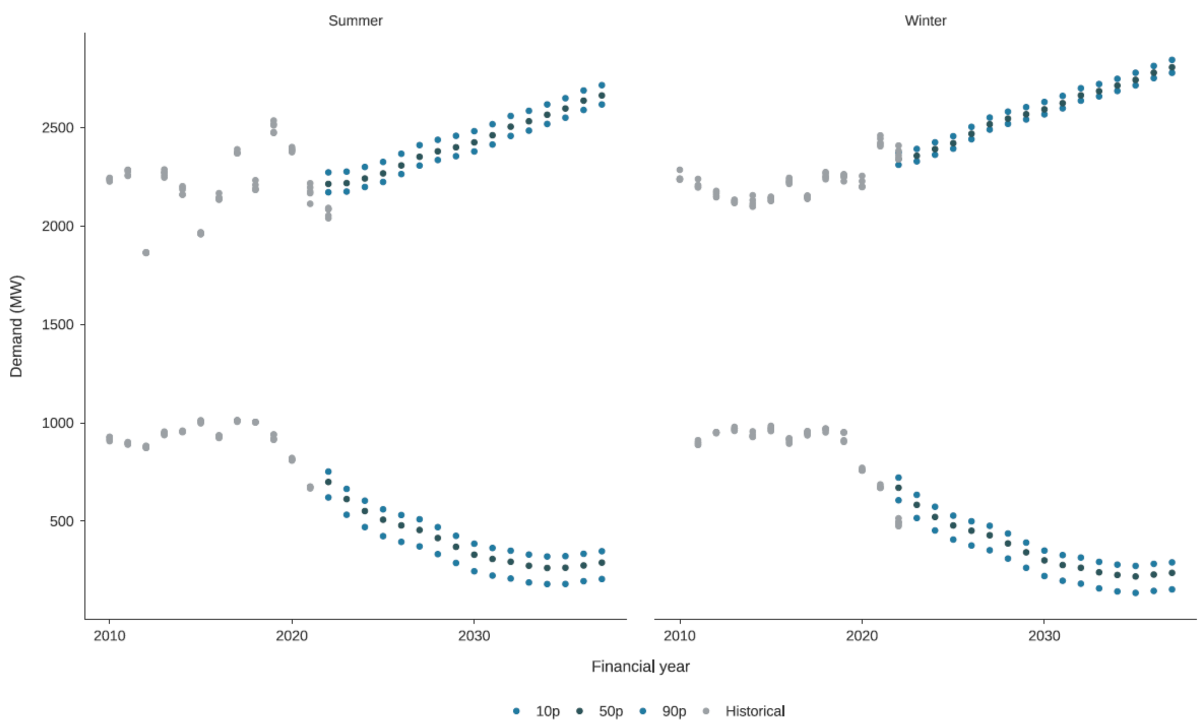
Historically maximum demand has occurred around 5-7pm in both summer and winter. As the use of rooftop PV and batteries is expanded over the forecast period, the maximum network load is forecast to occur later in the day, particularly during the summer months. By 2037 the peak demand is expected to take place between 6-8pm in summer, and 5-8pm in winter.

Most of the increase in maximum demand into the future results from the uptake of electric vehicles. Rooftop PV is forecast to have a substantial impact on summer maximum operational demand in the period 2022-2027. In the long run however, the capacity of rooftop PV to mitigate total maximum demand is limited by the expected shift towards convenience charging which occurs after sundown.

Rooftop PV is forecast to decrease minimum demand significantly. Electrification and electric vehicles mitigate this to some extent, depending upon the scenario. Higher uptake of these technologies increases minimum demand, but this is offset to some extent by the expected increase in rooftop PV associated with the more rapid electrification and uptake of electric vehicles.

Our analysis shows the number of winter peaking TNIs and ZSSs across Essential Energy's network will increase over time. This reflects the significant influence of electric vehicles to peak demand, and to a lesser extent electrification.

Figure 5: Minimum and maximum total network consumption forecast for 2022-2037



1 Introduction

1.1 Background and context

The electricity sector is currently undergoing a major transition

The electricity sector is currently undergoing a major transition which will have impacts many years into the future. The uptake of rooftop PV, battery energy storage systems, electric vehicles and electrification will all contribute to large changes in customers' electricity consumption, both through the volume and timing of the consumption. This will have major impacts on distribution networks, affecting network build out and cost recovery.

The uptake of these technologies and the nature of the broader energy transition will be influenced by broader policy, which will guide investment decisions in the NSW electricity sector, for example the NSW electricity infrastructure roadmap.

These developments are highly relevant to the operation of Essential Energy's business

As a regulated network, Essential Energy must submit to the Australian Energy Regulator (AER) forecasts of customer numbers, consumption and demand for the 2024-29 regulatory period. These forecasts will be used by the AER to ensure Essential Energy has the required revenue to operate and extend the network as necessary, based on forecast changes to the network.

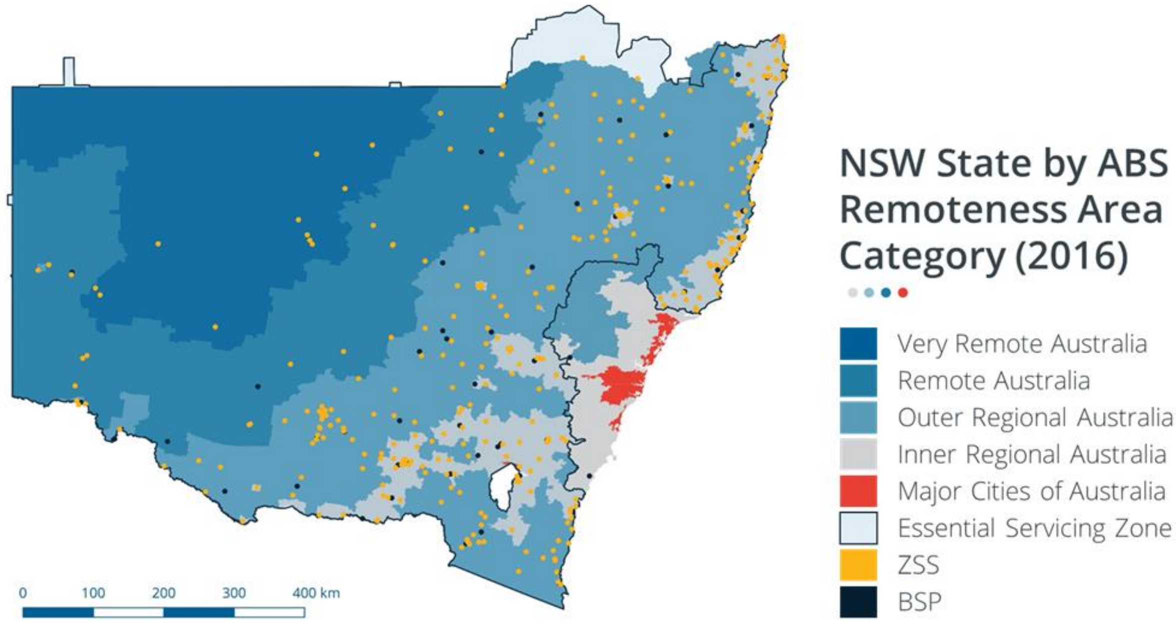
It is therefore important to have robust forecasts of customer numbers, consumption, and maximum demand over a sufficiently long timeframe to be able to suitably account for these effects. Considering developments in the wider energy market will be important in producing robust forecasts of these variables.

1.2 Essential Energy's service area

Essential Energy operates a distribution network across a vast and diverse service area

Essential Energy operates and maintains one of Australia's largest electricity distribution networks, across 95 per cent of NSW and parts of southern Queensland. Essential Energy takes electricity from generators and transmitters and, on behalf of retailers, distributes it to over 870,000 residential, commercial, and industrial end-use customers. Its vast service area covers a wide geographic spread and diverse demographics. Essential Energy's network comprises over 183,000km of overhead power lines and 390 zone substations (see **Figure 6**).

Figure 6: Essential Energy bulk supply points and zone substations



Source: Frontier Economics using Essential Energy data

1.3 Our scope

Frontier Economics developed forecasts of customer numbers, consumption and demand over 15 years

In this context, Essential Energy appointed Frontier Economics for the development and delivery of 15-year forecasts which can be used to understand the behaviour of consumers in their network area and the impact of annual consumption and maximum demand in Essential Energy's internal models.[1]

These forecasts will also be used as part of Essential Energy's Tariff Structure Statement (TSS), regulatory proposal and expenditure modelling. In addition, they will be used in discussions with the AER throughout the 2024-29 regulatory process.

Frontier Economics has developed forecasts of consumption and maximum and minimum demand for each financial year over the period to 2036/37 (the modelling period) (**Figure 7**). We do this at several different levels:

- for residential, business, commercial customers and controlled load across Essential Energy's network
- at each bulk supply point (BSP) where electricity is delivered from the transmission network to the distribution network, denoted by a Transmission Node Identifier (TNI)

1 In this report we refer to annual consumption forecasts and half-hourly demand forecasts, consistent with industry convention.

- at each Zone Substation (ZSS), where electricity is received from the bulk supply points and transformed for distribution along powerlines or underground cables through the distribution network
- for the total Essential Energy network.

Figure 7: Our scope

Item	Scope
Customer numbers and consumption	• Forecast customer numbers and consumption by customer type (tariff type) over 15 years • Forecast consumption at TNI and ZSS over 15 years
Demand	• Summer and winter maximum and minimum demand by customer type, TNI and ZSS over 15 years
New technologies	• RFQ asked for take up for rooftop PV, battery storage, electric vehicles and embedded generation over 15 years • We have also looked at electrification

Source: Frontier Economics

To develop these forecasts, we made assumptions about trends in new technologies, including distributed energy resources (DER), at the total network, TNI and ZSS level. For new technologies we consider three scenarios, created by adapting AEMO's ISP 2022 assumptions to Essential Energy's network. For minimum and maximum demand, we present the 10%, 50%, and 90% probability of exceedance (POE) values for maximum and minimum demand for summer and winter.

Table 1 summarises the inputs used, the methodology adopted and the forecasts produced for Essential Energy.

1.4 About this report

This report sets out our assumptions, methodology and results. It is structured as follows:

- Section 2 provides an overview of our methodology
- Section 3 discusses our approach to forecasting the uptake of new technologies
- Section 4 presents our TNI and ZSS consumption forecasting results
- Section 5 presents our invoiced consumption and demand forecasting results
- Section 6 presents our demand forecasting results.

Additional detail is provided in a series of appendices:

- Appendix A describes the data and methodology used to forecast TNI and ZSS consumption

- Appendix B discusses the data and methodology used to forecast invoiced consumption and demand
- Appendix C presents the presents the data and methodology used to forecast TNI and ZSS maximum and minimum demand.

Table 1: Summary of forecasts produced

Forecast	Inputs	Outputs	Section
Technology uptake	AEMO 2022 Draft ISP and supporting analysis	Estimates and growth profiles for rooftop PV, batteries, electric vehicles and electrification over the period 2021/22 to 2036/37	Section 3
Invoiced consumption and demand	EE invoiced consumption data over the period July 2008 to January 2022	Forecasts of invoiced consumption, max demand and customer numbers for each customer segment, tariff class and billing component over the period 2021/22 to 2036/37	Section 4, Appendix A
TNI and ZSS consumption	EE half hourly demand data over the period July 2009 to February 2022 for TNIs and July 2010 to September 2021 for ZSS	Consumption forecasts for each TNI, ZSS and the total Essential Energy network over the period 2021/22 to 2036/37	Section 5, Appendix B
Maximum/minimum demand	EE half hourly demand data over the period July 2009 to February 2022 for TNIs and July 2010 to September 2021 for ZSS	For each ZSS, BSP and the total Essential Energy network, the 10%, 50%, and 90% POE values for maximum and minimum demand for summer and winter, and the predicted half hour period the maximum/minimum demand will occur over the period 2021/22 to 2036/37	Section 6, Appendix C

Source: Frontier Economics

2 Methodology overview

2.1 Incorporating technology uptake

New technologies require a new approach to estimating demand

Historically, electricity consumption and demand has increased over time due to an increasing population and customer base, accompanied by an increase in economic activity. However, in recent years the historical link between energy consumption and these traditional drivers of consumption has changed.

Electricity demand for forecasting purposes can now be thought of in two parts:

- Demand that varies by long-established drivers such as time of day, weather, population growth and economic activity (proxied by Gross State Product or Gross Domestic Product)
- Demand that varies because of uptake of new technologies in the home or business (e.g., rooftop PV, batteries, electric vehicles (EVs), and energy-efficient lighting and appliances) and electrification.

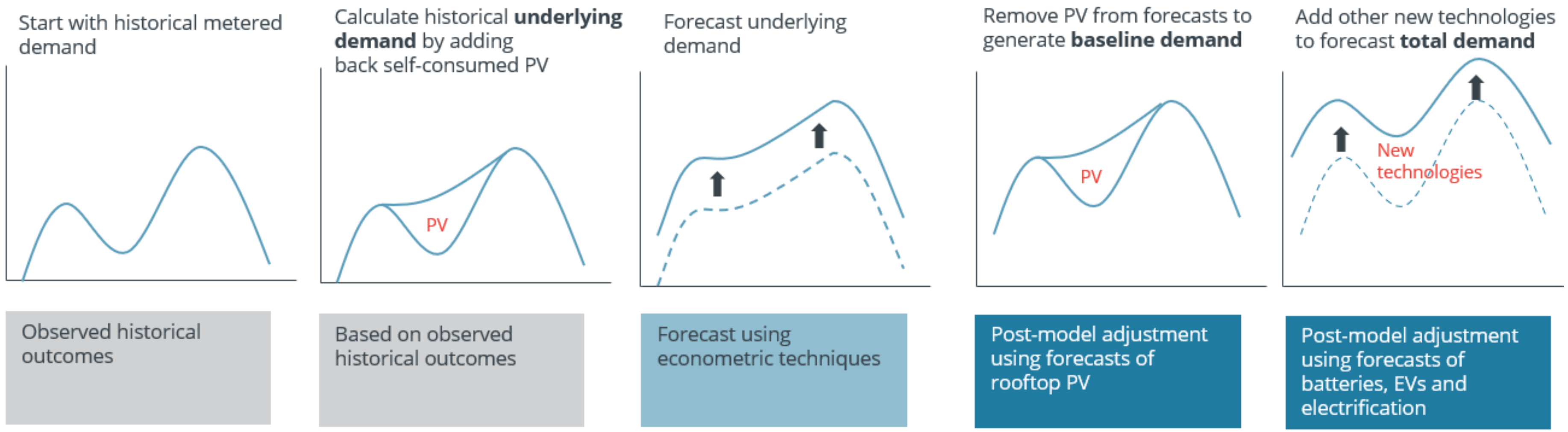
The uptake of new technologies is an increasingly important component in the development of energy demand and is expected to be the main driver of energy demand trends into the future. Technology uptake will impact peak and minimum demand, as well as overall energy consumption.

These two parts of electricity demand need to be treated differently in forecasting:

- The traditional drivers of demand are relatively predictable and can be projected forward using econometric approaches
- Technology-induced drivers of demand, and especially nascent technologies, are expected to have significant changes in rates of uptake and usage pattens, which mean that these need to be assessed independently and "added on" to the traditional forecast component via a post-model adjustment.

Figure 8 provides an overview of our forecasting approach, combining traditional and technology-induced drivers of demand.

Figure 8: Our approach to forecasting consumption and demand with new technologies



Source: Frontier Economics

2.2 Scenarios considered

We have looked at Essential Energy's and AEMO's forecasts of technology-induced drivers

Forecasting new technologies is complex given the significant uncertainty associated with selecting appropriate assumptions. We have considered two primary sources of information for forecasting technology-induced drivers of demand:

- Essential Energy provided us inputs for some technology-induced drivers. This included the forecasts of PV in Essential Energy's service area that formed inputs to its 2022 Statement of Corporate Intent (SCI) and some targeted analysis of EVs.
- AEMO, as part of its annual forecasting process, make public forecasts of PV, batteries, EVs, electrification, and hydrogen. Most recently, AEMO has made available technology uptake input data as part of its Inputs, Assumptions and Scenarios process for 2021[2].

Generally speaking, Essential Energy's forecasts for technology uptake are consistent, after scaling, with those made available by AEMO for the New South Wales region. However, in some cases these forecasts were not sufficiently well-developed (for example they covered a subset of Essential Energy's service area) to form a network wide view.

We adapt AEMO's forecasts of technology-induced drivers to develop forecasts for Essential Energy's service area which reflect the best publicly available information, are internally consistent and facilitate scenario analysis

Our approach has been to adapt AEMO's forecasts of technology-induced drivers to reflect the characteristics of Essential Energy. This ensures Essential Energy's forecasts reflect the best available publicly available information, are internally consistent and facilitate scenario analysis. We consider three scenarios (**Figure 9**):

- Low: Based on AEMO's Progressive Change scenario (the scenario formerly known as Net Zero 2050).
- Central: Based on AEMO's Step Change scenario. AEMO's consultation with energy industry stakeholders found the Step Change scenario is widely considered to be the most likely[3].
- High: Based on AEMO's Strong Electrification sensitivity. This sensitivity is based on the Hydrogen Superpower scenario, but with limited hydrogen uptake and reduced energy efficiency.

A brief description of each scenario is illustrated in **Figure 9**.

[2] AEMO consulted on an input assumptions update for the 2022 Integrated System Plan (ISP), which included an update for one relevant component of our forecasts, namely rooftop PV uptake. However, this update only affects the levels, and not growth rate, of rooftop PV forecasts, and so these forecasts are the identical for our purposes.

[3] See Section 2.3 of AEMO' s Draft 2022 Integrated System Plan pp29-30

Figure 9: Scenarios considered

Low: Progressive change

Net zero by 2050

Investment in renewable generation and storage starts more slowly and picks up pace in the 2030s and 2040

Central: Step change

Most likely case based on consultation - Net zero by 2035

Rapid transformation, with significant investment in renewable generation, storage and firming generation as coal plants exit

High: Strong electrification

Net zero by 2035

With stronger and faster electrification of transport and heavy industry (but with limited hydrogen uptake) supported by investment in renewable generation and storage

Source: Frontier Economics, based on AEMO's 2021 IASR and 2022 ISP

AEMO identified what it considered to be a series of plausible, distinct, internally consistent scenarios to cover a range of future outcomes.[4] We used AEMO's Step change scenario as the central case because this is considered to be the most likely case based on AEMO's consultation. We used Progressive change as the low case since it represents a less ambitious uptake of new technologies compared to Step Change. We did not consider AEMO's Slow change scenario to be an appropriate low case, since it will not reach the decarbonisation objectives set out in Australia's Emissions Reduction Plan. We used AEMO's Strong Electrification as a high case because it represents a more ambitious uptake of new technologies compared to Step Change. We did not consider Hydrogen superpower to be appropriate, because this assumes a very significant and rapid increase in demand associated with the development of a hydrogen export industry. In practice most hydrogen electrolysers are likely to be connected to the transmission network, rather than distribution networks. Strong electrification provides the opportunity to consider scenarios involving the more rapid deployment of new technologies, separate to the development of a hydrogen export industry.

One potential limitation of adopting AEMO's forecasts of technology-induced drivers in line with their respective scenarios is that the range of outcomes for Essential Energy's network area is not based on the best- and worst-case scenario for each technology-induced driver, but is based on a best- and worst-case for the scenarios as a whole. For example, the worst-case scenario for peak demand on the Essential Energy network may be a scenario that has low battery growth and high electrification levels. However, because AEMO has developed its scenarios against a narrative, to make scenarios internally consistent, there are no scenarios that feature low battery growth and high electrification levels.

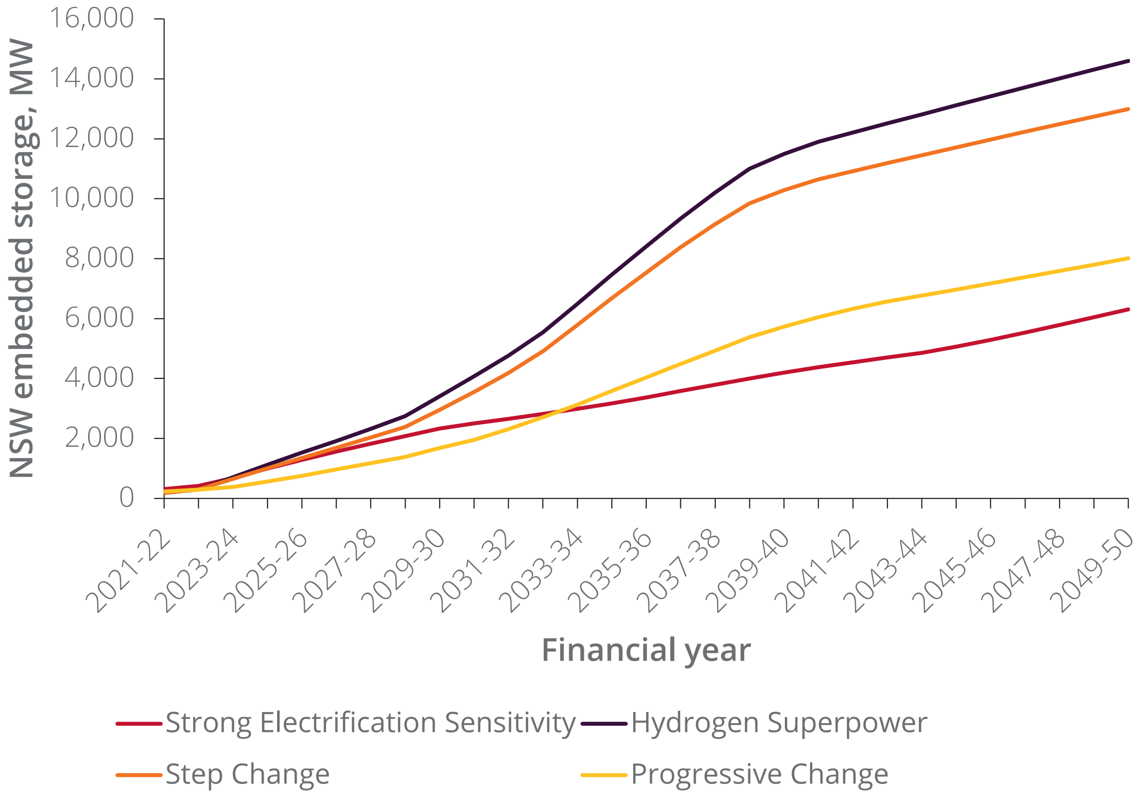
While AEMO provides a detailed Inputs, Assumptions and Scenarios Report outlining these scenarios and input assumptions, not every assumption for each scenario and sensitivity is discussed. Therefore, our understanding of the drivers behind some of the assumptions adopted in scenarios is limited. For example, in the Strong Electrification sensitivity, battery storage uptake is considerably less than the scenario it is based on (Hydrogen Superpower). This is illustrated in **Figure 10**. AEMO describes the Strong Electrification sensitivity as follows[5], and based on this limited information, it is unclear to us why battery storage would be considerably lower than the Hydrogen Superpower scenario.

[4] AEMO, 2021 Inputs, Assumptions and Scenarios Report, Final report, July 2021, p12.

[5] See pp25 of AEMO's 2021 Inputs, Assumptions and Scenarios Report

Strong electrification – representing a high emissions-reduction future, aligned with the decarbonisation objectives of the Hydrogen Superpower scenario, only in this future, hydrogen uptake is limited and energy efficiency is also more muted. This leaves the majority of the emissions reductions to be achieved through electrification, testing the outer bounds of the existing system. No export hydrogen or associated green steel manufacturing facilities are therefore included in this sensitivity. Other assumptions are by default consistent with the Hydrogen Superpower scenario, unless explicitly identified as unique for this sensitivity in the IASR Assumptions Book, and in this IASR.

Figure 10: NSW embedded storage, installed capacity, MW



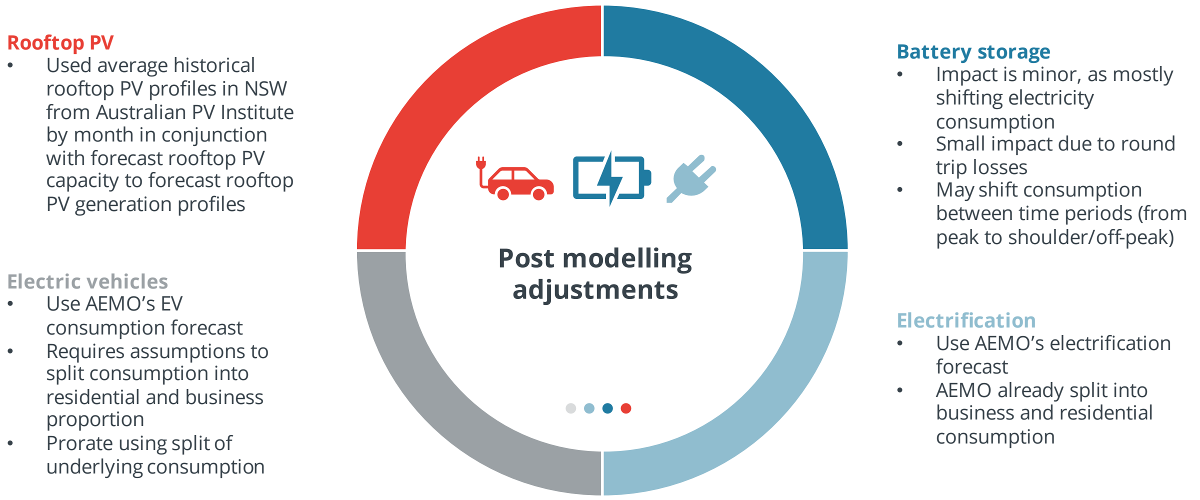
Source: Frontier Economics analysis of AEMO IASR data

It is important to recognise the significant uncertainty and complexity associated with forecasting the uptake of new technologies. Despite its limitations, using AEMO's forecasts of technology-induced drivers as a starting point ensures our forecasts for Essential Energy reflect the best available publicly available information, are internally consistent and facilitate scenario analysis.

3 Technology uptake

This section details the data and methodology used to produce estimates and growth profiles for the post model adjustments. It considers in turn rooftop PV, batteries, electric vehicles and electrification. Further context on historical trends and existing forecasts for each technology is presented in Appendix.

Figure 11: Post model adjustment methodology



3.1 Rooftop PV

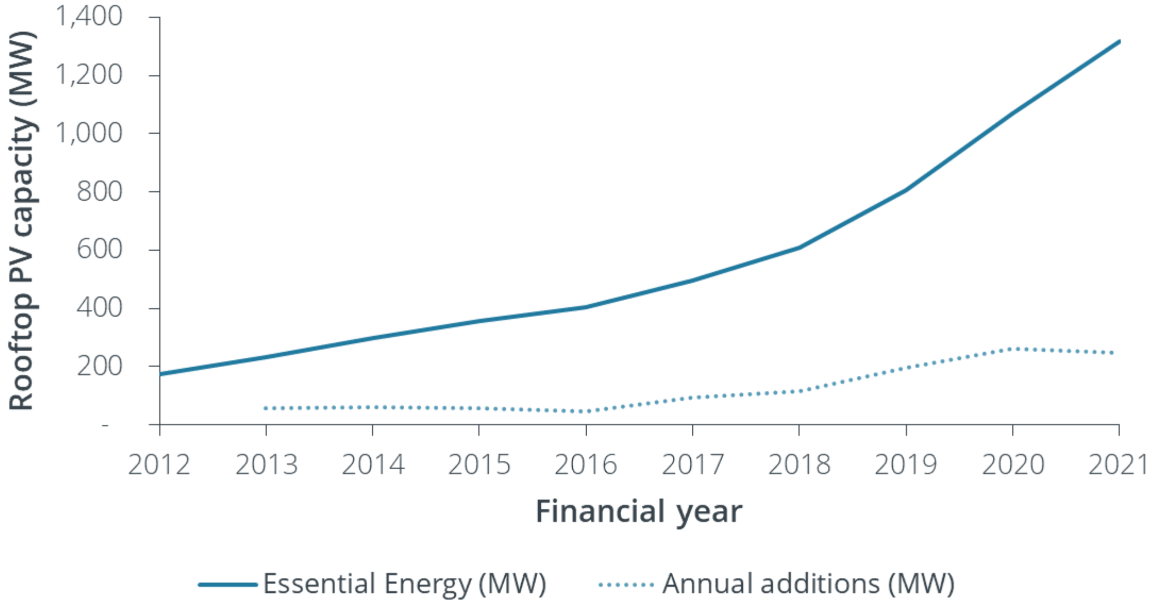
Rooftop PV is not a new technology and therefore the impacts of rooftop PV on distribution networks is evident in all the historical period we consider for our forecast. To forecast underlying consumption, that is consumption including both invoiced consumption and any energy consumed from behind-the-meter rooftop PV, it is therefore necessary to add an estimate of rooftop PV consumption to historical invoiced consumption data to develop an underlying demand forecast. This underlying demand forecast can then be converted to a baseline demand forecast by accounting for the impact of future rooftop PV generation.

3.1.1 Historical trends

Essential Energy has a higher penetration rate of rooftop PV than the rest of NSW. Essential Energy's network area contains about 33% of NSW's rooftop PV installations (including the ACT), whereas its consumption represents 19% of NSW's.

Figure 12 illustrates the installed rooftop PV capacity in the Essential Energy network area from financial years 2012 to 2021. The "Essential Energy (MW)" line shows the cumulative installed capacity, and the "Annual additions (MW)" dotted line shows the MW additions in each year. Rooftop PV has grown at a near-constant MW capacity until 2017, but since then annual additions have increased at an increasing rate. Essential Energy had around 1.4 GW of rooftop PV in its network area at the end of financial year 2021.

Figure 12: Installed rooftop PV capacity in the Essential Energy network area



Source: Frontier Economics' analysis of Essential Energy data

The impact of behind-the-meter solar in the NEM is important for forecasting consumption and demand because the level of uptake, and hence output, affects maximum and minimum demand as well as annual consumption. Generally speaking, experience in the NEM with behind-the-meter solar to date has been:

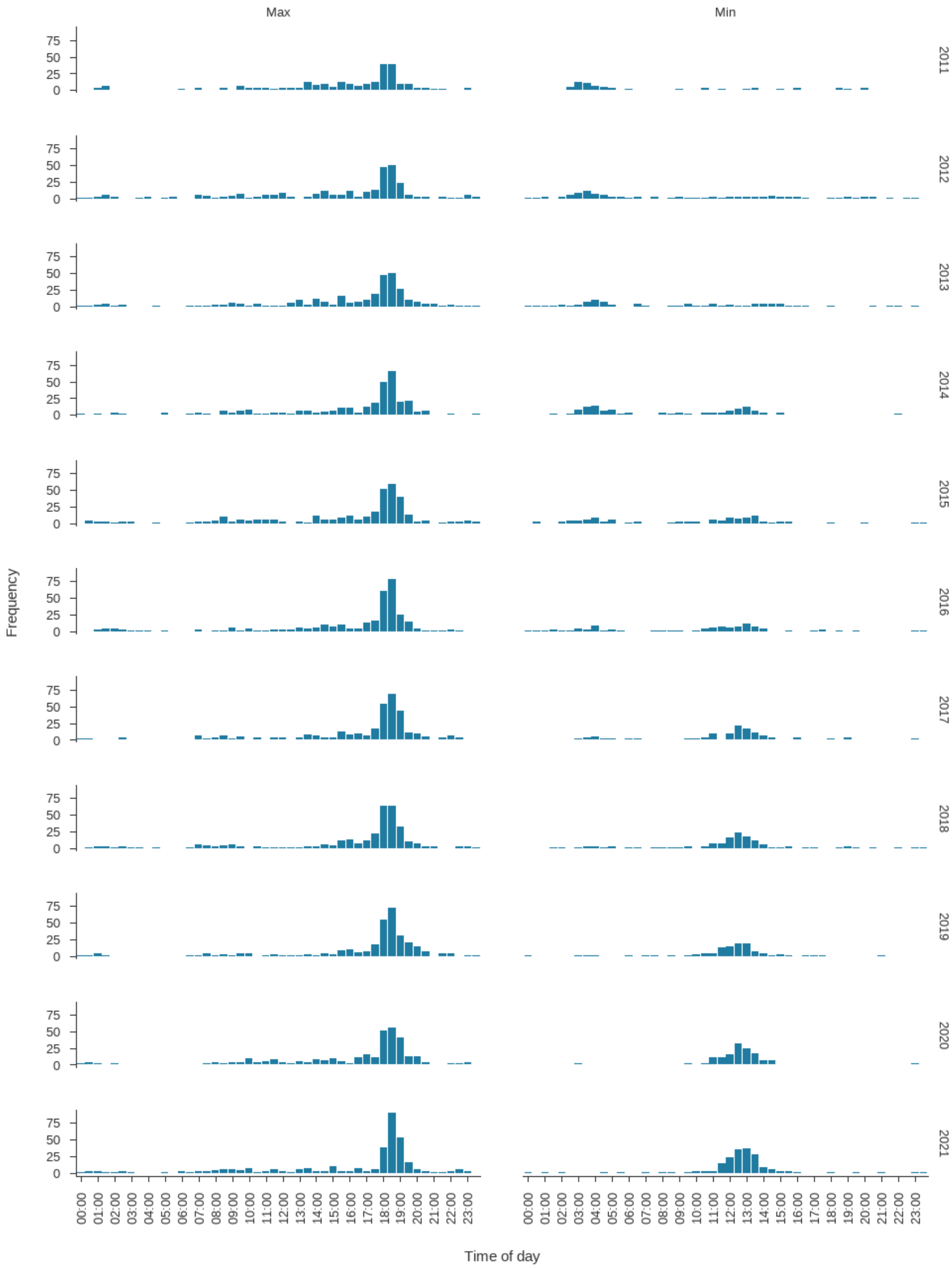
- Increasing rooftop PV penetration pushes the time of peak demand later in the evening, until additional rooftop PV no longer contributes to meeting peak demand (i.e., peak demand occurs after the sun goes down).
- Increasing rooftop PV penetration decreases demand levels during the day. Once minimum demand starts occurring while rooftop PV systems are producing output, additional rooftop PV penetration starts causing reductions in minimum demand (i.e., minimum demand values fall further).
- Increasing rooftop PV penetration decreases consumption levels as seen by network service providers. While customers may not change their behaviour after installing solar, some of their consumption will be met with generation from their solar systems.

Figure 13 illustrates the time of local minimum and maximum demand for Essential Energy's zone substations by calendar year. Each histogram in the chart shows how many zone substations have a minimum or maximum demand value at a particular time of day.

Maximum demand times generally occur late in the evening from the beginning of the period measured, with most values clustered around 6:30pm AEST. There is no clear trend of additional rooftop PV pushing the time of peak demand later in the evening at the zone substation level.

There is a trend observable in the times of minimum demand. In the early years measured, most of the minimum demand periods occur in the early morning, which is typical of demand patterns in times before rooftop PV. As PV penetration increases (as illustrated in aggregate in **Figure 12**), the time of minimum demands increasingly shifts to the middle of the day. By 2021, most minimum demand periods occur in the middle of the day, when rooftop PV is producing output.

Figure 13: Timing of local maximum and minimum demand for Essential Energy zone substations by calendar year (AEST)



Source: Frontier Economics analysis of Essential Energy's zone substation data. ***Note:*** *2021 includes data to the end of September. Only zone substations with a unique minimum or unique maximum are shown on this chart – many substations have a non-unique minimum of zero*

These historical trends indicate that, generally speaking:

- Further rooftop PV installations are unlikely to reduce peak demand, and

Further rooftop PV is installations are likely to further decrease minimum demand levels.

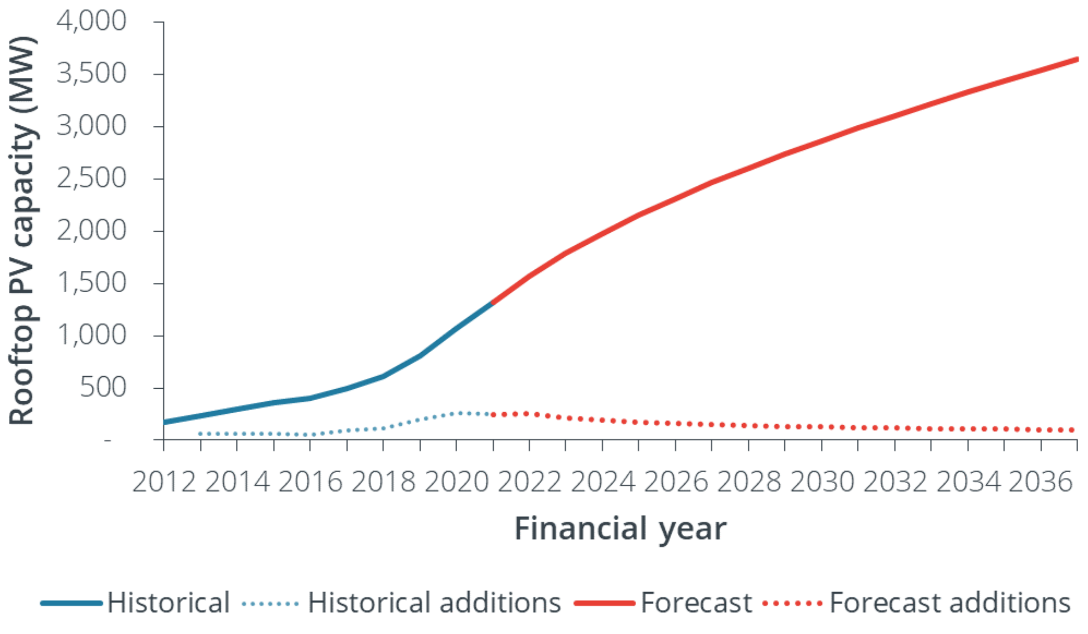
3.1.2 Existing forecasts

We have considered two sets of existing forecasts for rooftop PV uptake.

- Essential Energy have provided in-house forecasts of rooftop PV uptake for the Essential Energy network area.
- AEMO make public forecasts of rooftop PV uptake for the New South Wales region, which includes the ACT.

Essential Energy's in-house forecast is illustrated in **Figure 14**. PV installations are forecast to remain similar to current levels for the early 2020s (around 250MW/a), then taper off until the end of the forecasting period to around 100MW/a by 2037.

Figure 14: Essential Energy's in-house rooftop PV forecast

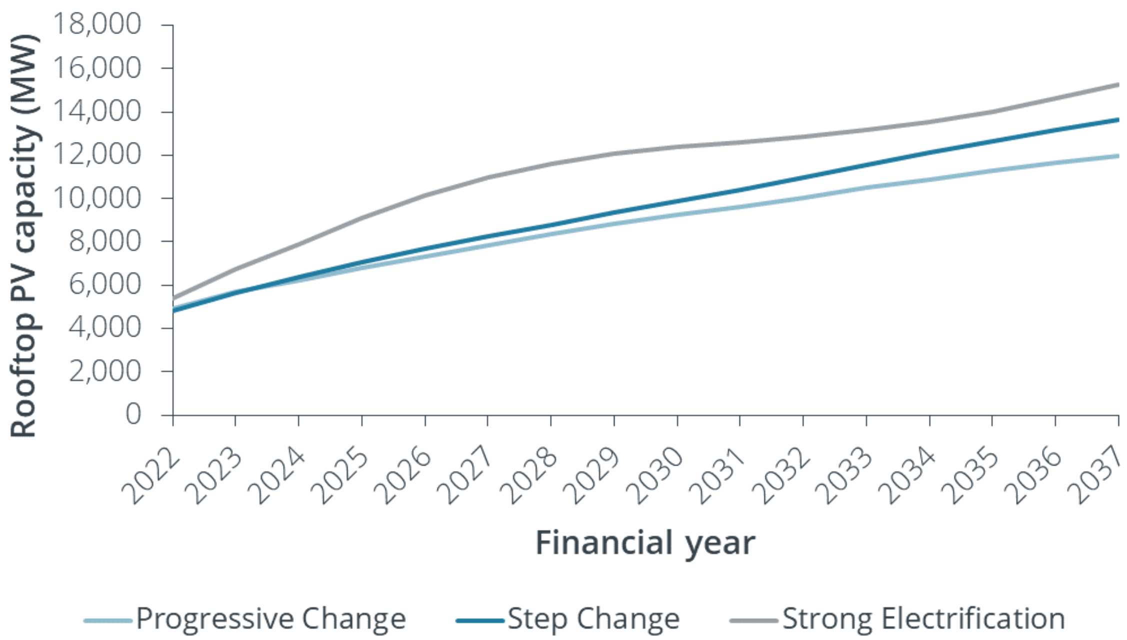


Source: Frontier Economics analysis of Essential Energy data

As part of AEMO's annual forecasting processes, it produces demand assumptions including rooftop PV uptake for each NEM region, including NSW. For its latest release, used in the Draft 2022 Integrated System Plan, AEMO engaged the CSIRO to develop rooftop PV uptake forecasts. Three of the five scenarios forecast by CSIRO for AEMO are presented in **Figure 15**, where the "Step Change" scenario was voted by stakeholders to be the most likely (hence 'central') scenario.

The CSIRO's forecast exhibits growth in rooftop PV in all scenarios. Growth in the 'Progressive Change' and 'Step change' scenarios are similar, only diverging materially in the early 2030s. Growth in the 'Strong Electrification' scenario occurs earlier, with significantly higher forecasts for the late 2020s, although this trend reverts in the 2030s with smaller differences by the end of the period.

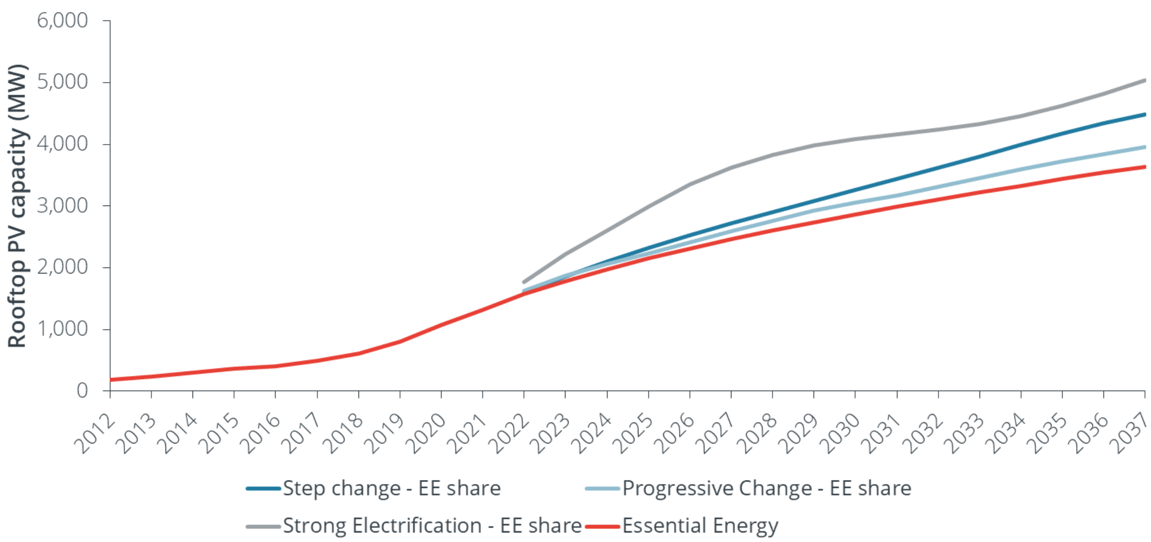
Figure 15: CSIRO rooftop PV forecasts for NSW produced for AEMO



Source: Frontier Economics analysis of AEMO data

To compare the AEMO forecasts with Essential Energy's in-house forecast, we scale down AEMO's forecast by Essential Energy's share of NSW rooftop PV at 33%. The result of this transformation is illustrated in **Figure 16**, showing each of the forecasts alongside actuals on a like-for-like basis.

Figure 16: Comparison of actual and forecast rooftop PV uptake, Essential Energy network area, MW



Source: Frontier Economics' analysis of AEMO and Essential Energy data

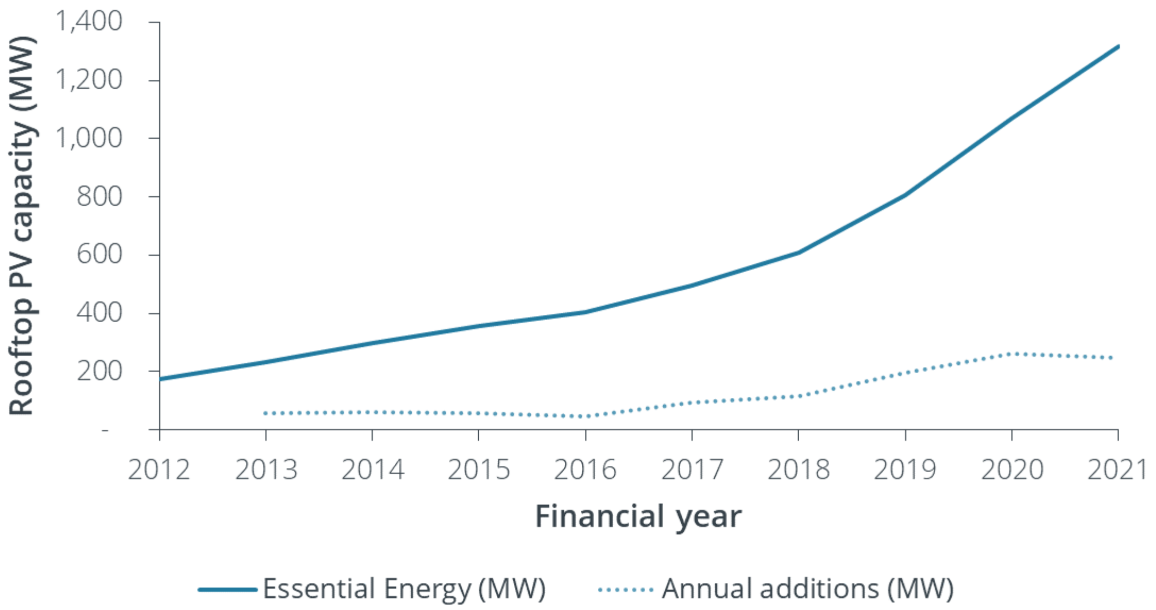
The Essential Energy in-house forecast and the AEMO Progressive Change and Step Change scenarios all follow a similar trajectory and represent generally similar outcomes. Essential Energy's forecast is 850 MW lower than AEMO's Step Change (most likely) scenario by 2037. Essential Energy's in-house forecast is substantially lower than AEMO's Strong Electrification scenario, being around 1,400MW lower in 2037.

3.1.3 Our approach

Behind-the-meter rooftop PV has had a significant presence in the Essential Energy network area (see **Figure 17**) in the historical data period we consider, and so our treatment of it in forecasting future demand is more complex than a nascent technology, such as electric vehicles.

As noted in Section 2, we forecast demand in two components – that affected by long-established drivers, and demand affected by technology uptake. With the uptake of rooftop PV and the majority of customers on net meters, we no longer have metered measures of underlying demand. This is because electricity generated by rooftop PV and consumed by the owner of the system happens 'behind-the-meter', i.e., is not in historical metered demand.

Figure 17: Installed rooftop PV capacity in the Essential Energy network area



Source: Frontier Economics' analysis of Essential Energy data

As noted in Section 1.3, our scope is to forecast consumption for all Essential Energy (in aggregate), as well as minimum and maximum demand consumption at the ZSS and TNI levels. These forecasts are based on two different sets of historical data. The aggregate forecast is based on historical billing data, i.e., as metered on customer premises. The ZSS and TNI forecasts are based on metered flows at ZSSs and TNIs. Without rooftop PV, the sum of flows and the sum of metered data should reconcile, because any demand at points of customer meters will need to flow through ZSSs and TNIs.[6] With rooftop PV, however, exports arising from excess PV generation may be consumed by customers within the same ZSS or TNI, and so this electricity will

6 Allowing for the appropriate losses across the network

not be counted in flow data. Therefore, we take different approaches for forecasting demand at the aggregate level and at the ZSS and TNI levels.

Forecasting the aggregate levels of consumption

At the aggregate level, our approach is as follows:

- For the historical period under consideration, we estimate what demand would have been without any rooftop PV (underlying demand) by adding back estimates of unmetered demand (self-consumption).
- We then forecast underlying demand.
- We forecast the uptake of rooftop PV systems in the Essential Energy network area.
- We use this forecast of PV systems to estimate the impact on consumption by netting off estimated unmetered demand from PV generation from the forecast of underlying demand.

To estimate historical underlying demand, our approach is as follows:

- Calculate an estimate of gross PV generation in the Essential Energy network area by multiplying the capacity factor by the level of PV and number of hours in each year the installed capacity of rooftop PV in the Essential Energy network area, by year.
- Subtract billed exports to derive an estimate of rooftop PV self-consumption
- Add this self-consumption figure to the metered consumption figure to derive an underlying consumption estimate that includes self-consumed PV.

After our underlying demand forecasting process, we subtract off estimates of future self-consumption from underlying demand. We estimate future self-consumption of rooftop PV by estimating forecast gross generation and projecting forward an average self-consumption ratio from the historical estimates derived in step 1:

- Calculate an estimate of future gross PV generation in the Essential Energy network area by indexing gross PV generation by forecast rooftop PV capacity. We forecast rooftop PV capacity by applying AEMO's growth rates for each scenario to Essential Energy's current rooftop PV capacity
- Apply a self-consumption ratio, derived from historical estimates for Essential Energy, to estimate future rooftop PV self-consumption
- Subtract future self-consumption from underlying consumption to estimate baseline consumption.

To estimate forecast gross generation, we use AEMO's Step Change rooftop PV forecast for the NSW region, pro-rated to the Essential Network area based on Essential Energy's current share of rooftop PV relative to NSW's share (33%).[7] We use AEMO's forecast in preference of Essential Energy's in-house forecast because AEMO's forecast and documentation is publicly available, widely accepted, as well as being consistent with Essential Energy's in-house forecasts and offers the ability to select different scenarios in addition to a central or most-likely scenario. We multiply AEMO's installed capacity forecast, pro-rated by a factor of 33%, by the estimated capacity factor and the number of hours in the year to derive gross generation.

[7] We conducted a high-level check of PV saturation levels in Essential Energy's network area in Section 3.1.4.

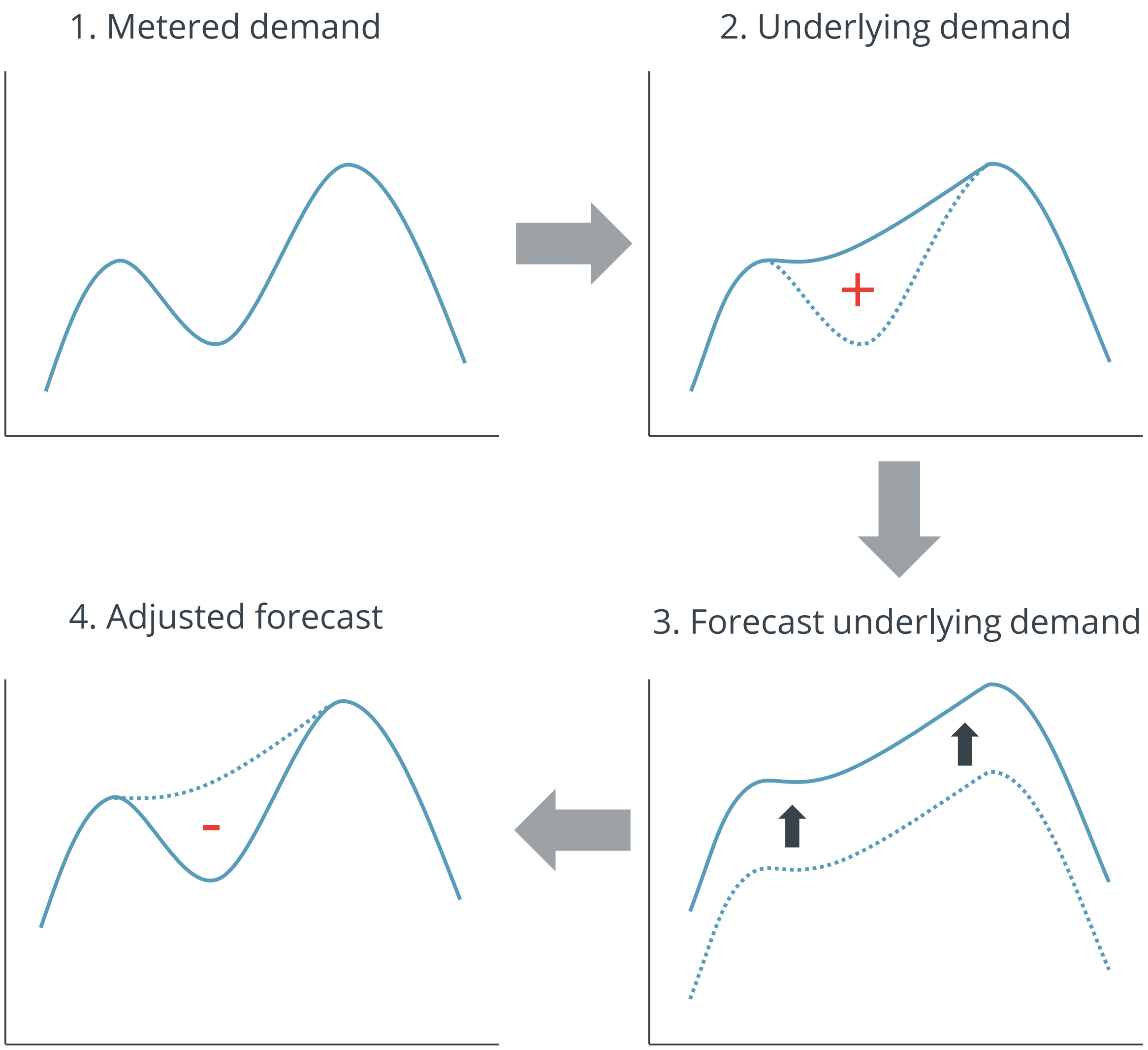
Forecasting demand and consumption at the TNI and ZSS level

At the TNI and ZSS level, our approach is as follows.

- For the historical period under consideration, we estimate what demand would have been without any rooftop PV (underlying demand) by adding back estimates of gross generation.
- We forecast underlying demand using this adjusted demand.
- We forecast the uptake of rooftop PV systems in the Essential Energy network area.
- We use this forecast of systems to estimate the impact on minimum and maximum demand and consumption by netting off estimated gross PV generation from the forecast of underlying demand.

This process is illustrated in **Figure 18**.

Figure 18: Treatment of rooftop PV in forecasting demand at the TNI and ZSS level



To estimate historical underlying demand at the TNI and ZSS levels (step 1), we make use of the following data:

- Metered zone substation/TNI data, which we assume nets out all rooftop PV generation, provided by Essential Energy.
- The installed capacity of rooftop PV by zone substations/TNI, by year, provided by Essential Energy.
- An estimate of gross half-hourly rooftop PV generation profiles for the Essential Energy network area, from the APVI.

To calculate underlying demand, we multiply installed PV capacity by ZSS/TNI by the relevant profile values and add this on to metered ZSS/TNI profile data.

As a forecast of the uptake of rooftop PV systems (step 3), we use AEMO's Step Change solar PV forecast for the NSW region, pro-rated to the relevant ZSS/TNI on the basis of that ZSS/TNI's share of rooftop PV relative to NSW's share. As for our aggregate consumption forecasts, we use AEMO's forecast in preference of Essential Energy's in-house forecast. This is because AEMO's forecast and documentation is publicly available, widely accepted, as well as being consistent with Essential Energy's in-house forecasts. It also offers the ability to select different scenarios in addition to a central or most-likely scenario.

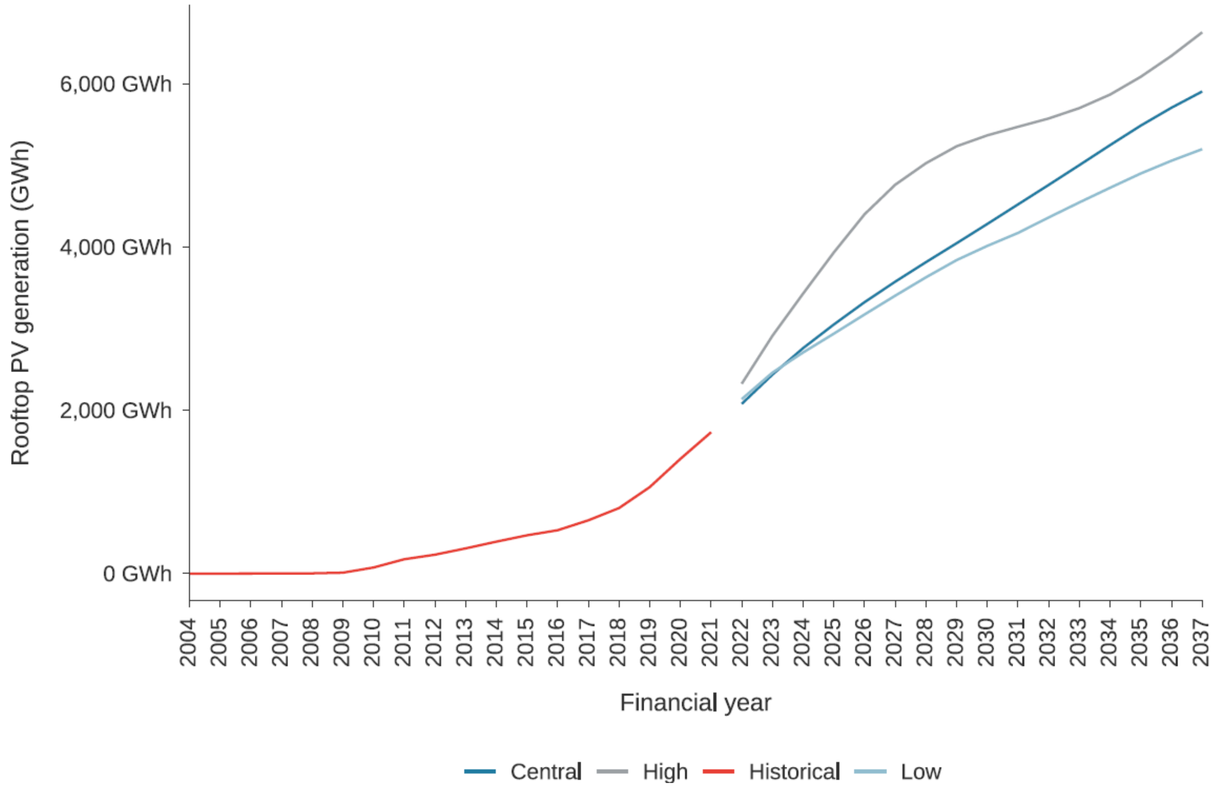
To estimate the impact on minimum and maximum demand and consumption (step 4), we estimate future gross PV generation by multiplying forecast rooftop PV installed capacity by half-hourly rooftop PV generation profiles that are applied as part of our synthetic year generation process (ensuring demand levels and PV generation levels are consistent) (More detail on the synthetic year generation can be found in section 6.3). We then subtract this profile of gross generation from the underlying demand forecast for each TNI and ZSS.

With this adjusted half-hourly series, we can estimate the impact of rooftop PV by calculating new minimum and maximum demands and consumption levels and comparing with historical values.

3.1.4 Result

Figure 19 presents annual rooftop PV gross generation for Essential Energy's network for the three scenarios which are Low – AEMO Progressive Change, Central – AEMO Step Change and High – AEMO Strong electrification. The data shows a continued and consistent growth in PV capacity and generation for Essential Energy.

Figure 19: Rooftop PV generation for Essential Energy service area



Source: Frontier Economics analysis

Given that Essential Energy already has a high proportion of households with rooftop solar, and rooftop PV growth rates are forecast to continue growing, saturation of rooftop PV (i.e. the upper limit of sites that can host rooftop PV) in the Essential Energy network area is of concern. To confirm whether saturation limits are likely to be a problem we assess the potential of residences to host PV in Essential Energy's network area. To do this, we:

- Calculate the number of separate and semi-detached dwellings in the Local Government Areas (LGAs) using the ABS's 2011 Census data[8] (around 600,000).
- Multiply the number of households by a notional kW capacity (7kW, approximately the average size of installs today).[9]

The result of this calculation (4.2 GW) provides an indication of saturation levels, noting that:

- Not all households will be suitable for rooftop PV, for example because of shading, roof shape, or roof condition.
- The number of households have grown since 2011 and are projected to continue to grow to 2037.
- The notional capacity used (7kW) may not suit all customers and the 7kW may reflect a bias towards larger customers.

8 2011 is the most recent census that provides dwelling structure by LGA – the 2016 census only provides dwelling structure by state, and the 2021 census results are yet to be reported.

9 We adopt an estimate of current rather than historical capacity, since we are testing a forward looking upper bound.

- This calculated figure does not include small business.

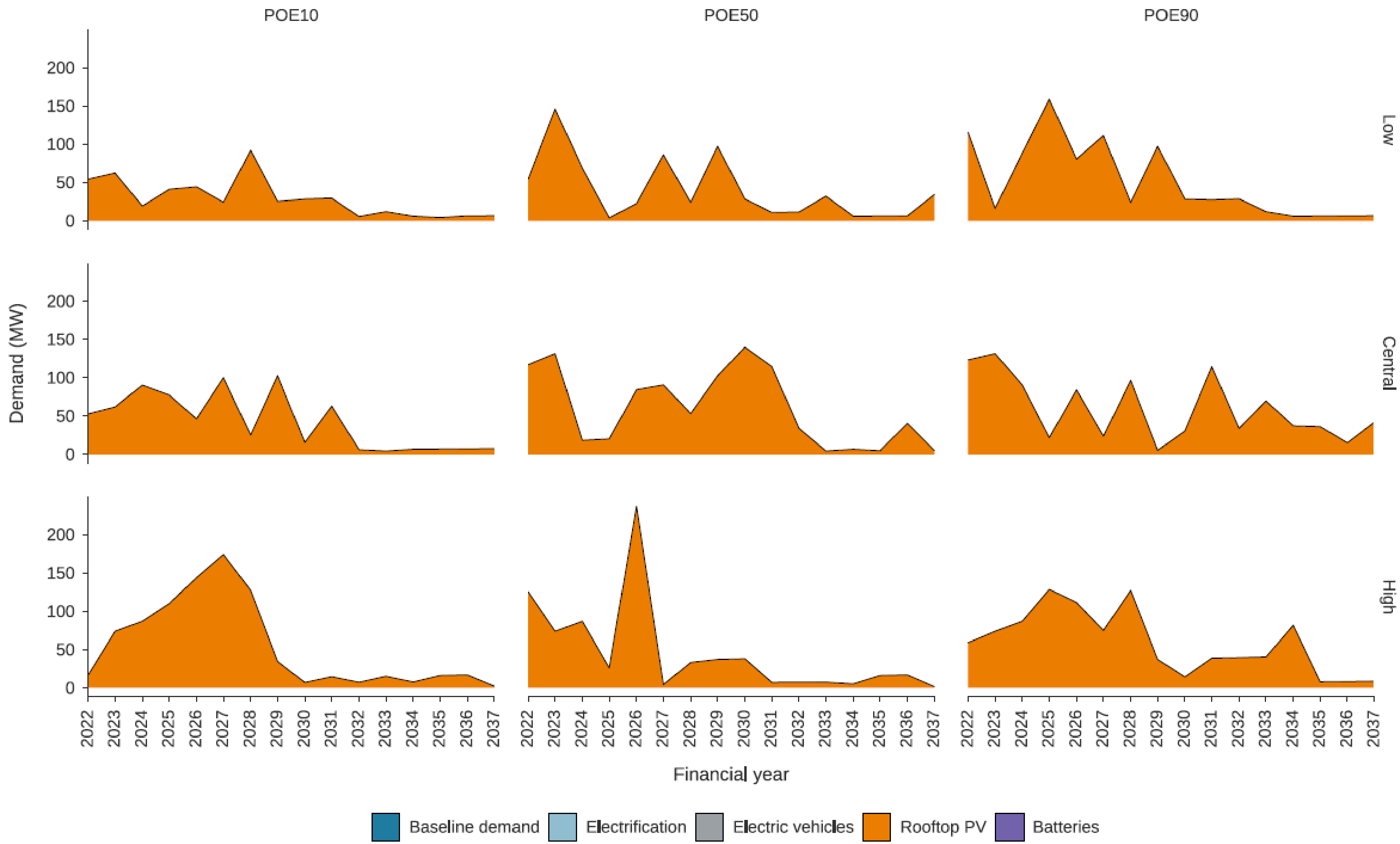
Taking into account the above, we consider that the pro-rated AEMO PV forecasts are unlikely to exceed saturation levels by 2037, when considering suitable sites including separate and semi-detached dwellings. We note that there may be other technical limitations (beyond maximum demand) that may limit rooftop PV in certain areas.

Figure 20 and **Figure 21** show the forecast contribution of rooftop PV to winter and summer maximum demand, respectively, over the forecast period for POE90, POE50 and POE10 for each of the low, central and high cases. As expected, the contribution of rooftop PV during times of maximum demand is minimal in winter, since maximum demand typically occurs after sundown. There is one year where this is not entirely the case for the Central and High scenarios, in 2029 and 2030 respectively. However, maximum demand reverts to after sundown in subsequent years.

In summer, the contribution of rooftop PV is much more volatile, and depends upon when maximum demand occurs. Since rooftop PV generates much later into the evening in summer, it can still contribute small amounts to reducing maximum demand. Although it is volatile, a general pattern occurs where the contribution is most in early years, but as the timing of maximum demand gets pushed later into the evening, the contribution decreases.

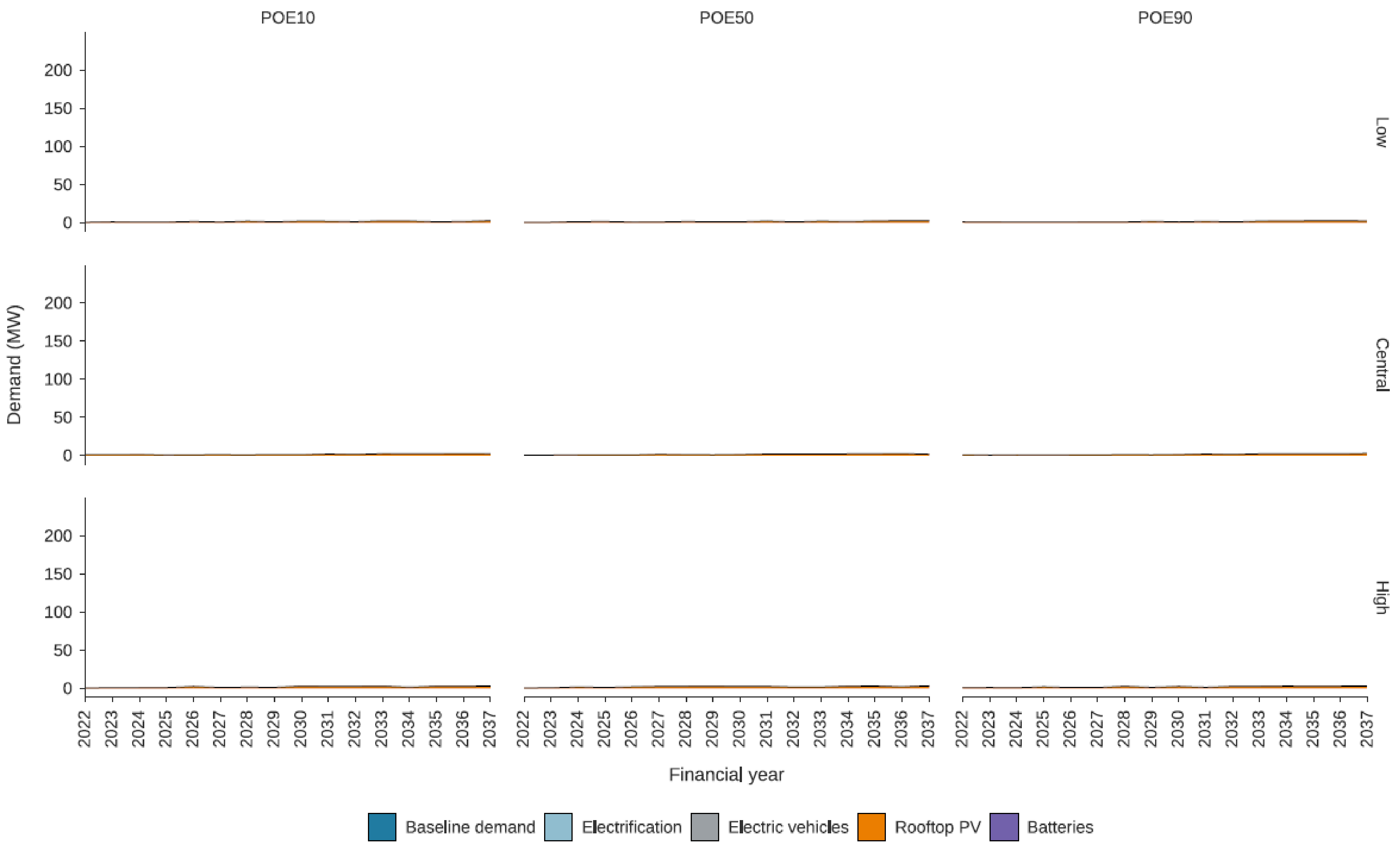
Figure 22 and **Figure 23** show the forecast contribution of rooftop PV to winter and summer minimum demand, respectively, over the forecast period for POE90, POE50 and POE10 for each of the low, central and high cases. The analysis shows the contribution of rooftop PV during times of minimum demand is significant and growing, for both summer and winter periods. This is consistent with experience across the National Electricity Market, where the increasing penetration of rooftop PV is a key driver of minimum demand.

Figure 20: Contribution of PV to aggregate summer maximum demand



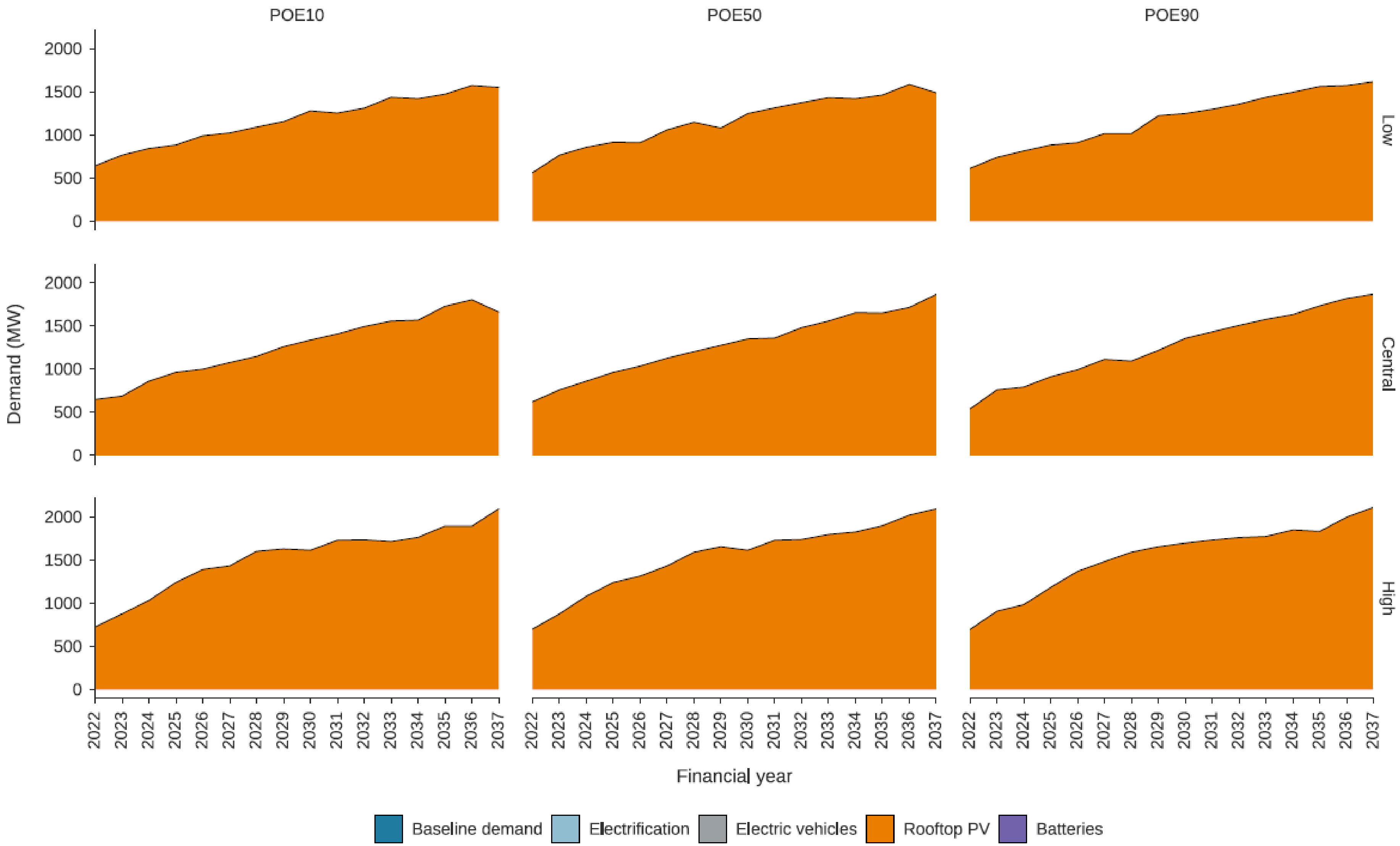
Source: Frontier Economics analysis

Figure 21: Contribution of PV to aggregate winter maximum demand



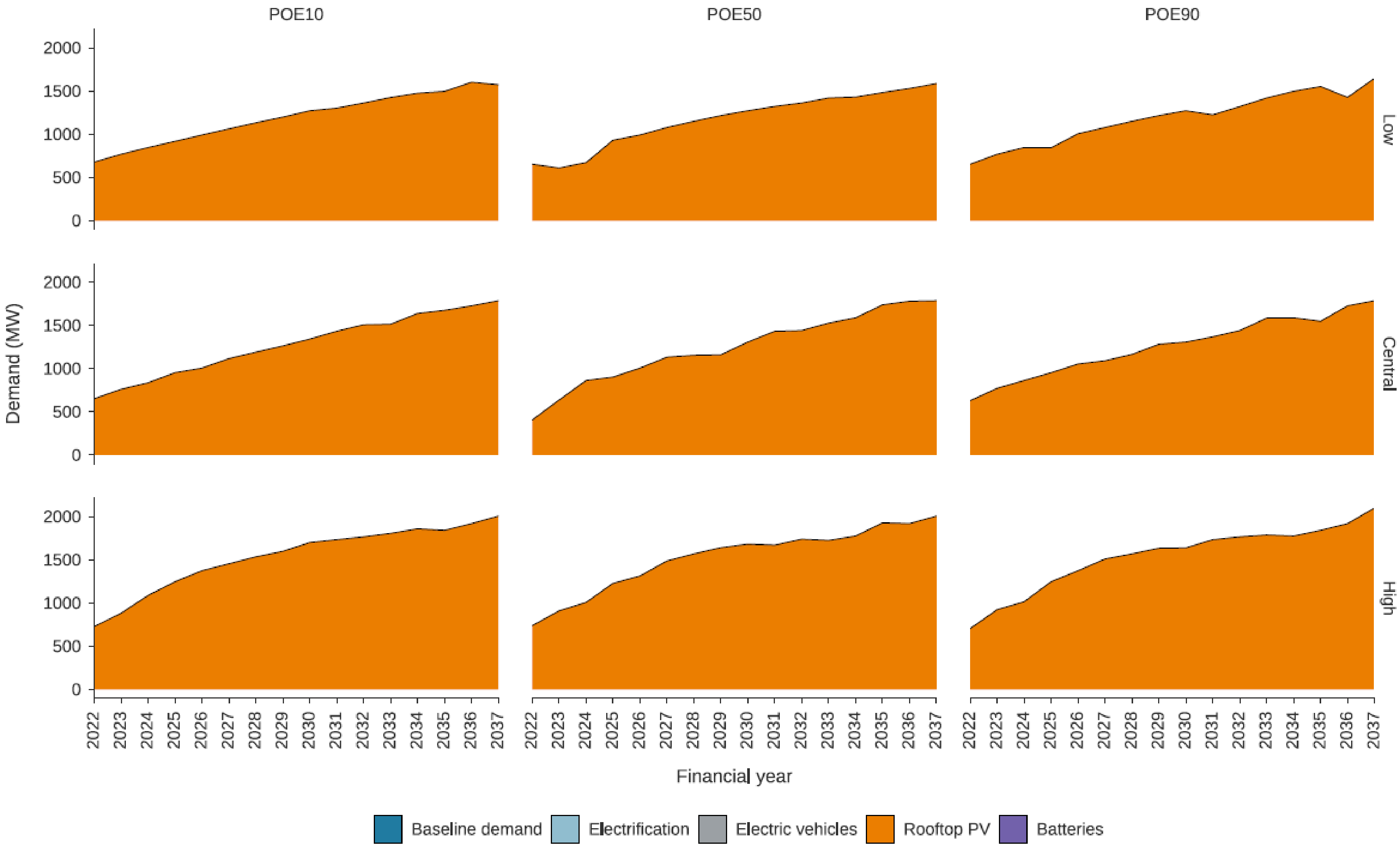
Source: Frontier Economics analysis

Figure 22: Contribution of PV to aggregate summer minimum demand



Source: Frontier Economics analysis

Figure 23: Contribution of PV to aggregate winter minimum demand



Source: Frontier Economics analysis

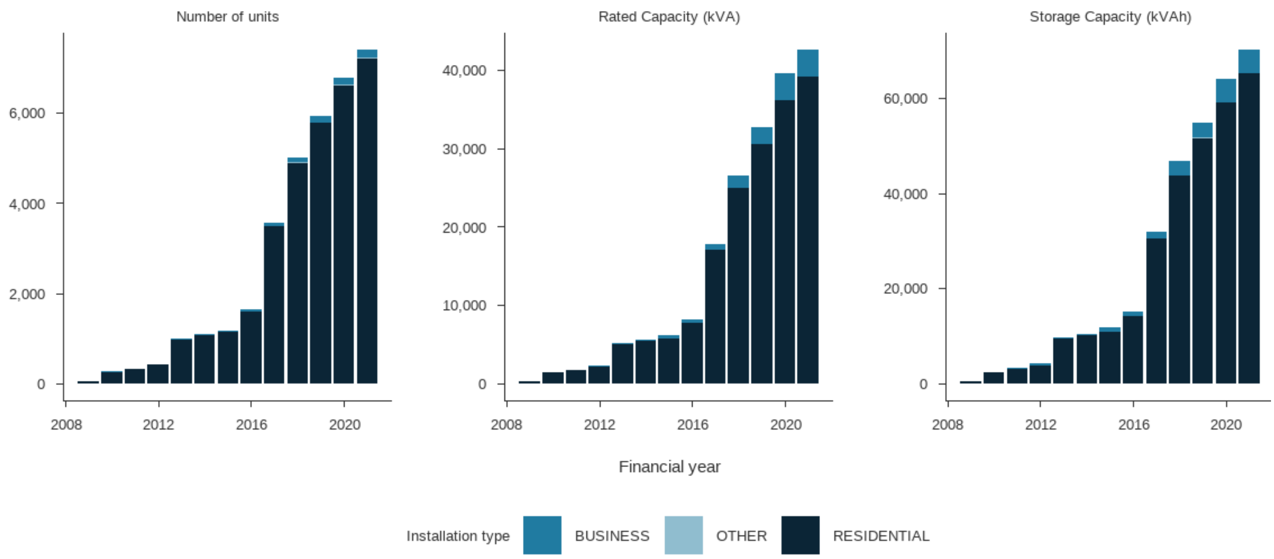
3.2 Batteries

Our analysis of batteries focuses on behind-the-meter batteries. Utility scale batteries are considered in the context of embedded generation.

3.2.1 Historical trends

Behind-the-meter batteries are a relatively new addition to the National Electricity Market. **Figure 24** illustrates the cumulative number of battery installations, rated capacity, and storage capacity in NSW from 2008 to 2021, according to AEMO's DER Registry[10].

Figure 24: Battery installations, rated capacity and storage capacity, NSW, 2008-2021



Source: Frontier Economics analysis of AEMO DER registry

Battery uptake was modest for the period 2008 to 2017, at which point the growth rate increased significantly for the following two years before stabilising at around 600-800 installations per year. Trends in battery sizes (rated capacity and storage capacity) are relatively constant at around 5-6 kVA rated capacity and 9-10 kVAh storage capacity.

Overall, the number and size of batteries in NSW over the historical period we consider is not significant enough to warrant making pre- and post-model adjustments to demand in the same way we do for rooftop PV. Battery uptake for the whole of NSW in 2021 is estimated by the DER Registry at 40,000 kVA (40 MW with a 100% power factor), compared to 1.4GW of rooftop PV in the Essential Energy network area alone.

We note that due to the structure and levels of network and retail tariffs, there have historically been little incentive to install a battery without a rooftop PV system[11]. We expect these incentives

10 See https://aemo.com.au/energy-systems/electricity/der-register/data-der/data-dashboard, data retrieved 31st March 2022.

11 This is because batteries enable additional self-consumption of electricity generated from rooftop PV systems, thereby avoiding variable network tariffs. Batteries without behind the meter generation are not able to avoid network tariffs, which is where the majority of benefits of behind the meter storage arise.

to remain over the forecast period, although incentives are likely to soften over time as network and retail tariffs become more cost reflective.[12] For these reasons, we assume battery uptake in the Essential Energy network area has and will continue to be paired with rooftop PV.

Behind the meter batteries increase consumption because batteries are not 100% round-trip efficient[13] (around 80-90% round-trip efficiencies are typical[14]). While battery operation is technically at the discretion of the owner, there are two main ways in which batteries are, and we expect will continue to be, operated:

- To time shift energy, i.e. charge when rooftop PV would otherwise be exporting, and discharge when grid consumption would otherwise be required and there is stored energy in the battery.
- To respond to wholesale market price signals, for example as part of a Virtual Power Plant (VPP).

In both cases, we expect batteries to increase underlying consumption (due to efficiency losses), to reduce minimum demand (i.e., increase demand at times of minimum demand), and reduce peak demand, as we discuss below.

3.2.2 Existing forecasts

Essential Energy did not provide us with an in-house forecast of battery uptake.

As part of AEMO's annual forecasting processes, it produces demand assumptions including battery uptake for each NEM region including NSW. As with its rooftop PV forecast, for its latest release, AEMO engaged the CSIRO to develop battery uptake forecasts. Three of the five scenarios used by AEMO from CSIRO's modelling are presented in **Figure 25**. These are the three scenarios we use in our forecasts.

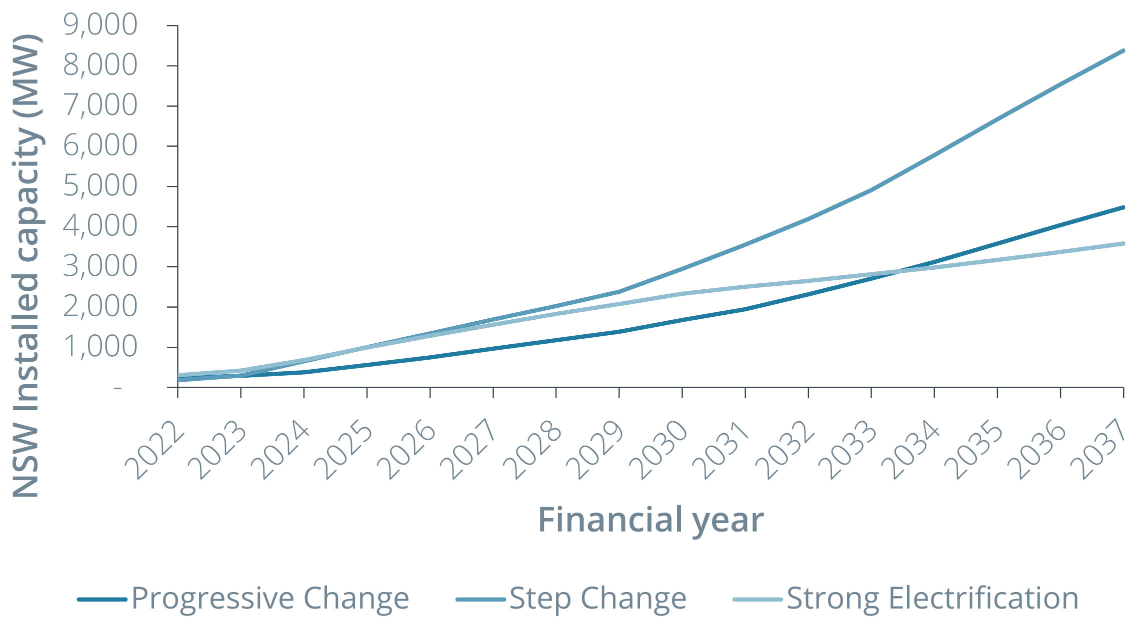
The CSIRO's forecast exhibits growth in installed battery capacity in all scenarios. Growth in the 'Step Change' and 'Strong Electrification' scenarios are similar until 2029, but then increasingly diverge. Growth in the 'Progressive Change' scenario mirrors that of the Step Change scenario, but at a lower level, achieving around half the growth over the period.

12 Based on our analysis the current arbitrage between peak and off-peak retail tariffs is around 15c/kWh, compared to a battery capacity price of around 27c/kWh.

13 Round trip efficiency refers to the percentage of energy put into a battery that is later retrieved.

14 See "Round Trip Efficiency" row of SolarQuotes' Solar Battery Storage Comparison Table, available https://www.solarquotes.com.au/battery-storage/comparison-table/, accessed 1st April 2022

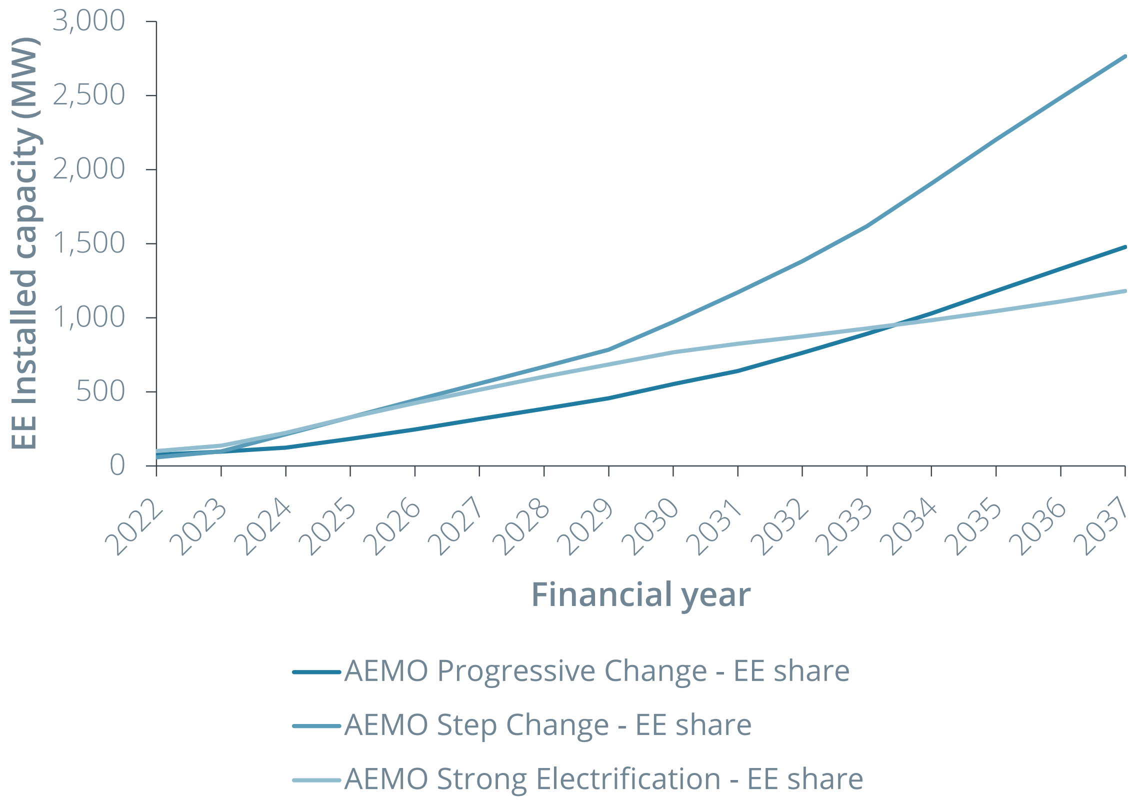
Figure 25: AEMO forecast of NSW installed battery capacity



Source: Frontier Economics analysis of AEMO data

To put these forecasts in the context of Essential Energy, we pro-rate AEMO's NSW forecast by Essential Energy's share of NSW PV, for reasons discussed in Section 3.2.1, as illustrated in **Figure 26**. This adjustment ensures we remain consistent with AEMO's forecasts while recognising the specific characteristics of Essential Energy's service area.

Figure 26: AEMO forecast of NSW installed battery capacity pro-rated to the Essential Energy Network area



Source: Frontier Economics analysis of AEMO and Essential Energy data

3.2.3 Our approach

In order to forecast the impact of batteries on minimum and maximum demand and consumption, we combine forecasts of installed capacity and battery operation profiles, and adjust underlying demand forecasts according to the level of rooftop PV in each TNI/ZSS, noting that we expect battery installations to continue to be paired with PV installations.

As noted in Section 1.3, our scope is to forecast consumption for all of Essential Energy (by tariff type and in aggregate), as well minimum and maximum demand consumption at the ZSS and TNI levels.

Forecasting the impact of batteries on consumption for Essential Energy in aggregate requires estimating the increase in consumption that arises due to battery losses. To estimate this, we:

- Pro-rate AEMO's forecast of NSW battery uptake according to Essential Energy's share of NSW rooftop PV (33%) to get a forecast of installed battery capacity (including rated and storage capacity).
- Calculate the losses arising from the daily cycling of these batteries according to AEMO's 30-minute behind-the-meter battery profiles.

Forecasting the impact of batteries on minimum and maximum demand for TNIs and ZSSs in Essential Energy's network area requires assessing the impact of the operation of different installed capacities of batteries in each TNI and ZSS. To estimate this, we:

- Pro-rate AEMO's forecast of NSW battery uptake according to Essential Energy's share of NSW rooftop PV (33%) to get a forecast of installed battery capacity (including rated and storage capacity).
- Pro-rate the forecast of Essential Energy's battery uptake according to each TNI/ZSS's share of Essential Energy rooftop PV to get a forecast of installed battery capacity (including rated and storage capacity) in each TNI/ZSS.
- For each TNI and ZSS, multiply their battery share by AEMO's 30-minute behind-the-meter battery profiles to estimate battery operation in each TNI and ZSS.
  a. AEMO provide four 30-minute battery profiles (winter weekday, winter weekend, summer weekday and summer weekend) for each year from 2022 to 2050 by each scenario.
- Subtract the profile of battery operation from the underlying demand forecast for each TNI and ZSS.

3.2.4 Result

Figure 27 presents the battery charge and discharge profile for Essential Energy's network area for the Central (Step Change), High (Strong Electrification) and Low (Progressive Change) case. The same battery charge and discharge profile is adopted for each scenario; the differences between scenarios reflect different assumptions in the number of batteries. It should be noted that AEMO's Strong Electrification case assumes there are fewer batteries than the Step Change case.[15]

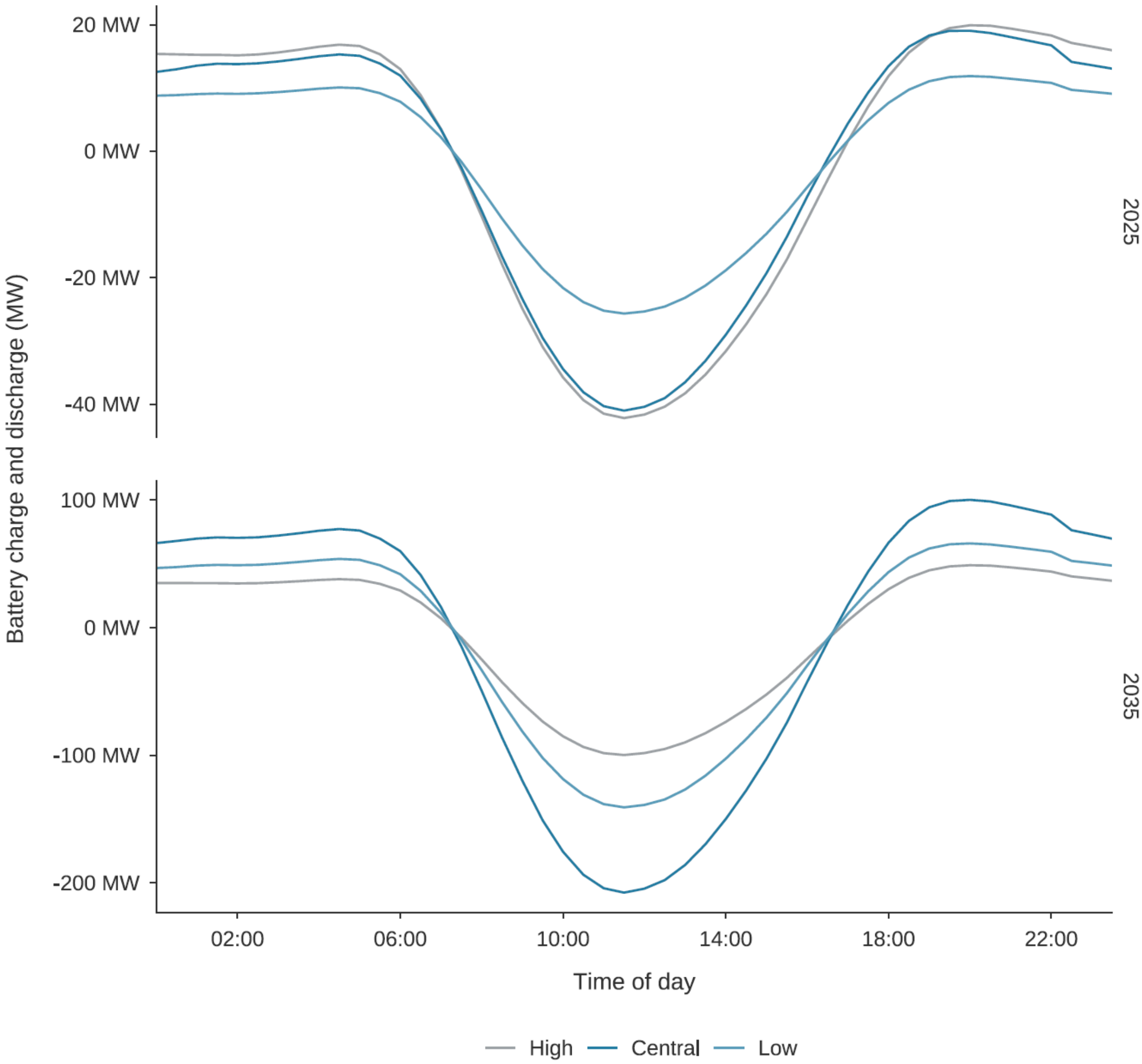
Batteries play an important role in offsetting minimum and maximum demand. Batteries reduce maximum demand and increase minimum demand. For ease of presentation these contributions are shown as positive in the following charts.

Figure 28 and **Figure 29** show the contribution of batteries to aggregate winter and summer maximum demand, respectively, for each of the scenarios considered and POEs modelled. As expected, the uptake in batteries means they have a greater impact towards the end of the modelling period. The contribution of batteries to aggregate winter and summer demand varies to reflect the Monte Carlo modelling of maximum demand, consistent with AEMO's analysis.

Figure 30 and **Figure 31** show the contribution of batteries to aggregate winter and summer maximum demand for each scenario and POE modelled. The results show batteries have an important and increasing role in offsetting the fall in minimum demand over the forecast period.

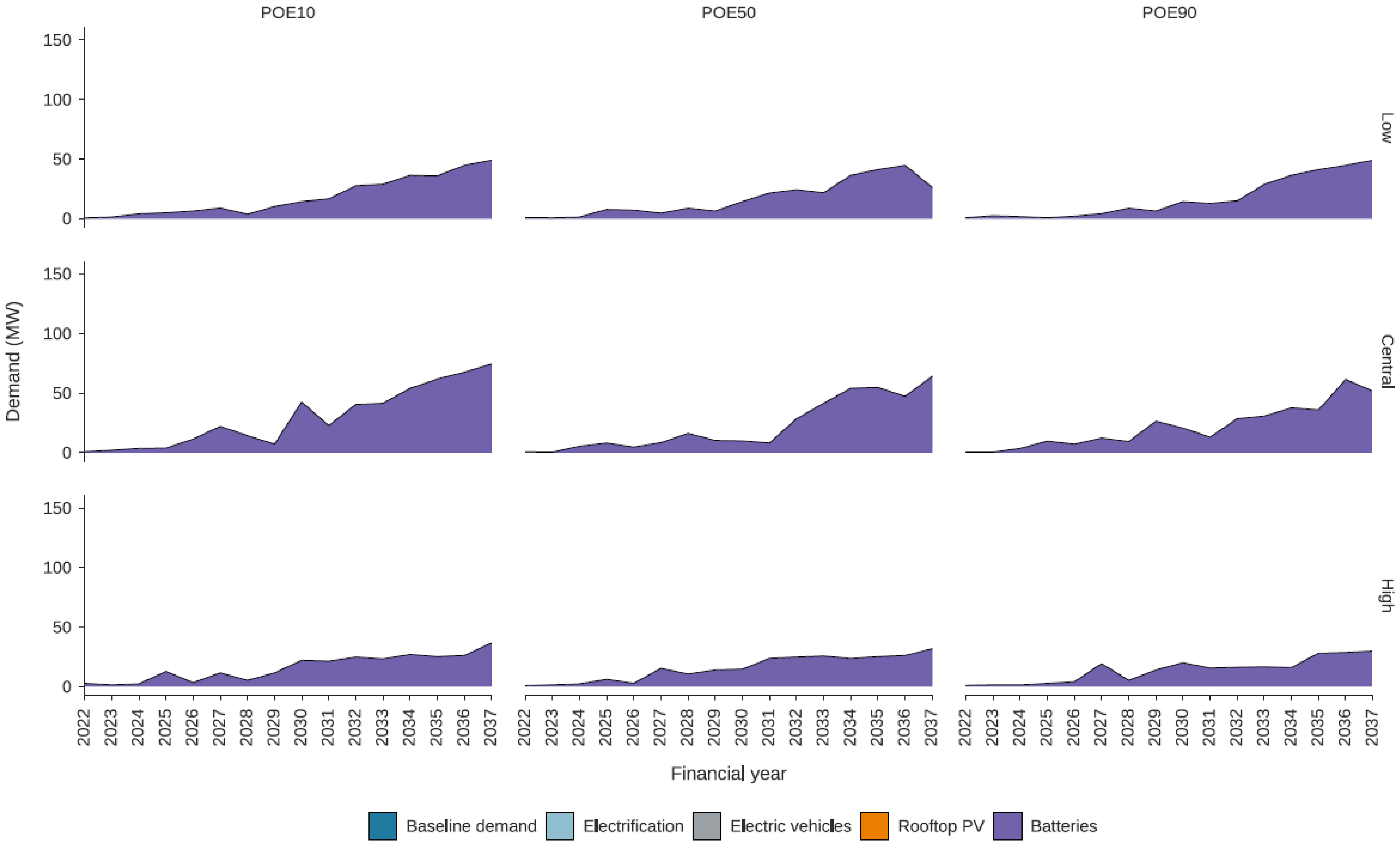
[15] Strong Electrification adopts primarily the same input assumptions as the Hydrogen Superpower scenario. Under the Hydrogen Superpower case battery uptake is lower because less people electrify in this case given the rapid uptake of hydrogen.

Figure 27: Battery charge and discharge profile



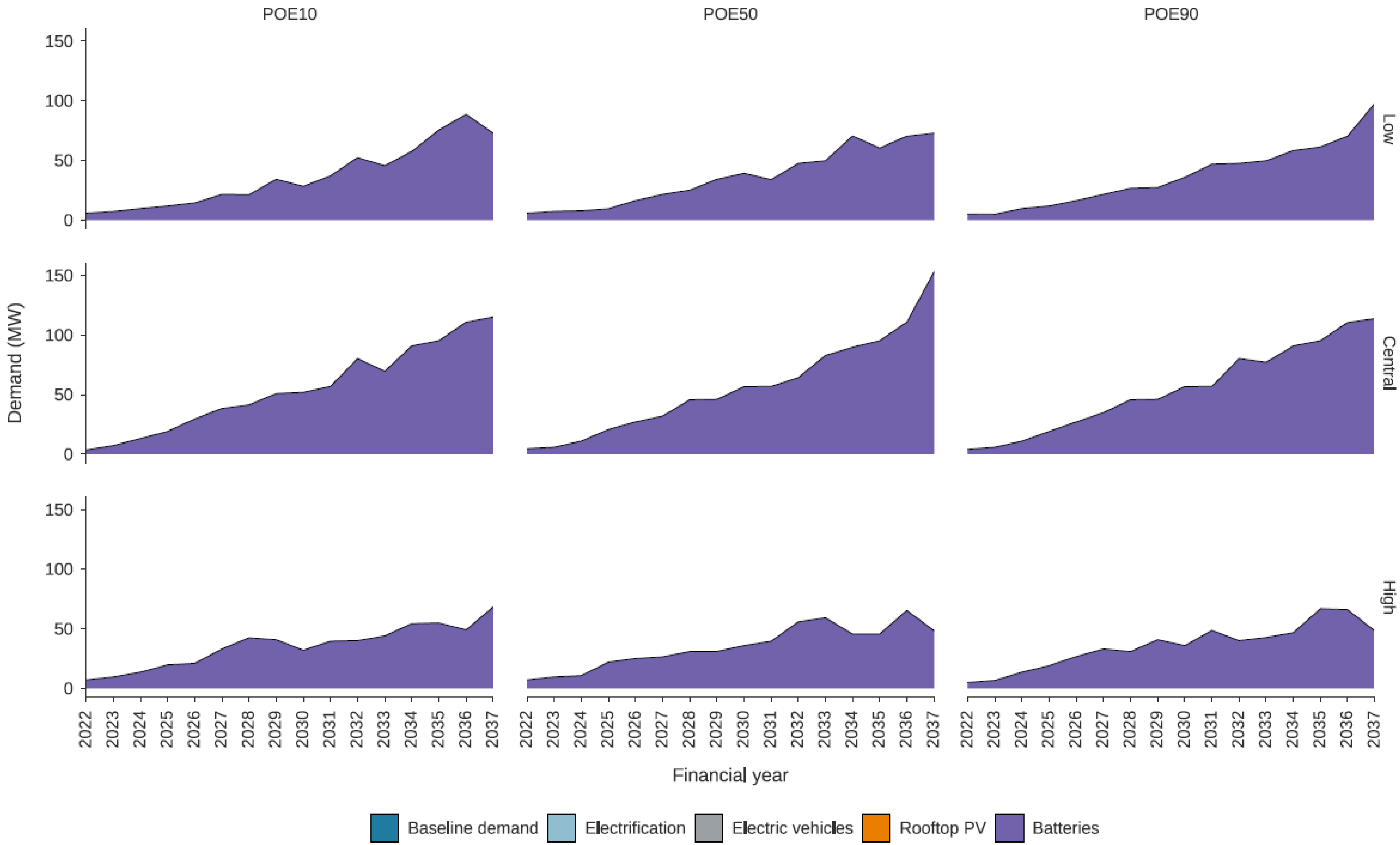
Source: Frontier Economics analysis

Figure 28: Contribution of batteries to aggregate summer maximum demand



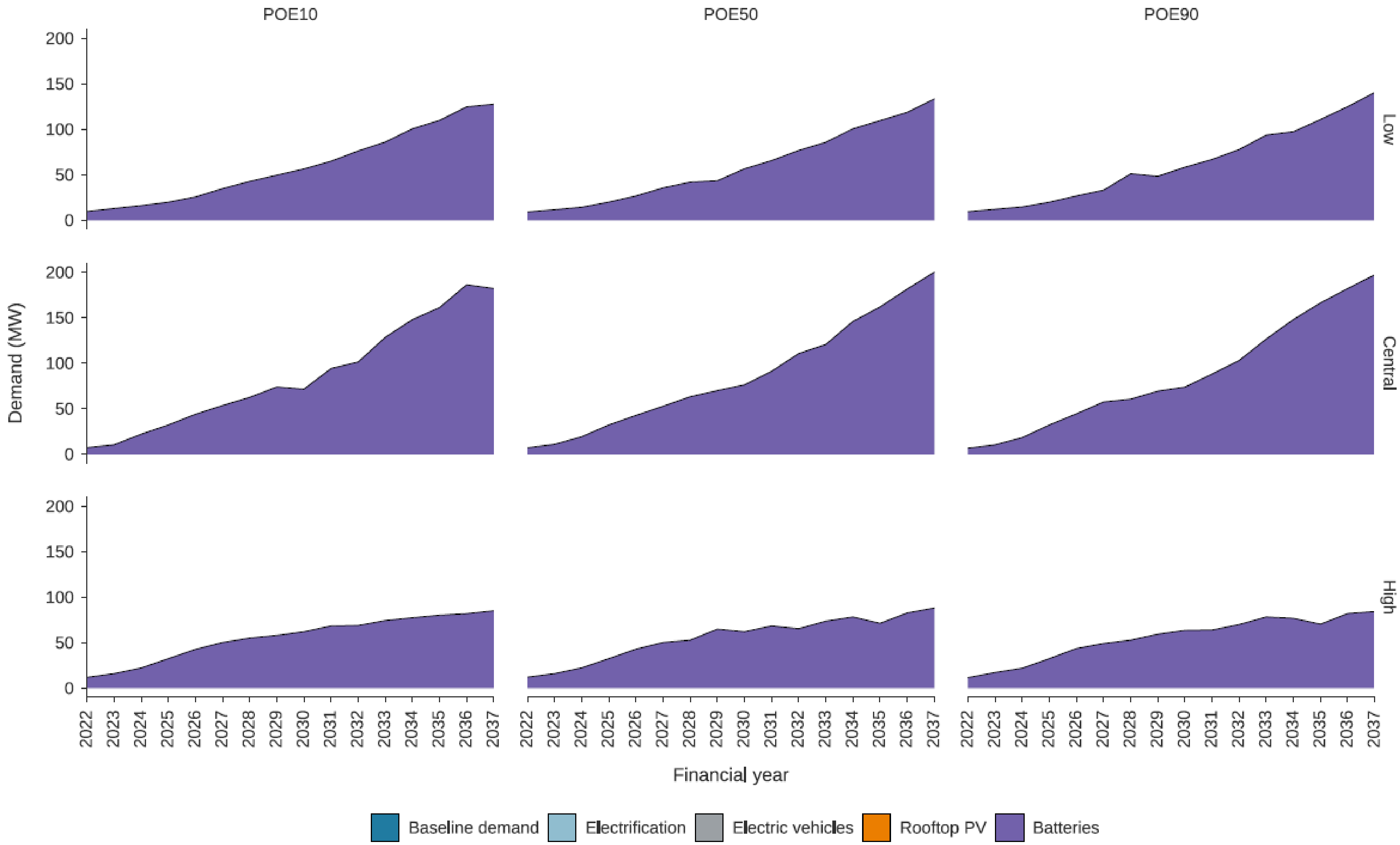
Source: Frontier Economics analysis

Figure 29: Contribution of batteries to aggregate winter maximum demand



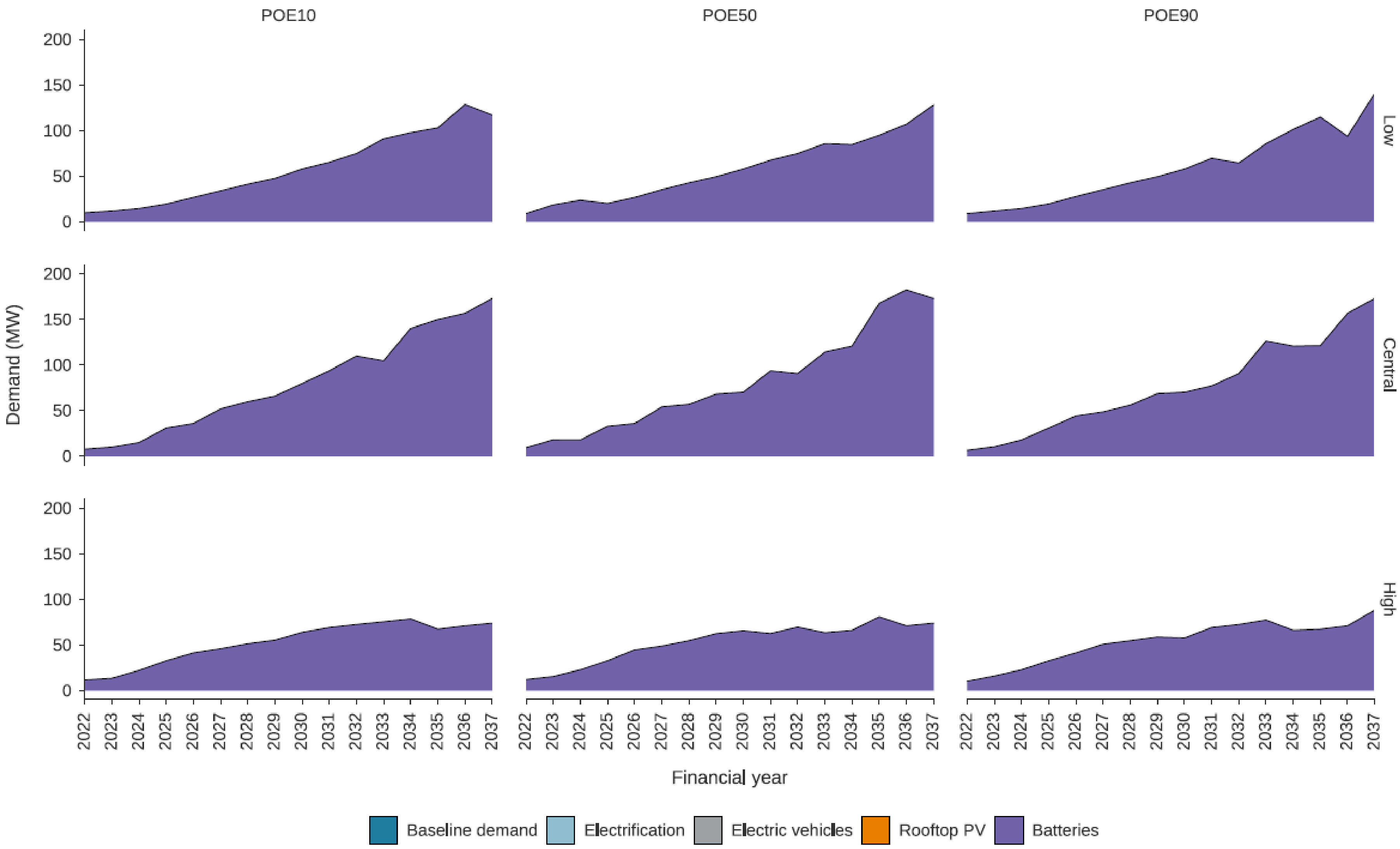
Source: Frontier Economics analysis

Figure 30: Contribution of batteries to aggregate summer minimum demand



Source: Frontier Economics analysis

Figure 31: Contribution of batteries to aggregate winter minimum demand



Source: Frontier Economics analysis

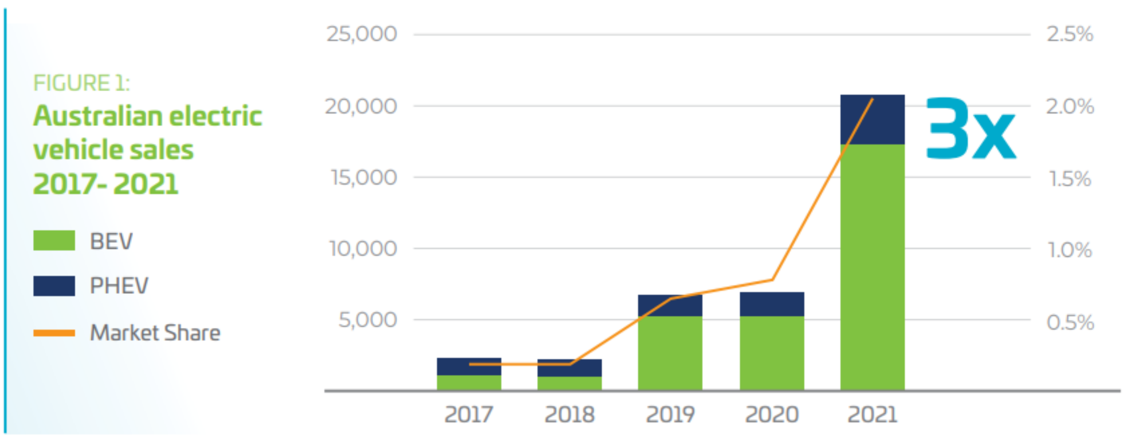
3.3 EVs

3.3.1 Historical trends

The number of EVs, together with charging patterns, are the key determinants of the contribution of EVs to consumption.

The electric vehicle market in Australia is nascent. In 2021, electric vehicles had a 2% market share of new sales, up from around 0.6% in 2019 and 2020. Electric vehicle sales for Australia (not cumulative) are presented in **Figure 32**. AEMO is forecasting that in 2022 EVs make up less than 0.04% of operational consumption.[16] Because the proportion of Australia's vehicle fleet contains so few EVs, we make no adjustment to historical data to reflect the impact of EVs on underlying demand.

Figure 32: Electric vehicle sales in Australia, 2017 to 2021



Source: Electric Vehicle Council, State of Electric Vehicles, April 2022

Although EVs are relatively new, there have been a number of studies on the charging patterns of EVs. A report commissioned by the Electricity Networks Australia[17] summarises a number of related studies on charging patterns, finding that the order of preference for charging locations is home, work, other destinations, and then service stations. Further, the report suggests the following on EV charging patterns:

> *On average, EV users charge their vehicles between three and four and a half times per week and the average session does not exceed four hours. Even though these values are*

[16] AEMO, 2022 Draft ISP Forecast.

[17] Electric Vehicle Uptake and Charging, a Consumer Focused Review, 28 April 2021, available https://www.energynetworks.com.au/miscellaneous/ev-uptake-and-charging-review-report-1/, accessed 1st April 2021

likely to change as the penetration of long-range EVs increase, such results are an evidence of habitual charging behaviour rather than irregular "empty-to-full" recharges

Different charging behaviours are likely to impact estimates of minimum and maximum demand. Charging patterns that draw from the grid during the day are likely to reduce peak demand (i.e. raise demand at times of minimum demand), and charging patterns that draw from the grid in the evening are likely to increase peak demand levels.

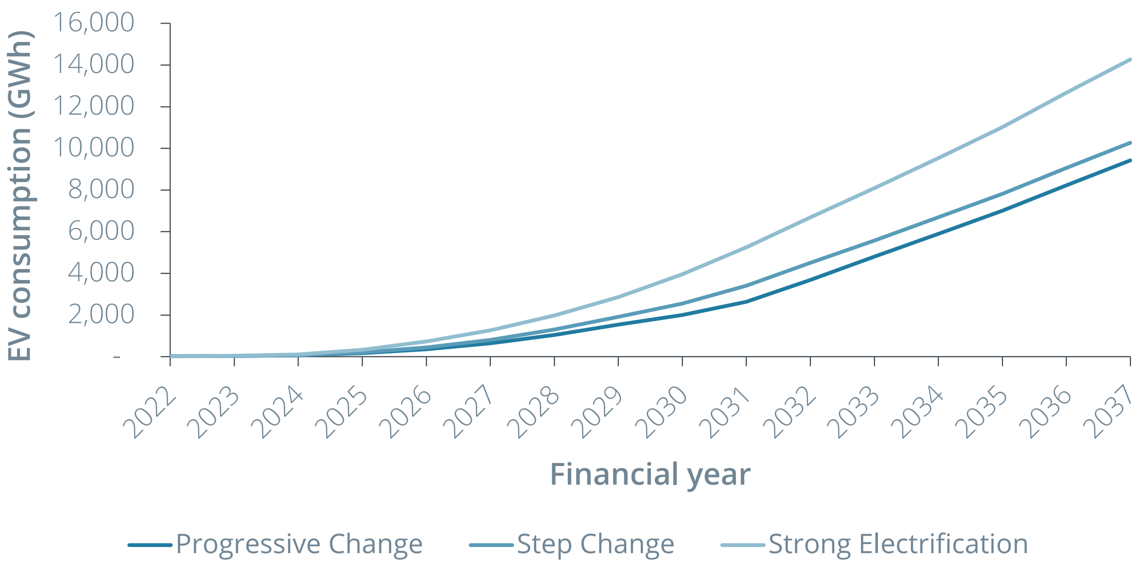
3.3.2 Existing forecasts

Essential Energy did not provide an in-house forecast of EVs.

As part of AEMO's annual forecasting processes, it produces demand assumptions including EV uptake for each NEM region including NSW. As with its rooftop PV and battery forecasts, for its latest release, used in the Draft 2022 Integrated System Plan, AEMO engaged the CSIRO to develop EV uptake forecasts. Forecasts for the three scenarios we have adopted are presented in **Figure 33**.

The CSIRO's forecast exhibits growth in EV uptake (including number of vehicles, consumption and demand) in all scenarios. Growth trends in all three scenarios are similar, although levels are different – the Strong Electrification scenario sees substantially more consumption than the Progressive and Step Change scenarios.

Figure 33: AEMO EV consumption scenarios for NSW



Source: Frontier Economics analysis of AEMO data

We considered the factors influencing EV take up in Australia (Box 1), and the extent to which these factors may influence the take up of EVs in Essential Energy's service area. There is some evidence that uptake may be slower in Essential Energy's service area, as we discuss in Section 3.3.3

Box 1: Factors influencing EV uptake in Australia

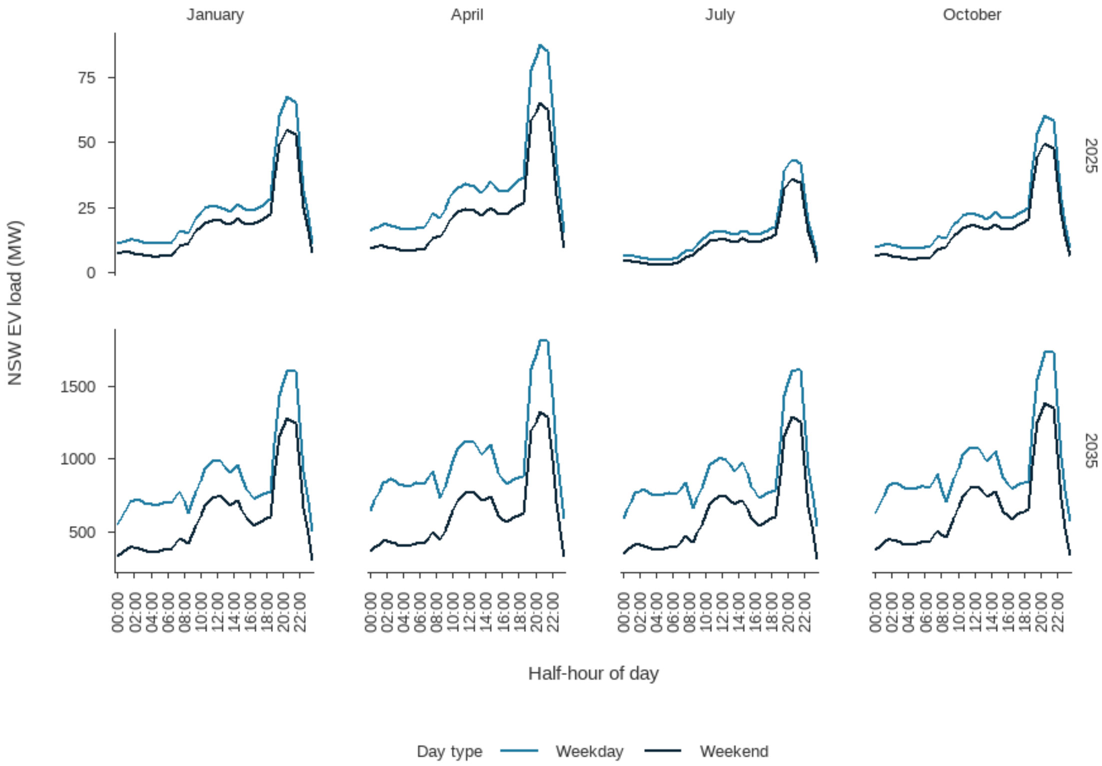
Research on EV uptake is still emerging, and there are mixed findings in the literature on the factors influencing EV uptake. There is no reliable, publicly available analysis on the uptake of EVs within Australian states and territories, including across NSW. In general terms:

- European studies conclude that residents in larger cities are more likely to buy EVs than regional and rural residents
- The development of charging infrastructure can reduce range anxiety, promoting EV uptake
- There is some qualitative evidence to suggest the rate of EV adoption is correlated with income or education, but this is not determinative. For example, SA and TAS have relatively high uptake rate given their relatively low income compared to other states.
- A key influence on EV uptake is Government policy. The NSW Government's Electric Vehicle Strategy sets a target of 50% of new vehicle sales to be electric vehicles by 2030.

Foley, B., Degirmenci, K. and Yigitcanlar, T., 2020. Factors affecting electric vehicle uptake: Insights from a descriptive analysis in Australia. Urban Science, 4(4), p.57; Wappelhorst, S., Beyond major cities: Analysis of electric passenger car uptake in European rural regions. NSW Government, NSW Electric Vehicle Strategy, Available at: https://www.nsw.gov.au/initiative/nsw-governments-electric-vehicle-strategy

Vehicle charging patterns are a key determinant of impacts on minimum and maximum demand. Because of this, the CSIRO and AEMO forecast future charging patterns as well as the uptake and overall consumption of electric vehicles. **Figure 34** illustrates AEMO's forecasts of NSW EV load for 2025 and 2035 by time of day and day type (weekday/weekend) for a month in each quarter. In earlier years of AEMO's forecasts, the majority of EV load is concentrated in the typical peak demand window (after 6pm), although in 2025 the addition in terms of NSW's total load is small. By 2035, charging patterns have changed, and more charging occurs during daytime hours and less during peak, although the EV load is still peaking and substantially higher than in 2025.

Figure 34: AEMO forecast of NSW EV load for 2025 and 2035 by time of day and day type, selected months



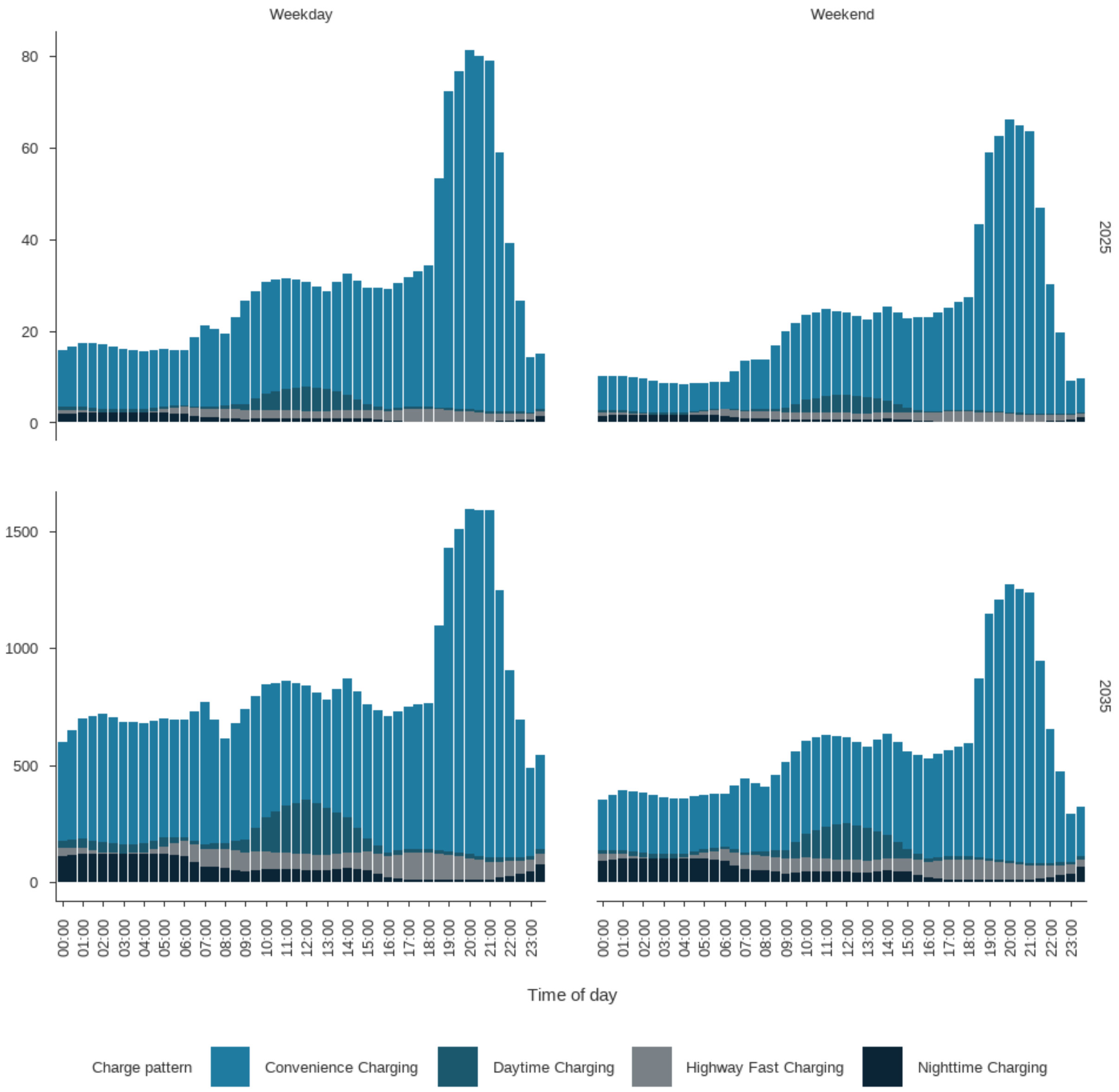
Source: Frontier Economics analysis of AEMO data

To break down these charging patterns further, **Figure 35** illustrates the contribution of each charging behaviour to the loads illustrated in **Figure 34**. Both years are heavily influenced by the 'convenience charging', which reflects charging through the peak demand period. In the latter years forecast, other charging patterns feature more strongly in the forecasts, although coincident convenience charging and its impact on peak demand is still the main driver of AEMO's/CSIRO's result.

AEMO's focus on convenience charging is consistent with feedback from Essential Energy's customers about their charging preferences.[18]

18 Woolcott Research & Engagement - Customer and Stakeholder Engagement for the 24-29 Regulatory Proposal – Phase 1

Figure 35: AEMO forecasts of NSW EV load for 2025 and 2035 by profile type, time of day and day type



Source: Frontier Economics analysis of AEMO data

3.3.3 Our approach

In order to forecast the impact of EVs on minimum and maximum demand and consumption, we combine forecasts of the number of EVs in operation, forecasts of EV charging behaviour, and data on the number of customers by type (business and residential) under each TNI/ZSS.

As noted in Section 1.3, our scope is to forecast consumption for all of Essential Energy (in aggregate), as well minimum and maximum demand consumption at the ZSS and TNI levels. As electric vehicles are for the most part[19] a load, our approach to forecasting consumption is similar at the aggregate and disaggregated levels.

We consider the characteristics of Essential Energy's service area by lagging the uptake of EVs to reflect the remoteness of the location. We do this by first mapping each TNI/ZSS to a remoteness area as defined by the ABS (**Figure 36**).

We then consider evidence of EV uptake across NSW to date. **Figure 37** shows the trends in EV uptake for each of the remoteness areas in NSW over the period 2019-2021. The values represent the number of motor vehicles that are electric vehicles as a proportion of all new motor vehicle sales. It shows EV take up in the major cities of NSW is increasing at a much faster rate than for regional areas, with is no EV take up for Very Remote NSW over this period.

Accordingly, we lag the uptake proposed by AEMO for outer regional, remote, and very remote locations to reflect the likely slower uptake in rural and regional areas. There is very limited information available on the likely nature and extent of this lag; we have developed assumptions based on our best estimates of likely outcomes, drawing on available data while recognising its limitations in predicting future behaviour. Our lag to remoteness measure is provided in **Table 2** and a map showing remoteness area along with Essential Energy network assets and area of operation is shown in.

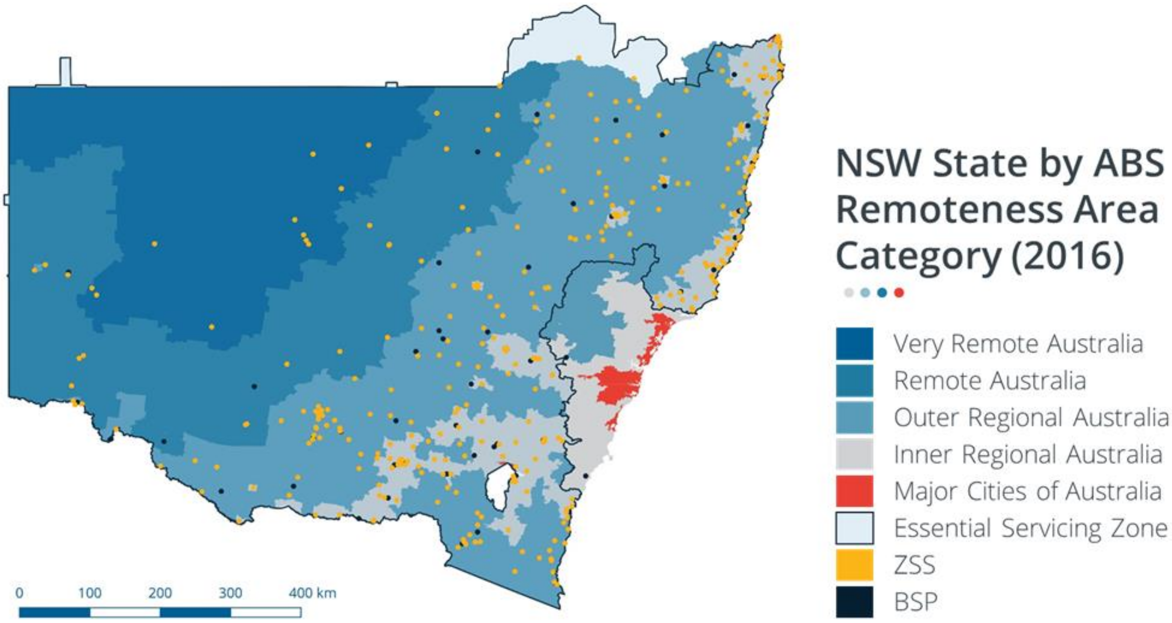
Table 2: EV uptake in Essential Energy's network area

Location	EV uptake rate
Major cities	AEMO's uptake rate
Inner regional	AEMO's uptake rate
Outer regional	2-year lag
Remote	3-year lag
Very remote	5-year lag

Source: Frontier Economics

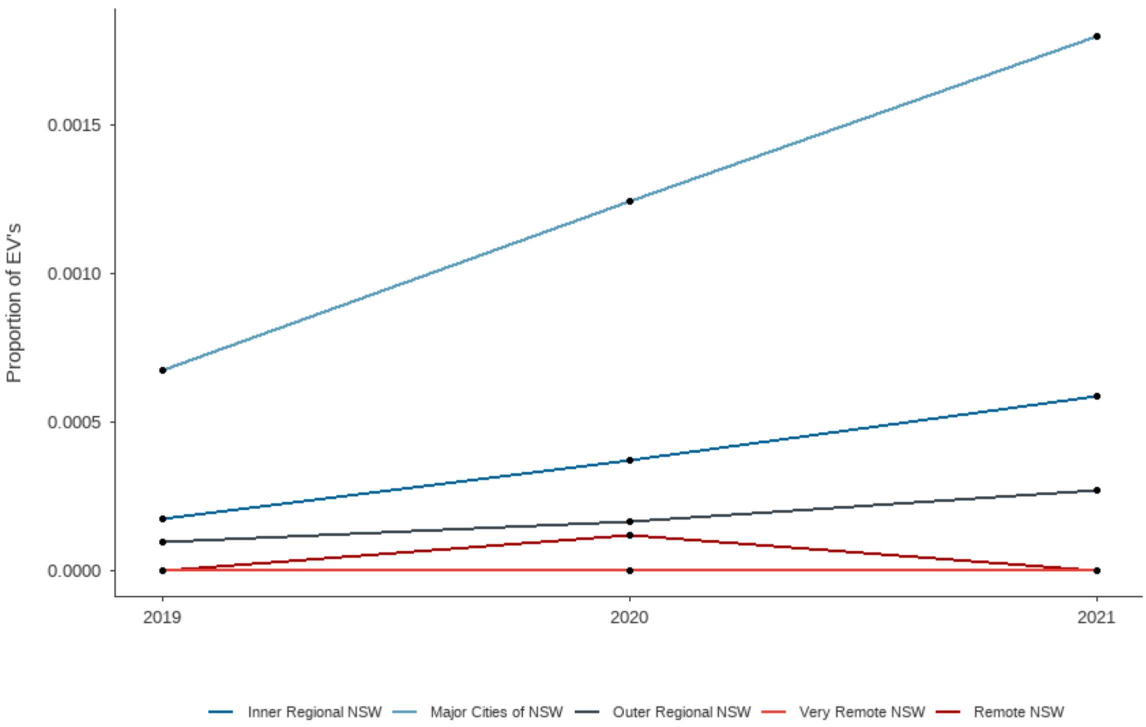
19 Two EV profiles provided by AEMO – 'Vehicle to Grid' and 'VPP' – have EVs acting like a battery in some instances. These profiles represent small amounts of energy, and so aggregate Essential Energy consumption is not adjusted for these losses.

Figure 36: NSW state by ABS remoteness area category



Source: ABS

Figure 37: EV uptake for remoteness areas in NSW



Source: Frontier Economics

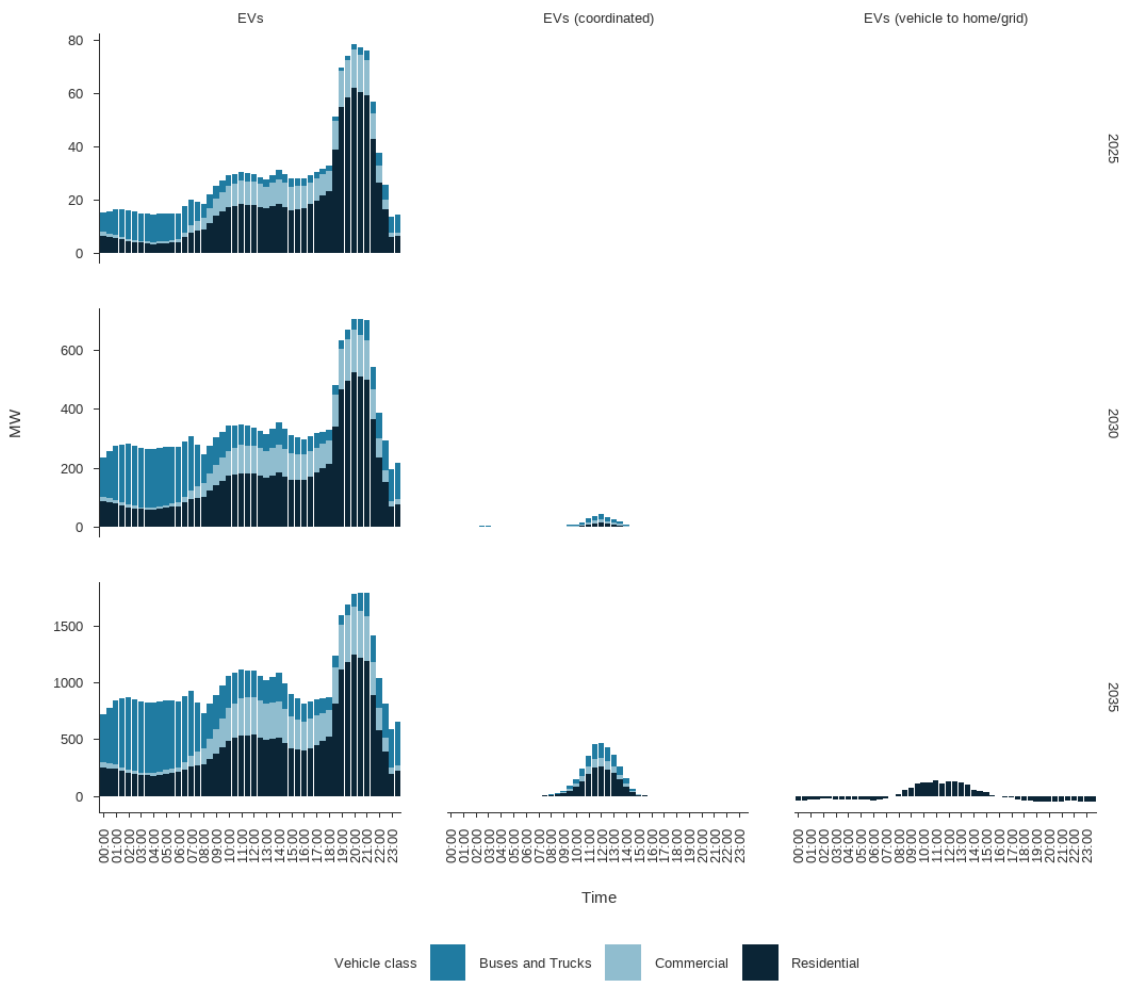
To forecast the impact of EVs on minimum and maximum demand and consumption for Essential Energy's network area, we:

- First, derive the charging profiles by taking AEMO's half-hourly load profiles for EVs, EVs with coordinated charging (EVs (coordinated)), and EVs that operate like a residential battery (EVs (vehicle to home/grid)) [20] and aggregate by month. This provides the monthly levels for the static profiles (e.g., daytime, night-time charging) that AEMO applies.
- We then expand AEMO's forecast charging profiles to take into account the number of vehicles. To do this we use the charging profiles (in kW per vehicle), number of vehicles by class (buses and trucks, commercial and residential), and profile allocation[21] (e.g., 95% of residential vehicles use convenience charging) from AEMO to get energy demand by class for each of the static profiles.
- Scale this demand to match the monthly levels derived in the first step. The effect of this is illustrated in **Figure 38**.
- Pro-rate this demand according to Essential Energy's share of NSW energy (around 19%) to get a forecast load profile of electric vehicles operating in Essential Energy's network area (before a lag is taken into account).
- Pro-rate Essential Energy forecast to TNIs/ZSSs according to their share based on mapping customer type at each location, based on customer tariff classes within each location, to vehicle class, as well as the proposed lag in take up at each location.
- Calculate annual aggregate load by summing EV consumption across Essential Energy's network area taking into account location to find the increment to invoiced consumption.
- Add this profile to our forecast of Essential Energy's underlying demand.

[20] See the "Demand trace data", "Regional files" section of AEMO's Current inputs, assumptions and scenarios page, accessed 8th April 2022

[21] For this data, see AEMO's Detailed Electric Vehicle Databook

Figure 38: Contribution of vehicle classes to demand by charge pattern, year and time of day, for a weekday in February



Source: Frontier Economics analysis of AEMO data

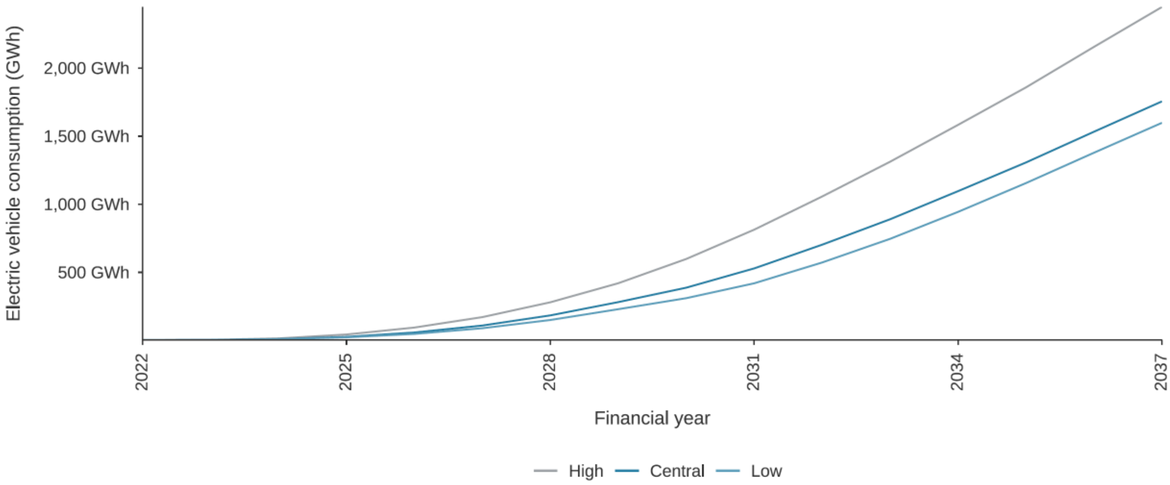
3.3.4 Result

Figure 39 shows annual consumption from electric vehicles. EV uptake across Essential Energy's service area is expected to be relatively slow in the near term, increasing rapidly towards the end of the modelling period. **Figure 40** shows how this annual consumption varies by vehicle class over the modelling period.

Figure 41 and **Figure 42** show the contribution of EVs to summer and winter aggregate maximum demand for the scenarios and POE cases modelled. As expected, the uptake of electric vehicles means that their contribution to maximum demand increases towards the end of the modelling period.

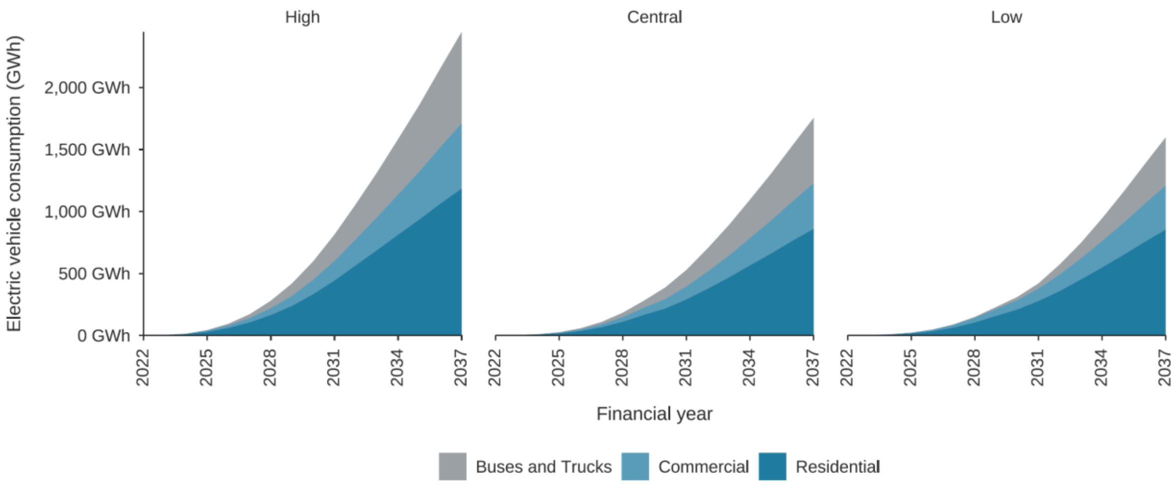
Figure 43 and **Figure 44** show the contribution of EVs to minimum demand for each scenario and POE over the modelling period. The analysis shows EVs have significant and rapidly increasing scope to offset minimum demand in both summer and winter over the modelling period.

Figure 39: Annual consumption from electric vehicles



Source: Frontier Economics analysis

Figure 40: EV consumption by scenario

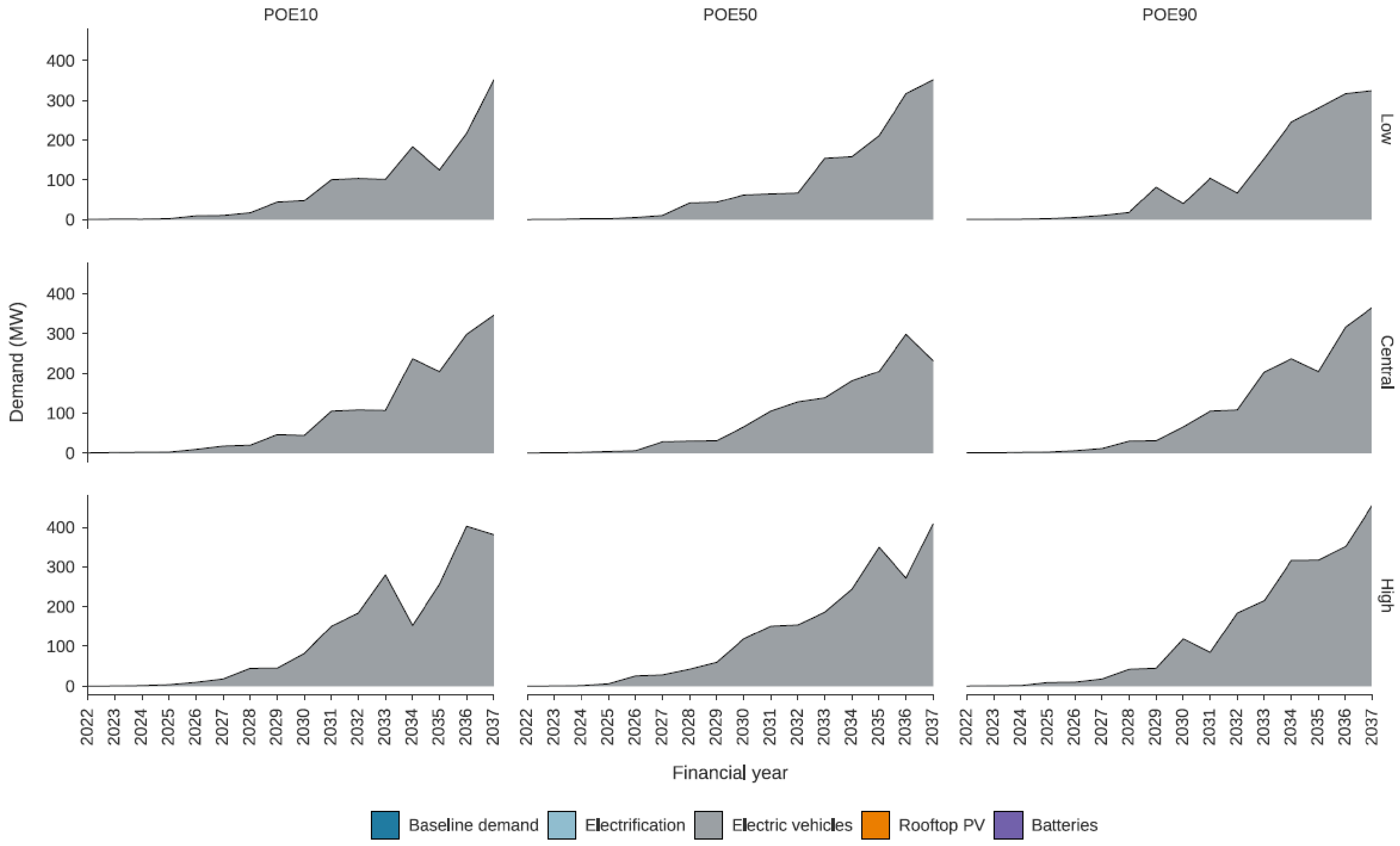


Source: Frontier Economics analysis

Figure 41: Contribution of EVs to aggregate summer maximum demand

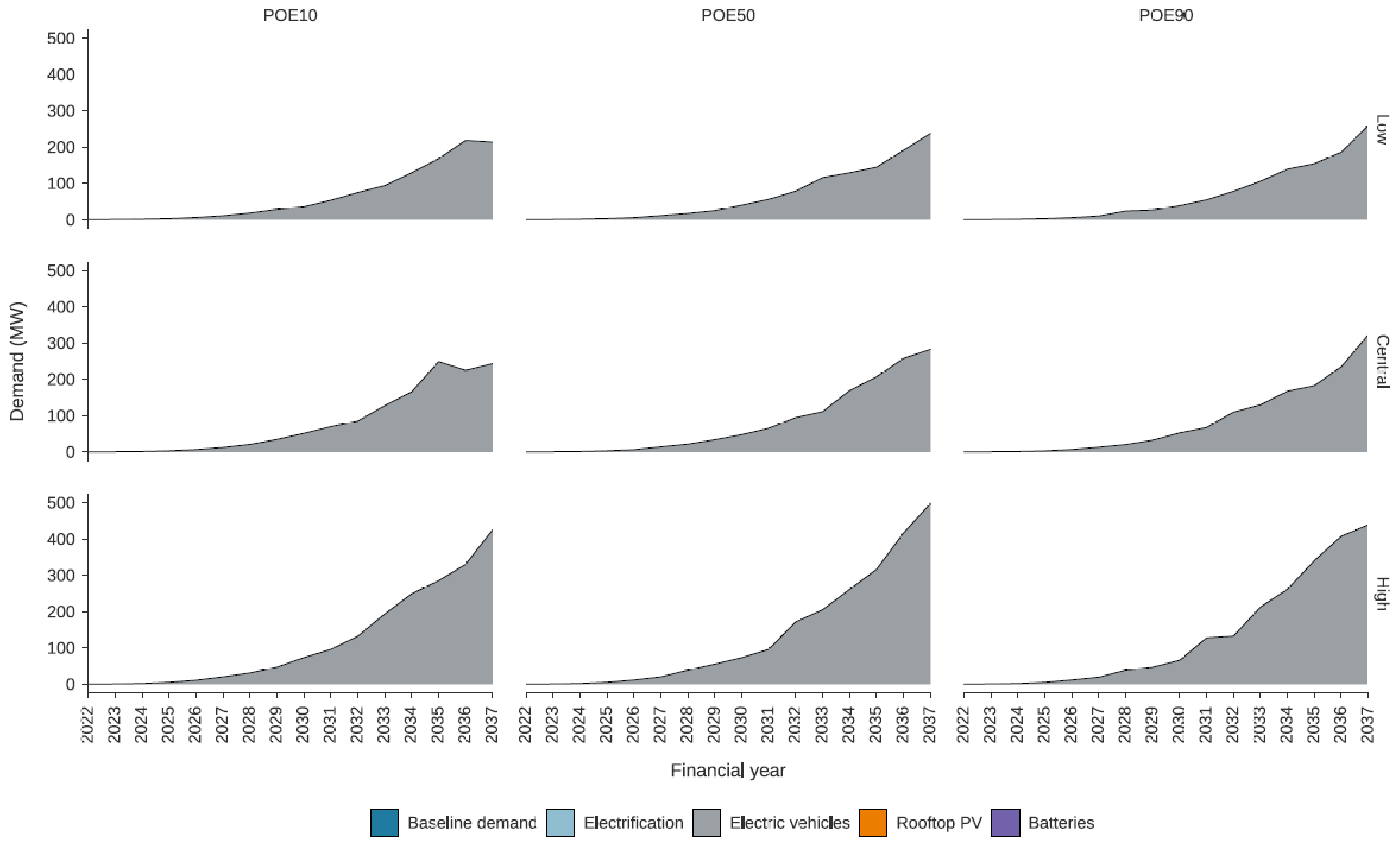
Source: Frontier Economics analysis

Figure 42: Contribution of EVs to aggregate winter maximum demand



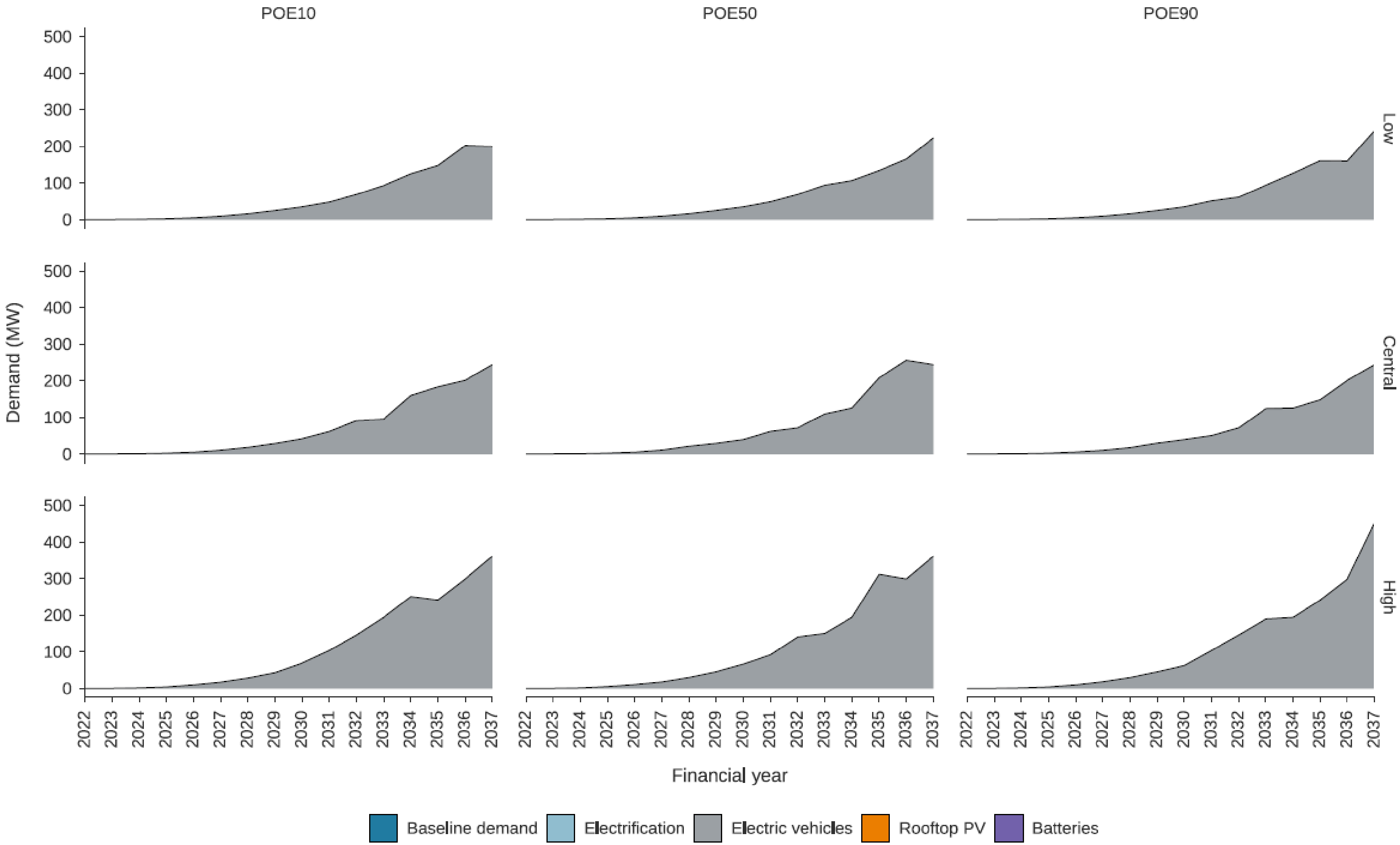
Source: Frontier Economics analysis

Figure 43: Contribution of EVs to aggregate summer minimum demand



Source: Frontier Economics analysis

Figure 44: Contribution of EVs to aggregate winter minimum demand



Source: Frontier Economics analysis

3.4 Electrification

Electrification refers to the substitution of non-renewable fuels (e.g., natural gas, LPG and wood) with electricity. Electrification technically occurs when end-users, for example, install reverse-cycle air conditioning to replace a gas heater or an induction cooktop to replace a gas cooktop.

3.4.1 Historical trends

According to its forecasting portal[22], AEMO does not attribute any historical growth in maximum demand or consumption to electrification.

3.4.2 Existing forecasts

Electrification of gas

For the 2022 ISP, AEMO engaged CSIRO to develop forecasts of electrification. The CSIRO developed annual forecasts of electrification for the business and residential sectors, and AEMO convert these annual forecasts into 30-minute load profiles to assess the impact on demand.

In each of the scenarios modelled by the CSIRO, gas demand from residences, business, and industry declines over time, although at different rates in the different scenarios. Natural gas declines are driven by decarbonisation objectives in CSIRO's model, which reflect different carbon budgets or policy-based emissions reductions targets. The CSIRO's trajectory for natural gas consumption declines for residential buildings is shown in **Figure 45**.

The method in which the annual electrification forecasts are transformed into half-hourly data is important because this will determine the impact of electrification on minimum and maximum demand. This is described in more detail in **Box 2**.

22 To view historical contributions to maximum and demand and consumption:

- Navigate to http://forecasting.aemo.com.au/Electricity/MaximumDemand/Operational
- Select ISP 2022, NSW, Step Change scenario, Summer, POE10
- Click the "CSV" button to download data file
- Filter downloaded data on 'Actual'

Figure 45: Fuel share in residential buildings 2020-2050, CSIRO

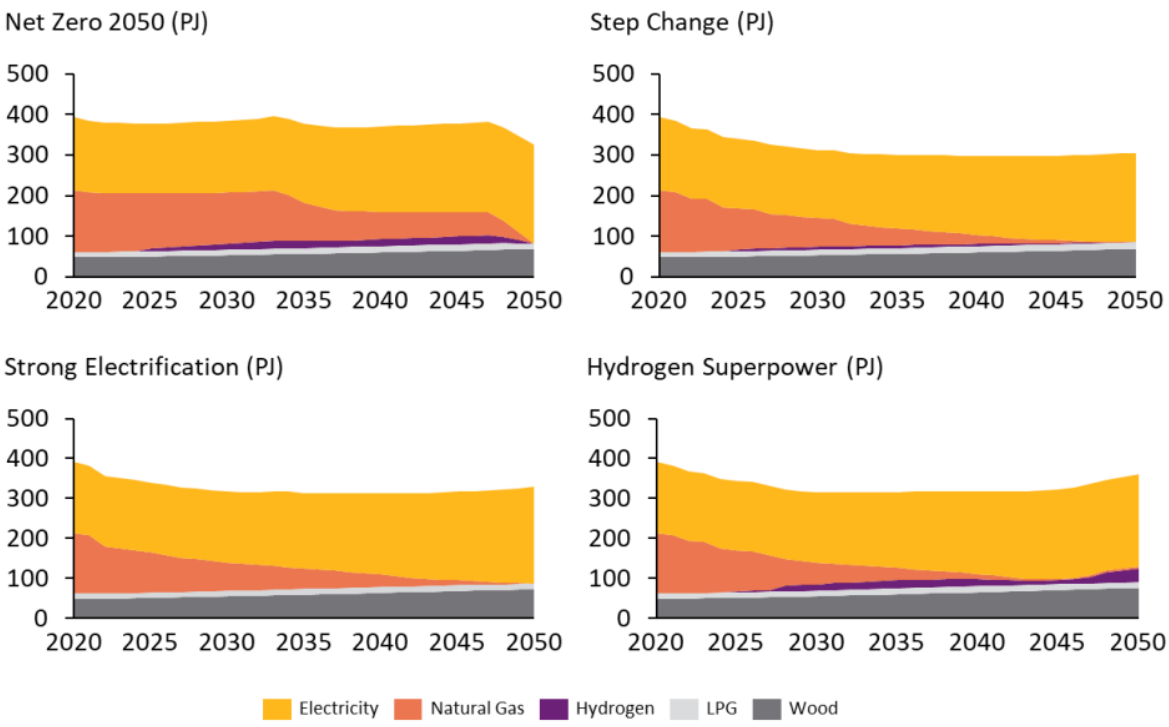


Figure 3-9: Fuel share in residential buildings across the four scenarios

Source: CSIRO [Multi Sector Modelling 2021](), pp51

Box 2: AEMO's load profile assumptions for electrification

"In converting the electrification consumption (excluding the transport sector) into half-hourly data, AEMO assumes:

- *Business consumption shows relatively low seasonality, on aggregate, and therefore electrification of the business sector (including industrials) is treated as a baseload.*
- *Residential electrification is primarily driven by gas to electricity fuel switching. To maintain the inherent seasonality of heating loads, AEMO assumes that electrified loads maintain the shape of consumption commensurate with the current residential and small commercial ("Tariff V") gas loads. This maintains the weather-induced consumption patterns on a daily basis, ensuring higher winter heating load than summer.*
    a. *apply half-hourly temporal resolution, the shape of the newly electrified loads is assumed to mirror existing electricity consumption patterns for that day, generally with more load in the day than overnight."*

Source: AEMO 2021 Inputs, Assumptions and Scenarios Report, pp45-46

3.4.3 Our approach

Electrification of gas

In order to forecast the impact of electrification of gas on minimum and maximum demand and consumption, we combine AEMO's/CSIRO's forecasts of annual electrification loads with AEMO's assumptions of how these impact 30-minute load profiles.

AEMO/CSIRO provide these forecasts on a regional basis. To determine Essential Energy's share of the NSW load impact, we pro-rate the NSW forecast down using Essential Energy's share of NSW gas consumption, given that electrification is primarily driven by gas consumption. We use gas consumption by LGA within Essential Energy's service area published by Jemena and gas consumption within Australian Gas Networks NSW gas business published by Australian Gas Networks. This places Essential Energy's share of NSW gas consumption in 2020/21 at around 12%.

AEMO's forecasts assume a significant increase in electrification in the short term. Given the characteristics of Essential Energy's service area we expect the increase in demand associated with electrification may take more time to emerge. We therefore gradually ramp up electrification over 5 years.

To allocate electrification to TNI/ZSSs, we further pro-rate the business and residential load down according to annual consumption by business and residential customers. Essential Energy provided us with data on tariff types by meter, which enabled us to aggregate consumption by customer type.

In pro-rating to the Essential Energy network area, and down to the TNI/ZSS level, we maintain AEMO's assumptions about how annual consumption figures are converted into half-hourly profiles, as discussed in **Box 2**.

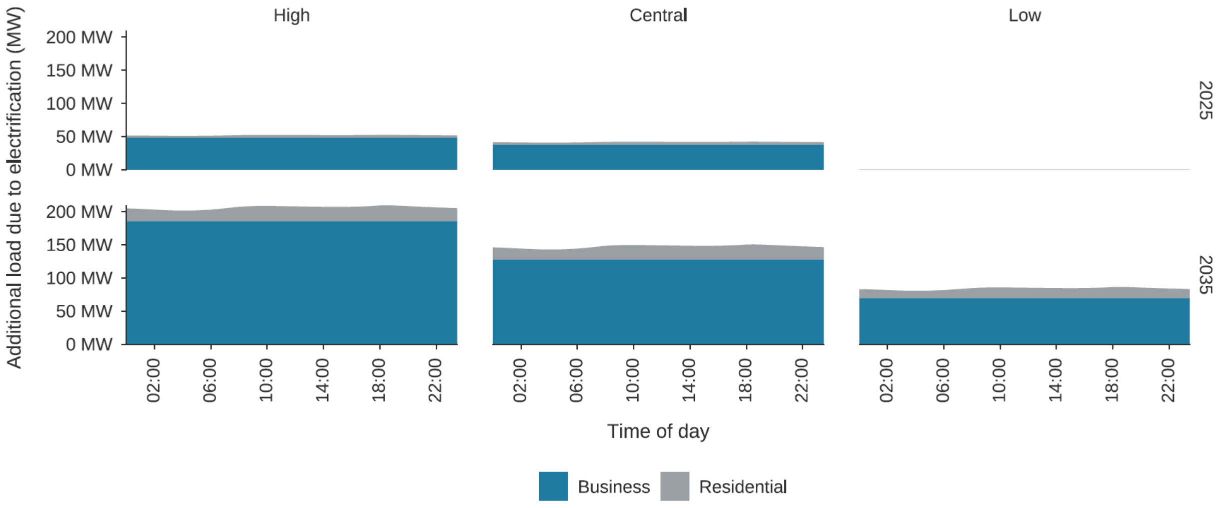
3.4.4 Result

Figure 46 shows the average electrification demand across the Essential Energy network for the high, central, and low case for 2030. The figure shows that the majority of electrification demand is attributable to business, rather than residential, customers.

Figure 47 and **Figure 48** show the contribution of electrification to summer and winter aggregate maximum demand for the scenarios and POE cases modelled. Since most electrification comes from businesses and the load profile of this additional electricity is assumed to be flat, the contribution to maximum demand is fairly consistent with the growth in electrification. A small amount of variation occurs due to the residential load profile, but this is only a minor part of electrification as a whole.

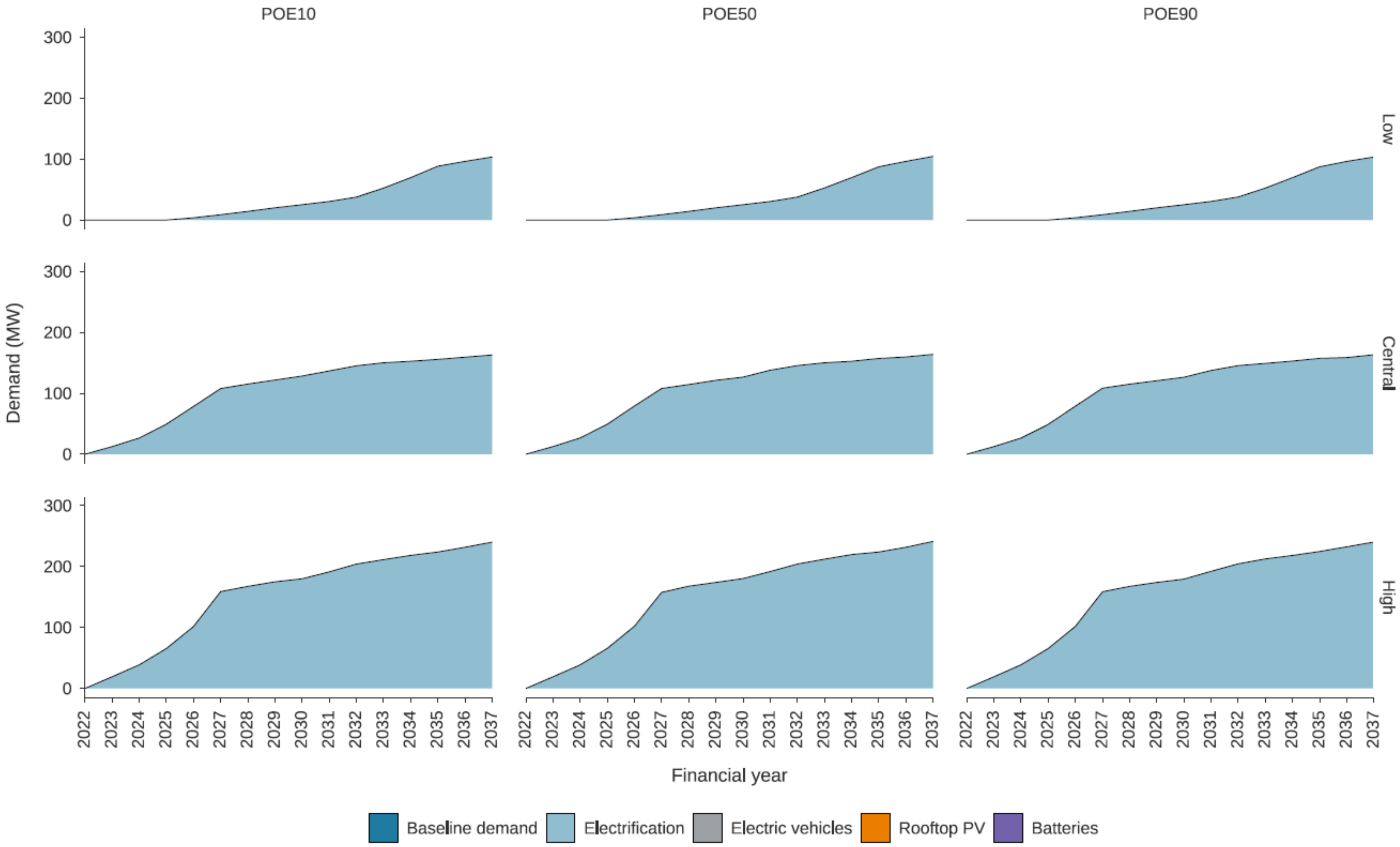
Figure 49 and **Figure 50** show the contribution of electrification to summer and winter aggregate minimum demand for each scenario for POE10, 50 and 90. The analysis shows that, similar to EVs, electrification has the potential to play a significant and increasing role in offsetting minimum demand.

Figure 46: Average electrification profile for business and residential customers across Essential Energy's network



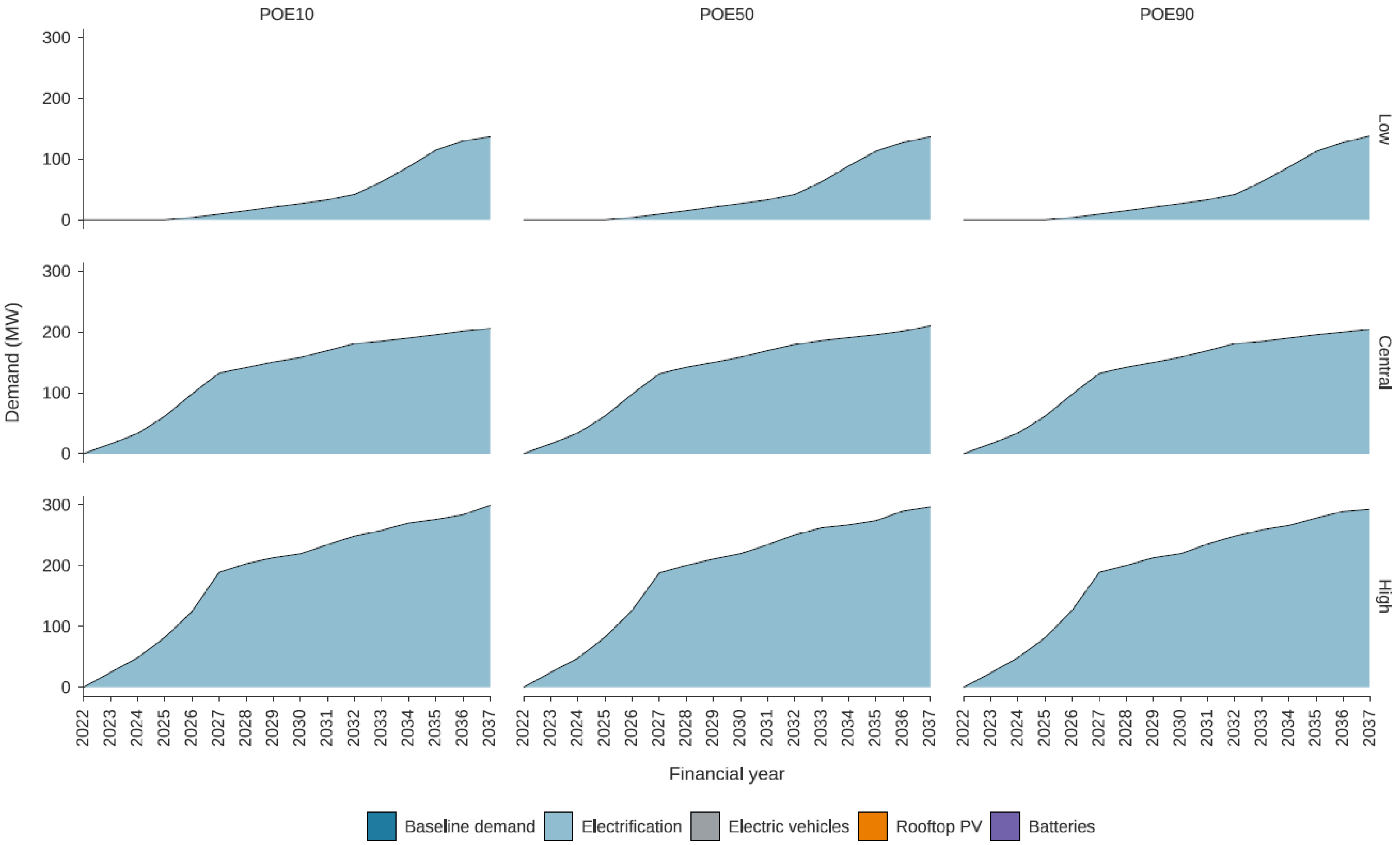
Source: Frontier Economics analysis

Figure 47: Contribution of electrification to aggregate summer maximum demand



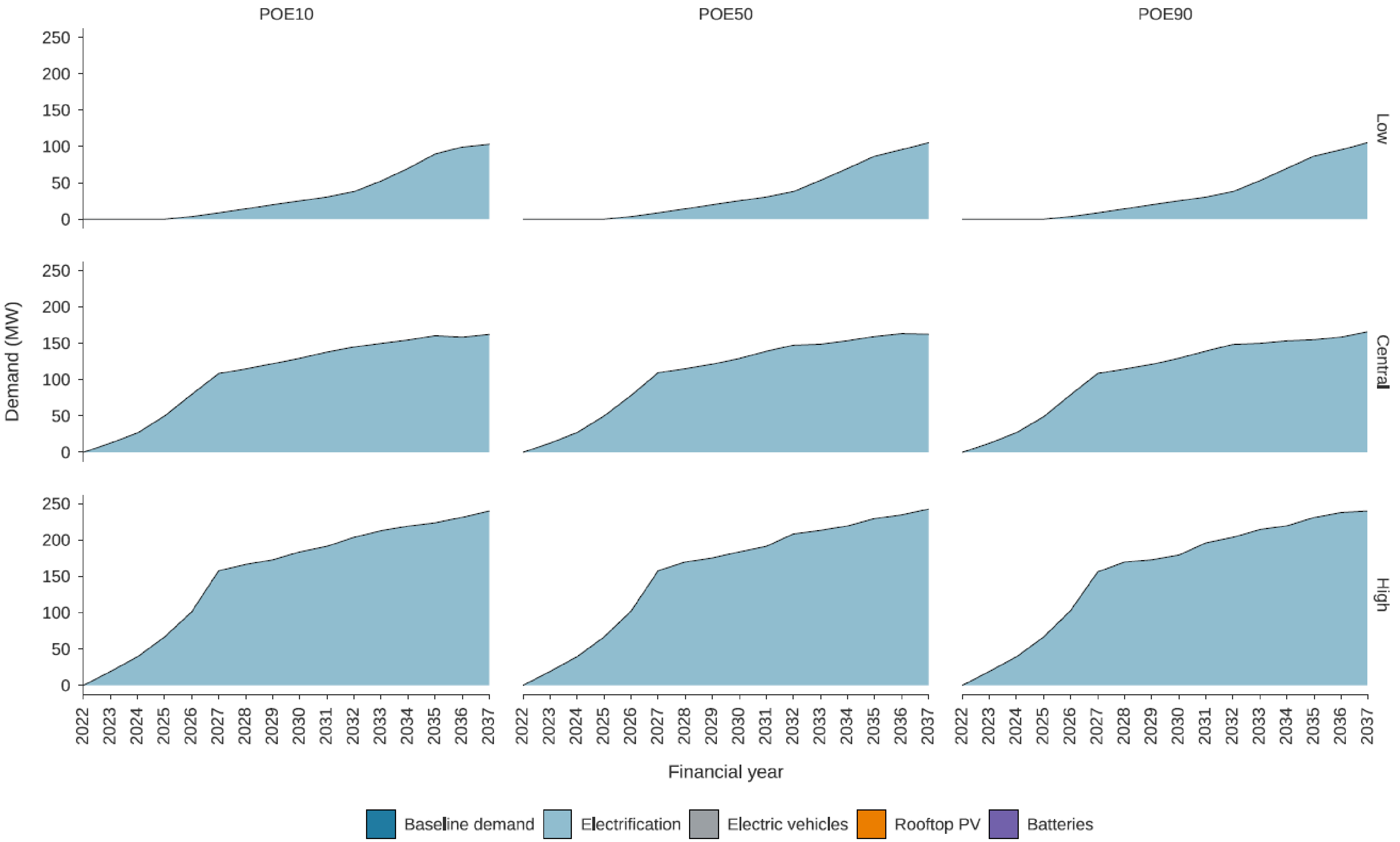
Source: Frontier Economics analysis

Figure 48: Contribution of electrification to aggregate winter maximum demand



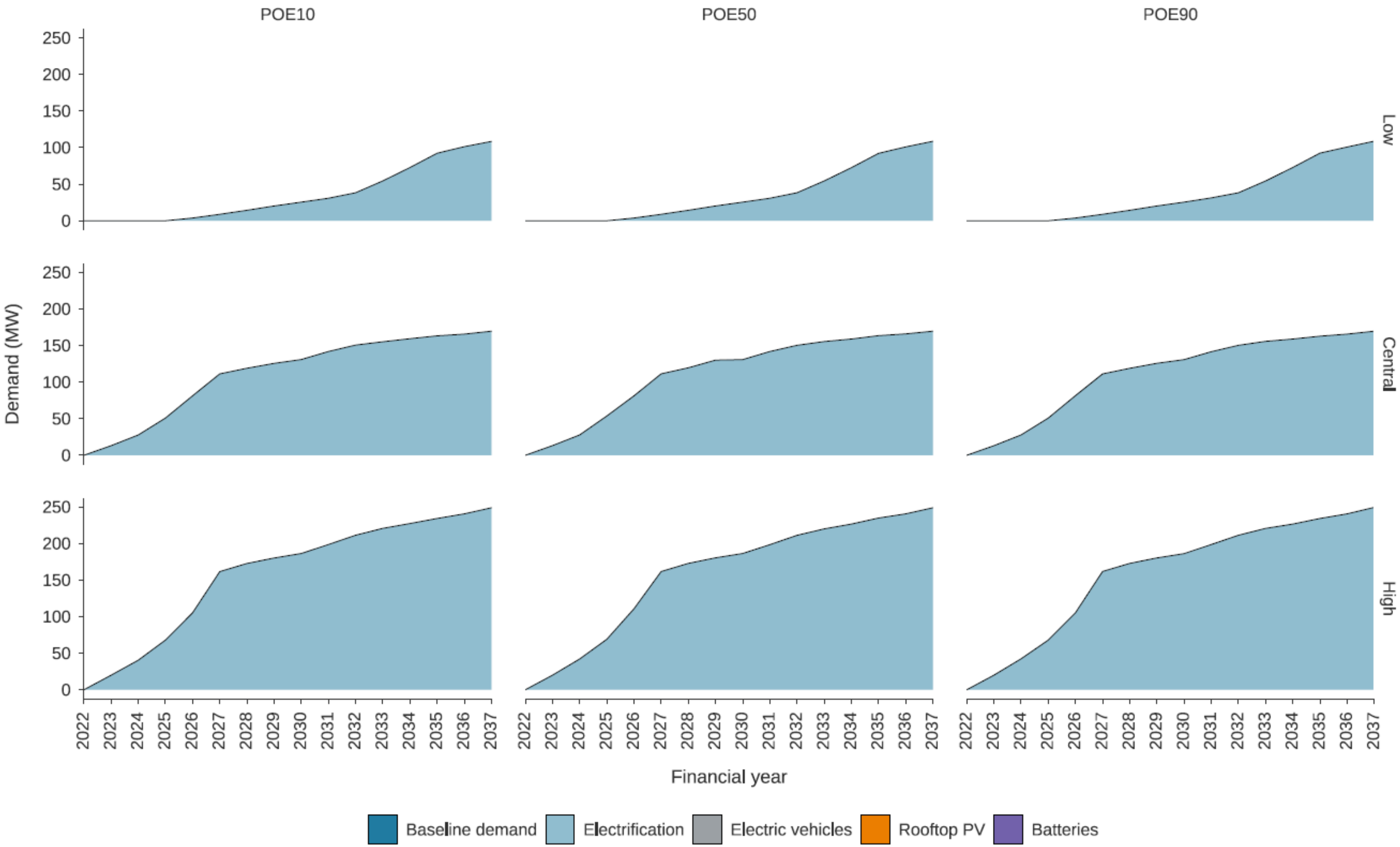
Source: Frontier Economics analysis

Figure 49: Contribution of electrification to aggregate summer minimum demand



Source: Frontier Economics analysis

Figure 50: Contribution of electrification to aggregate winter minimum demand



Source: Frontier Economics analysis

4 TNI and ZSS consumption forecasting

This section details the methodology used to generate consumption forecasts for each Bulk Supply Point (BSP) and Zone Substation (ZSS), up until the 2037 financial year.

We provide the following forecasts up to the 2037 financial year:

- Consumption forecasts for each of the 75 active BSP's, where electricity is delivered from the transmission network to the distribution network, denoted by a Transmission Node Identifier (TNI)
- Consumption forecasts for each of the 348 active ZSS's, where electricity is received from the bulk supply points and transformed for distribution along powerlines or underground cables through the distribution network.
- For both ZSS's and BSP's, we provide forecasts both with and without the effects of PV generation.

We provide further detail on the data and methodology used to generate the forecasts in Appendix A.

4.1 Data and methodology overview

Essential Energy provided Frontier Economics with historical consumption and customer data to inform our analysis:

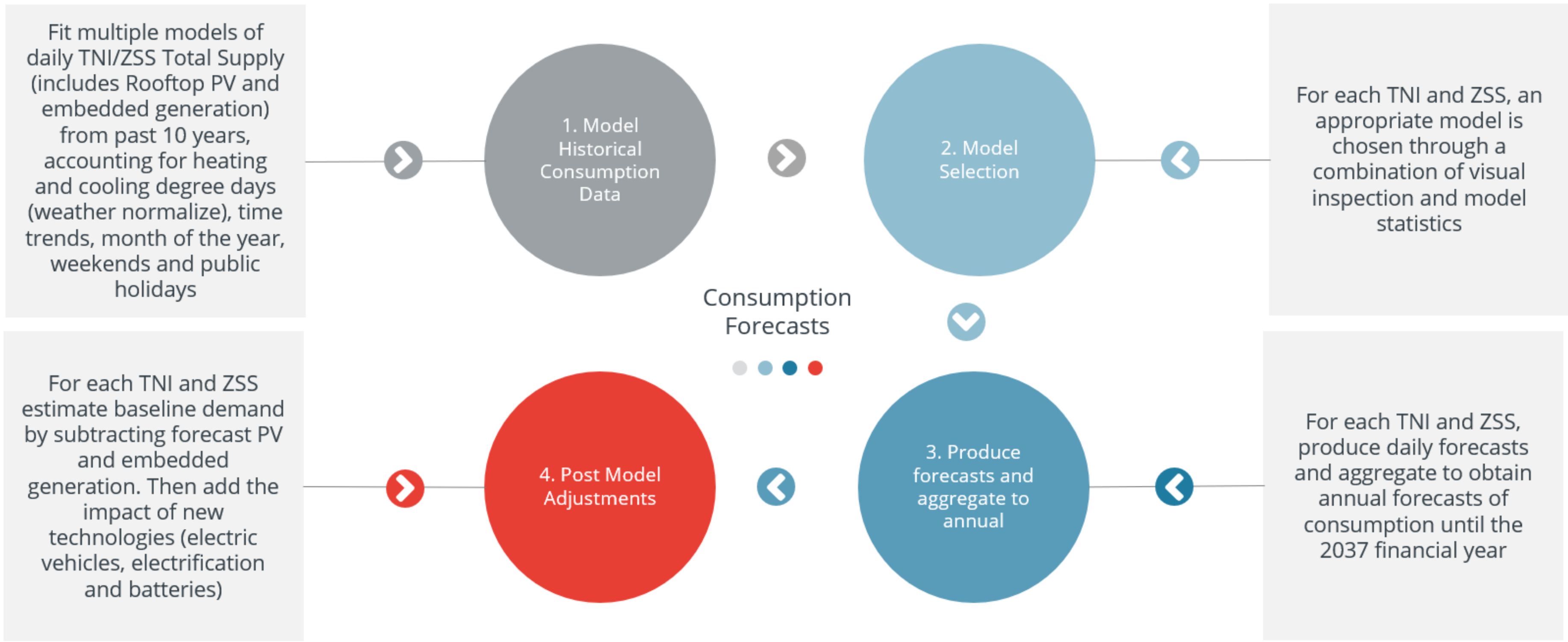
- Half-hourly demand by TNI over the period from July 2009 to February 2022, which we aggregated to daily to forecast consumption
- Half-hourly demand by ZSS over the period from July 2010 to September 2021, which we aggregated to daily to forecast consumption.

In preparing this data for analysis we excluded observations where there were negative consumption values after accounting for rooftop PV and embedded generation, there was significant evidence of inactivity, and outliers. The historical data is adjusted to consider self-generated PV and embedded generation to approximate underlying consumption.

In modelling the changes in underlying consumption, we account for factors such as local weather conditions. We utilised half hourly weather data from the Bureau of Meteorology (BOM), geo-mapping the BSPs and ZSSs (site) to the nearest weather station with sufficient data for the relevant period. The particular methodology following in data cleaning is described in **Appendix A.**

Using the data described above, we forecast the electricity consumption for the period 2022-2037 in four stages, as described in **Figure 51**.

Figure 51: TNI and ZSS forecasting methodology



Source: Frontier Economics

As the various sites exhibit differing consumption behaviour, each site was forecast independently. Each site was modelled using econometric models which accounted for time trends, heating degree days, cooling degree days, as well as other time characteristics. The results of each model were analysed, and the best performing model was selected. The appropriateness of model fit was determined subjectively based on a set of criteria: logical economic significance of relevant factors, sensible time trends, statistical model fit. Preference was given to simple models that were able to capture the changes in historical data, without producing unrealistic forecasts for the future. See **Appendix A** for detail on the model specification.

The selected models were then used to generate fitted weather normalised consumption estimates for the remaining years in the period at the daily level. Daily consumption forecasts were aggregated by financial year to give total forecast underlying consumption per site for each year across 2022-2037.

Since we model underlying consumption, we need to adjust the historical data to consider self-generated PV and embedded generation, as discussed in Section 3.1. Post-model adjustments were then made to consider the impact of new technologies. As discussed in Section 2 this involves adjusting underlying consumption to:

- Remove the impact of self-consumed PV (for invoicing, TNI and ZSS data) and embedded generation (for TNI and ZSS data)
- Forecast underlying consumption
- Add back self-consumed PV and embedded generation to forecast baseline demand
- Add the impact of EVs, batteries and electrification

The final forecasts at the TNI and ZSS level are reported at the Total Supply (Includes Generation and PV) and Total Supply net of PV.

To model electricity usage at the daily level the half hourly data is then aggregated by summing the total MW load across the day.

To determine the impact new technologies will have on consumption for each TNI and ZSS, we use our estimates for batteries, electric vehicles and electrification, as described in Sections 3.2.1, 3.3.1 and 3.4.1, respectively. The half-hourly profiles were aggregated to the annual level, to determine the increased consumption due to electric vehicle uptake and electrification.

Depending upon where an embedded generator is located, it may decrease the amount of electricity metered at a TNI or ZSS. To determine the impact of embedded generation on Essential Energy's network area, we split embedded generation into existing generation and future generation. To forecast their impact, we:

- Calculate an average capacity factor for each **existing embedded generator**, and assume they will continue to generate at this capacity factor in the future, and;
- Assume that any **future embedded generators** with a connection agreement will generate according to the average NSW large scale wind or solar profile, depending upon its type. Essential Energy provided the list of future embedded generators, as well as the connection point.

Large loads are customers who consume a particularly large amount of electricity, and typically require special network infrastructure to service. For our analysis we assume that existing large loads continue to consume electricity at the rate they have historically. Modelling future large loads is complex given the uncertainty associated with the nature and timing of these loads and the potential to double count increases in load reflected in the historical data and post-model adjustments such as electrification. We therefore undertake a sensitivity on potential future large loads and their contribution to consumption.

If hydrogen is to become a large part of NSW's energy mix in the future, hydrogen electrolysers are expected to provide most of the hydrogen required. To generate hydrogen, electrolysers require large amounts of electricity, which is likely to come from renewable generation. We expect most electrolysers to be connected to the transmission network, rather than distribution networks. As a result we assume a limited number of hydrogen electrolysers will be connected to Essential Energy's network area, and most of them co-located with renewables. This means the amount of electricity hydrogen electrolysers consume from Essential Energy's network is likely to be small and of most relevance to minimum demand. Given the uncertainty over future hydrogen loads we analyse the potential impact via a sensitivity on minimum demand, as we discuss in Section 6.3.

The results of our analysis are presented in Section 4.2.

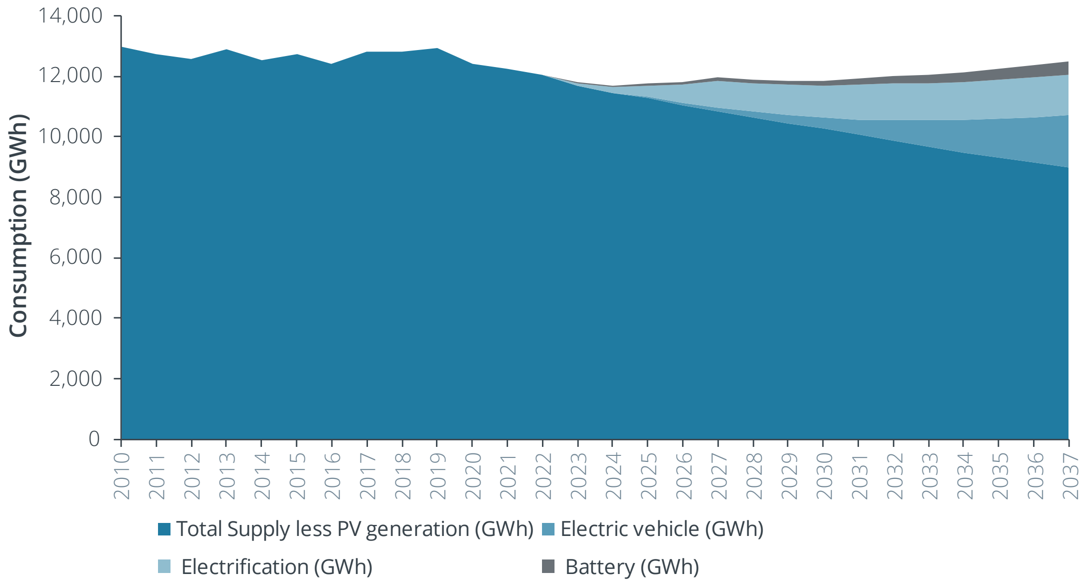
4.2 Results

We forecast consumption for each TNI and ZSS. **Figure 52** and **Figure 53** show forecast consumption for all TNIs and ZSS, respectively. The analysis shows baseline consumption (consumption excluding PV) is declining over the period, reflecting the increasing penetration of rooftop PV and embedded generation. This decline is offset by the significant increase in consumption associated with electrification, EVs and batteries.

Consumption for all TNIs is forecasted to bottom out in 2024 at 11,789 GWh before increasing to 12,941 GWh by the year 2037. This represents a net increase in consumption of 5.7% in 2037 compared to 2021 actuals. The analysis shows electrification ramps up relatively quickly and makes a consistent contribution to consumption over the forecast period. The contribution of EVs to consumption ramps up over the forecast period, reflecting the gradual take up of EVs.

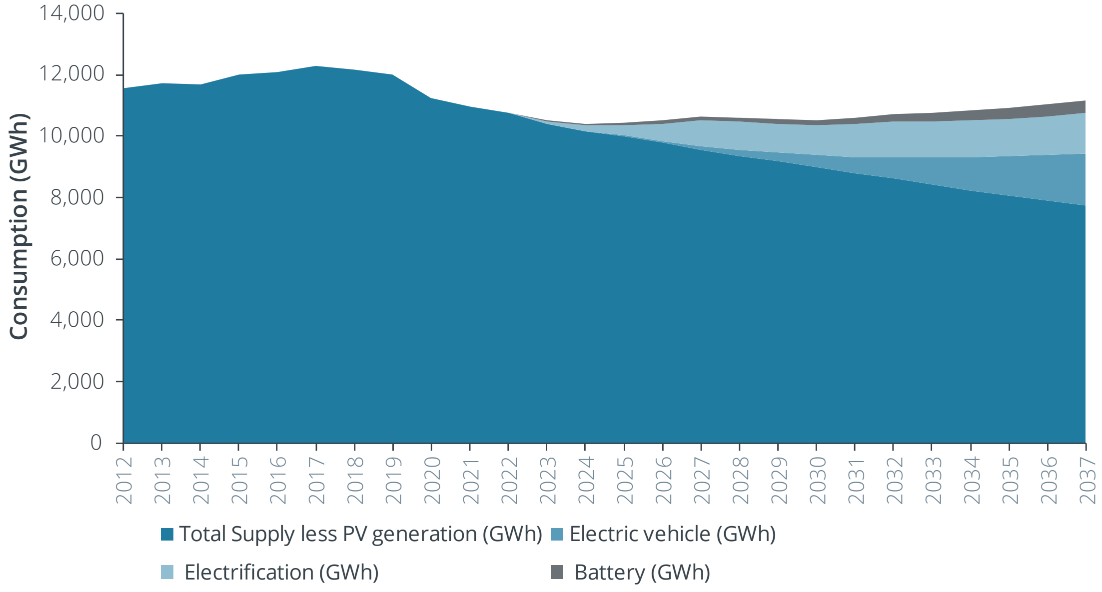
Aggregate consumption across all ZSS is forecast to fall by 4.6% from 10,961 GWh in 2021 to a low of 10,459 GWh in 2024. In 2037 ZSS consumption is forecast to be 11,617 GWh, or 6.0% higher than 2021. Similar to TNIs, electrification and EVs drive this profile over time.

Figure 52: Forecast TNI consumption



Source: Frontier Economics analysis

Figure 53: Forecast ZSS consumption



Source: Frontier Economics analysis

4.3 Sensitivities

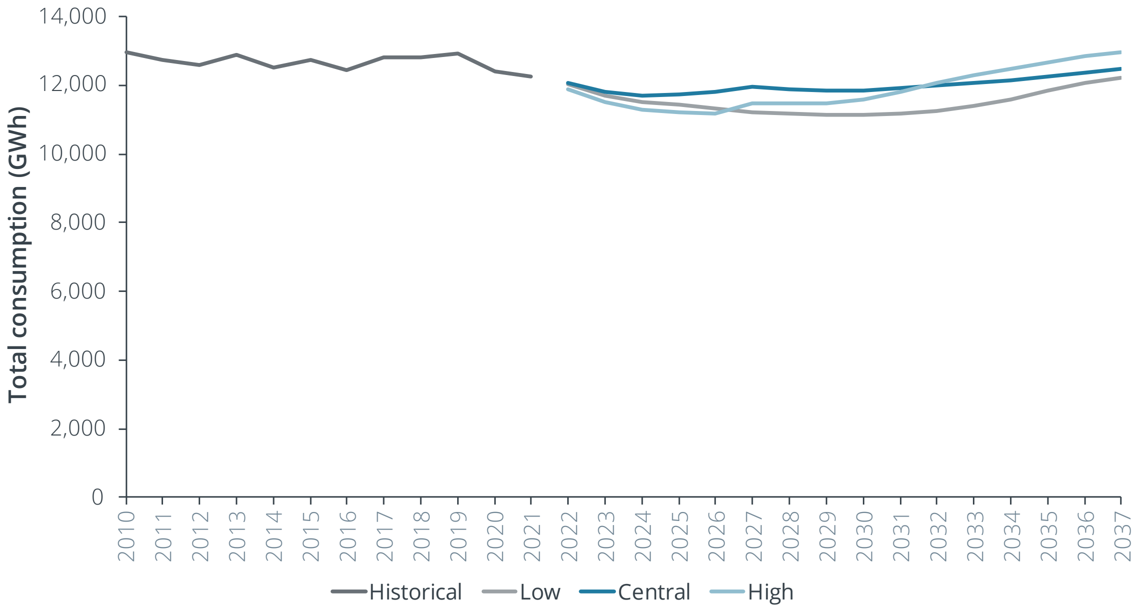
4.3.1 New technologies

The results presented above were based on AEMO's Step Change scenario. We conducted two sensitivities to test the impact of changes in these assumptions:

- A low case based on AEMO's Progressive change scenario
- A high case based on AEMO's Strong electrification scenario.

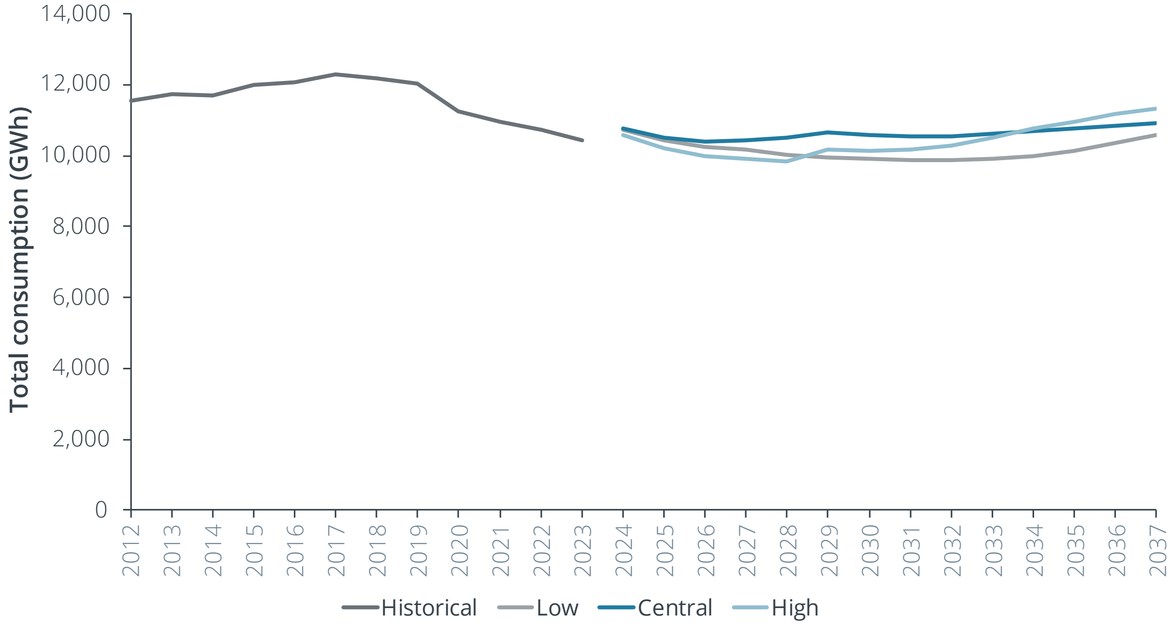
The results of the analysis for TNI (**Figure 54**) and ZSS (**Figure 55**) consumption are presented below. The analysis demonstrates there is inconsistent growth across the low, central and high scenarios over the forecast period, driven by uptake rates of rooftop PV, electric vehicles and electrification. At the end of the forecast period, TNI consumption under the low case is 2.1% lower than central, and consumption under the high case is 3.8% higher than central. Similarly, ZSS consumption under the low case is 3.1% lower than central, and consumption under the high case is 3.7% higher than central. **Figure 56** to **Figure 59** shows the breakdown of the new technology components (i.e., EV, electrification and batteries) for the low and high scenarios, for both TNI and ZSS total consumption.

Figure 54: TNI consumption compared across scenarios



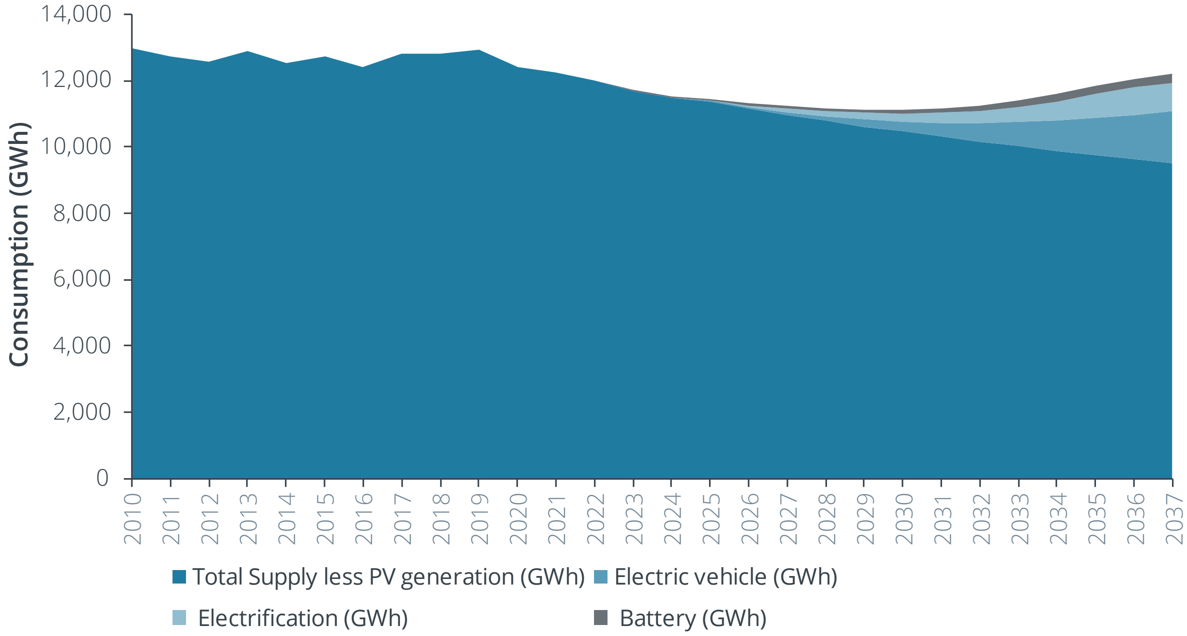
Source: Frontier Economics analysis

Figure 55: ZSS consumption compared across scenarios



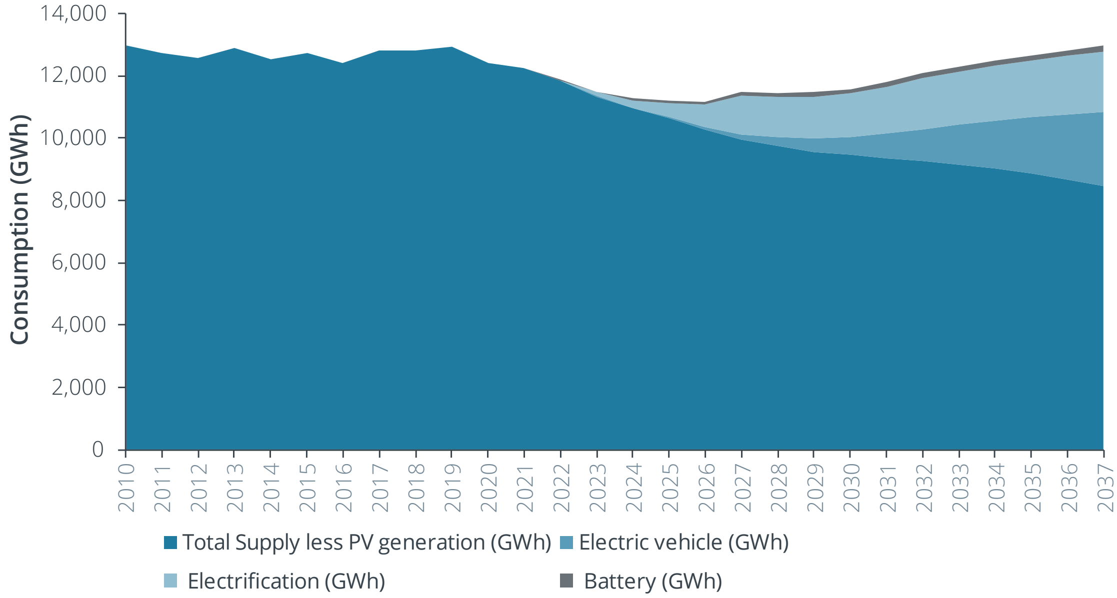
Source: Frontier Economics analysis

Figure 56: TNI consumption: low new technologies case



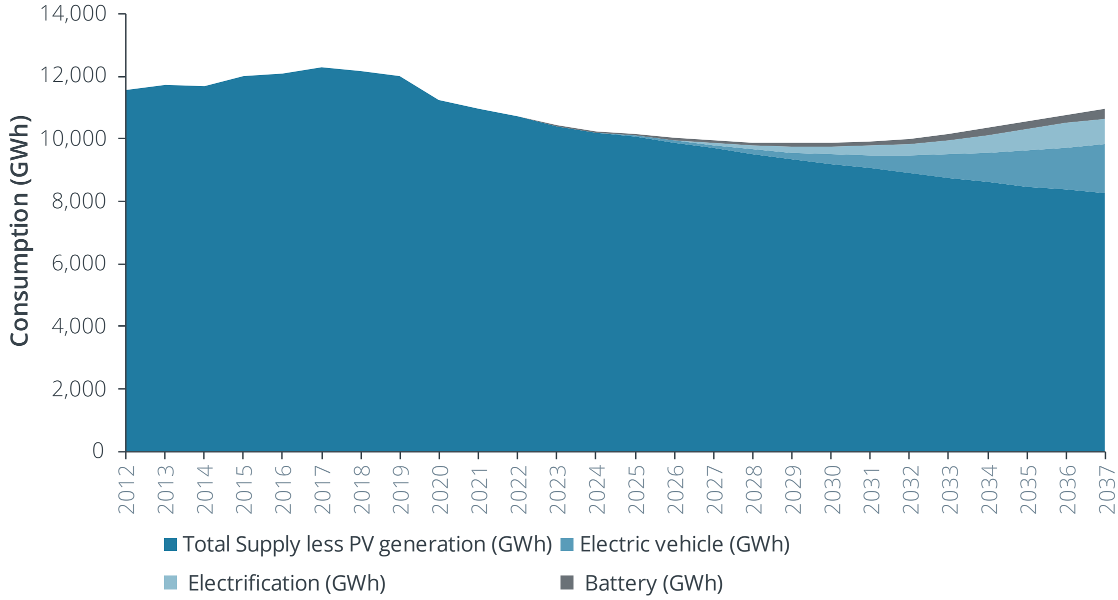
Source: Frontier Economics analysis

Figure 57: TNI consumption: high new technology technologies case



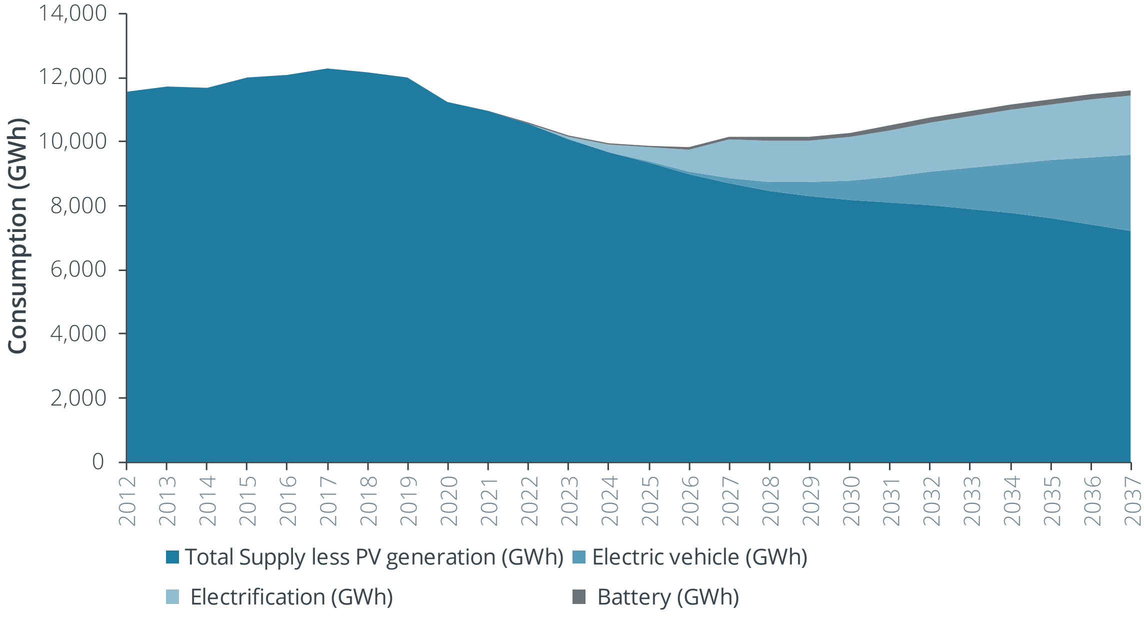
Source: Frontier Economics analysis

Figure 58: ZSS consumption: low new technologies case



Source: Frontier Economics analysis

Figure 59: ZSS consumption: high new technologies case



Source: Frontier Economics analysis

5 Invoiced consumption and maximum demand

This section details the data and methodology used to generate forecasts for customer numbers, invoiced energy consumption and invoiced maximum demand, up until the 2037 financial year.

We provide the following forecasts up to the 2037 financial year:

- Invoiced consumption, max demand and customer numbers for each customer segment (e.g., LV Business Continuous, HV Demand etc[23]) and tariff class (e.g., BHND1CO, BLND1CO) including export tariffs.
- For each customer segment and tariff, the consumption allocated to each billing component e.g., Off Peak, Shoulder, Off-Peak.
- For each customer segment and tariff, the maximum invoiced demand for each billing component e.g., Off Peak, Shoulder, Off-Peak.

We discuss in turn below the forecasting of customer numbers, invoiced consumption and maximum demand.

Further detail on the data and methodology used to produce the forecasts is presented in **Appendix B**.

5.1 Customer numbers

5.1.1 Data and methodology overview

Essential Energy provided Frontier Economics with historical monthly customer numbers by tariff category over the period from July 2008 to January 2022. This data was not geographically identified, only reporting total customer numbers across the Essential Energy network by tariff category. The monthly series is aggregated to the financial year for model fitting.

For each customer segment (e.g., business, residential, etc.) we considered both a short-term time series model (including only trend variables) and a long-term causal model (which relates customer numbers to macroeconomic drivers including population, dwelling numbers, electricity prices and gross state product (GSP). Data for these macroeconomics factors was gathered from the ABS. We selected the models that provided the best fit for each customer category. The short-term model uses a simple trend, and the long-term model accounts for GSP for business customers, and dwellings for residential customers. See **Appendix B** for a detailed description of the modelling methodology and selection criteria employed.

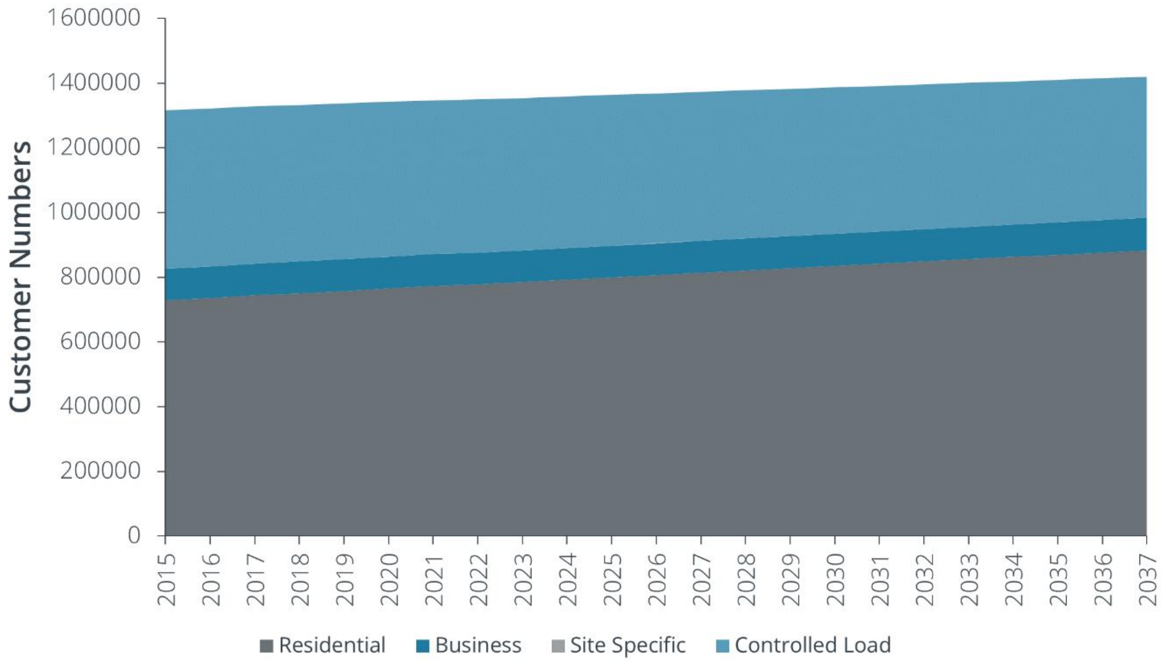
[23] The customer segments are LV Business Continuous, HV demand, Controlled Loads, LV Demand, LV Residential Continuous, LV Residential Demand, LV Residential TOU, LV Residential Interval TOU, LV TOU over 100 MWh/yr, LV TOU under 100 MWh/yr, Site Specific and Subtransmission. These customer segments are further segmented into 40 tariff classes.

Thee selected models were then blended to develop forecasts over the relevant period, adopting a weighting method consistent with AEMO's demand forecasting methodology. The forecasts utilised AEMO's forecast GSP data, and the forecast dwellings by ABS and DPI. The results of these models and forecasting are presented in Section 5.1.2 and are used in the modelling of invoiced consumption and maximum demand.

5.1.2 Results

Customer numbers are forecast to grow over the modelling period, consistent with the growth reflected in the historical data and the ongoing population growth in Essential Energy's service area (**Figure 60**).

Figure 60: Total invoiced customer numbers



Source: Frontier Economics

5.2 Invoiced consumption

5.2.1 Data and methodology overview

Essential Energy provided Frontier Economics with historical monthly invoiced consumption per connection the period from July 2008 to January 2022. The monthly series is aggregated to the financial year for model fitting, with no data cleaning required.

To forecast electricity consumption, we performed analysis on consumption per connection, where a customer is defined as an electricity connection. The forecasts for consumption per connection are then multiplied by the forecast customer numbers produced in Section 5.1 to get total forecast invoice consumption by customer segment.

In modelling consumption per connection, for each customer segment we considered both a short-term time series model and a long-term causal model. The models were selected and blended following the same methodology described for customer numbers in Section 5.1 and Appendix B.

The short-term model selected uses a simple trend, and the long-term model includes GSP for business customers, and dwellings for residential customers. Weather normalisation variables were also tested but showed no significance in modelling per connection consumption. This is likely due to there being not enough variation in the historical weather data when aggregated to the annual level.

Using the forecast GSP and dwelling data, the blended models were used to forecast invoice consumption per connection over the relevant period. Combining this with the customer number forecasts in Section 5.1, as well as the post model adjustment DER data described in Section 3 we produced the forecast total invoice consumption per customer type, presented in Section 5.2.2.

In addition, we also considered several sensitivities relating to population growth, new technology assumptions, and the addition of planned future large loads. The large load sensitivities rely on data provided by Essential Energy, described in Sections 0 and 6.3.

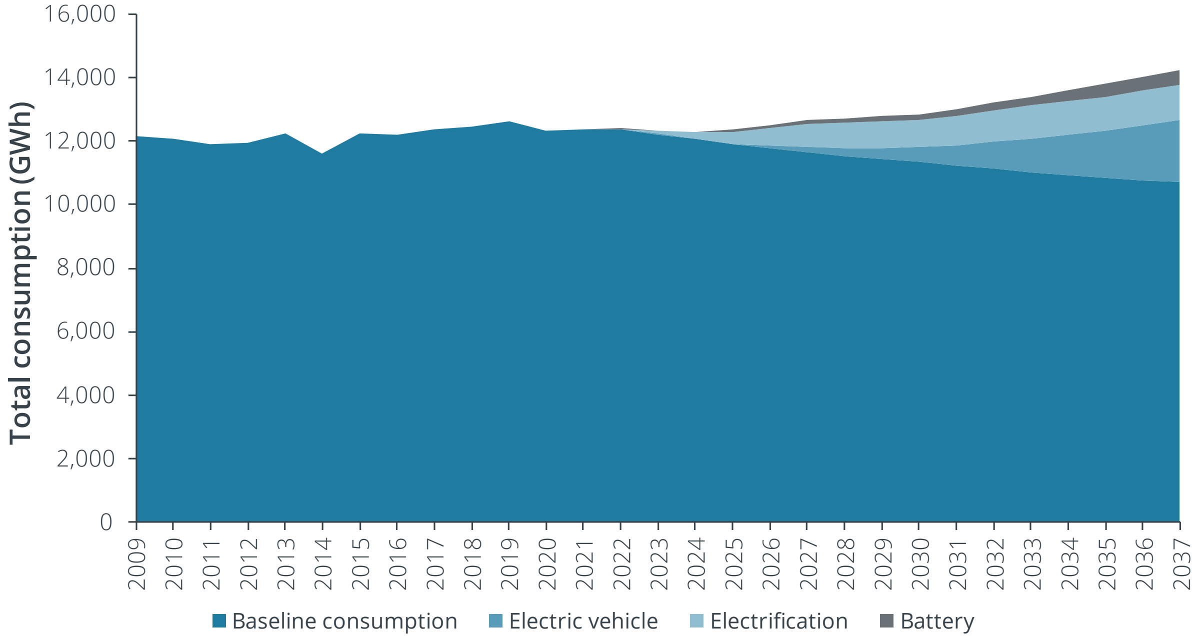
5.2.2 Results

Total invoiced consumption is forecast to increase over the period, driven by new technologies

Figure 61 presents total invoiced consumption across Essential Energy's network area. These results are not directly comparable to the TNI and ZSS forecasts, because invoiced consumption includes exported PV (which is consumed and invoiced to another customer), but TNI/ZSS consumption does not include any PV.

We forecast Essential Energy's consumption to be relatively steady in the near term and increasing over the longer term, largely reflecting the impact of new technologies on demand. Baseline consumption is forecast to continue to fall, consistent with historical trends in energy efficiency and increasing rooftop PV penetration. This reduction is offset over the forecast period by increasing customer numbers and increased demand driven by electrification and electric vehicles.

Figure 61: Total invoiced consumption

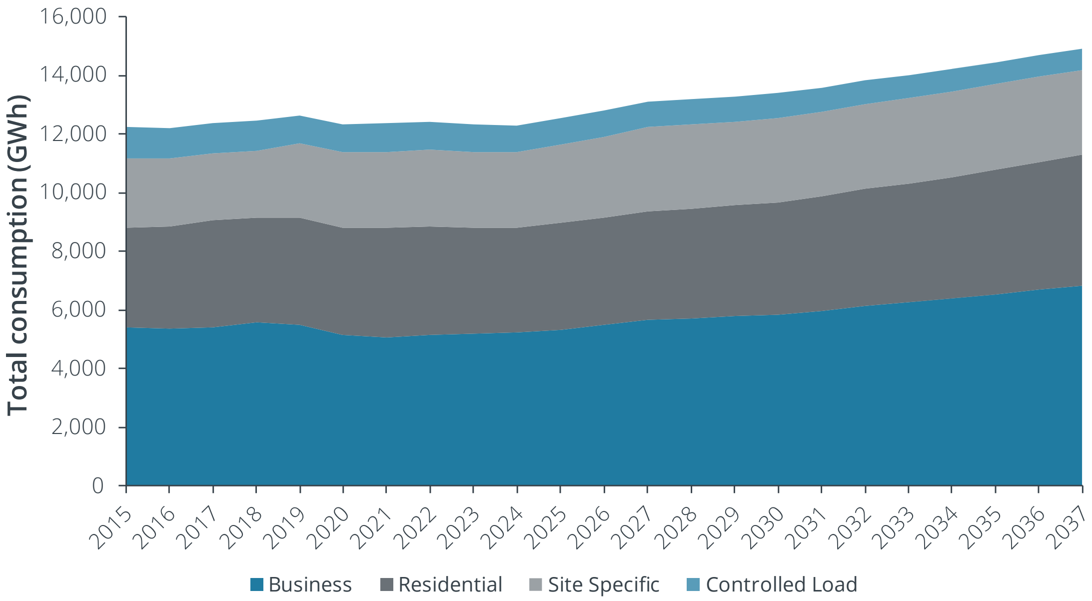


Source: Frontier Economics

Consumption by customer type is presented in **Figure 62**. Business consumption is increasing over the forecast period, primarily due to increased electrification. Residential consumption is expected to fall in the short term due to the continued uptake of rooftop PV, but increase towards the end of the forecast period as electric vehicle uptake increases. Controlled load is expected to decline reflecting the historical reduction in customer numbers.[24]

24 For the purposes of this analysis we assume switching away from controlled load is captured in the trend for residential consumption.

Figure 62: Total invoiced consumption by customer type

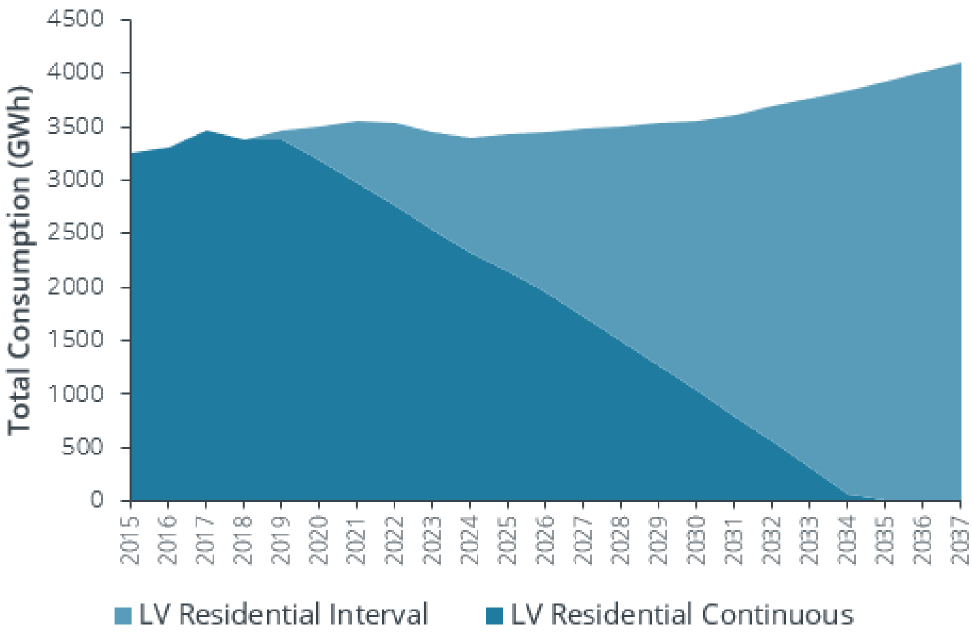


Source: Frontier Economics

Residential consumption over the period moves from predominantly LV continuous tariffs to time of use tariffs, requiring interval meters (see **Figure 63**), consistent with the forecast increase in penetration associated with smart meters over the modelling period. We forecast 90% of Essential Energy's customers will be using smart meters by 2033, slightly later than the target of 90% by 2030 set out in the AEMC's Directions Paper[25], but likely to be appropriate given the characteristics of Essential Energy's service area. We forecast residential consumption and then allocate between LV continuous and interval meters the assumed rate of uptake of interval meters.

25 AEMC, Review of the regulatory framework for metering services, Directions paper, September 2021.

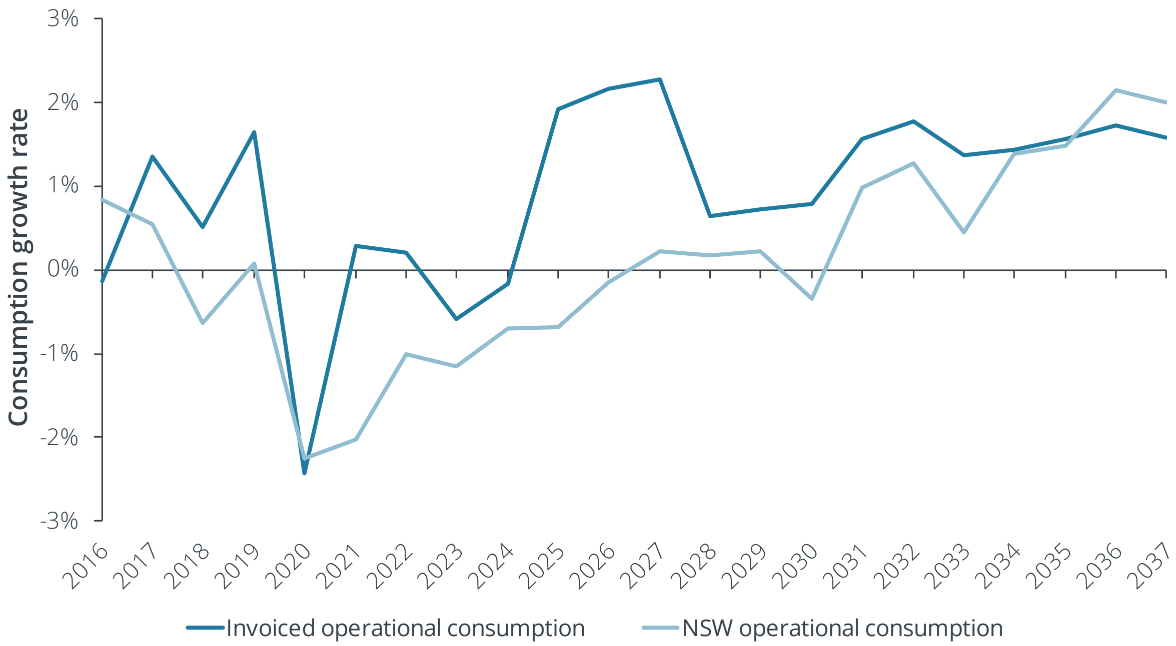
Figure 63: Transition from residential continuous to residential TOU interval consumption



Source: Frontier Economics analysis

Figure 64 compares the forecasts for invoiced consumption against AEMO's consumption forecasts. The analysis demonstrates our forecasts are consistent with the trends in AEMO's demand forecasts for NSW over the modelling period.

Figure 64: Comparison of forecast growth rates



Source: Frontier Economics Analysis

5.2.3 Sensitivities

We considered several model sensitivities for invoiced consumption forecasts. These include:

- The assumptions surrounding the integration and adoption of new technologies such as batteries, EVs and electrification
- The addition of planned future large loads
- An increase in population growth in Essential Energy's service area.

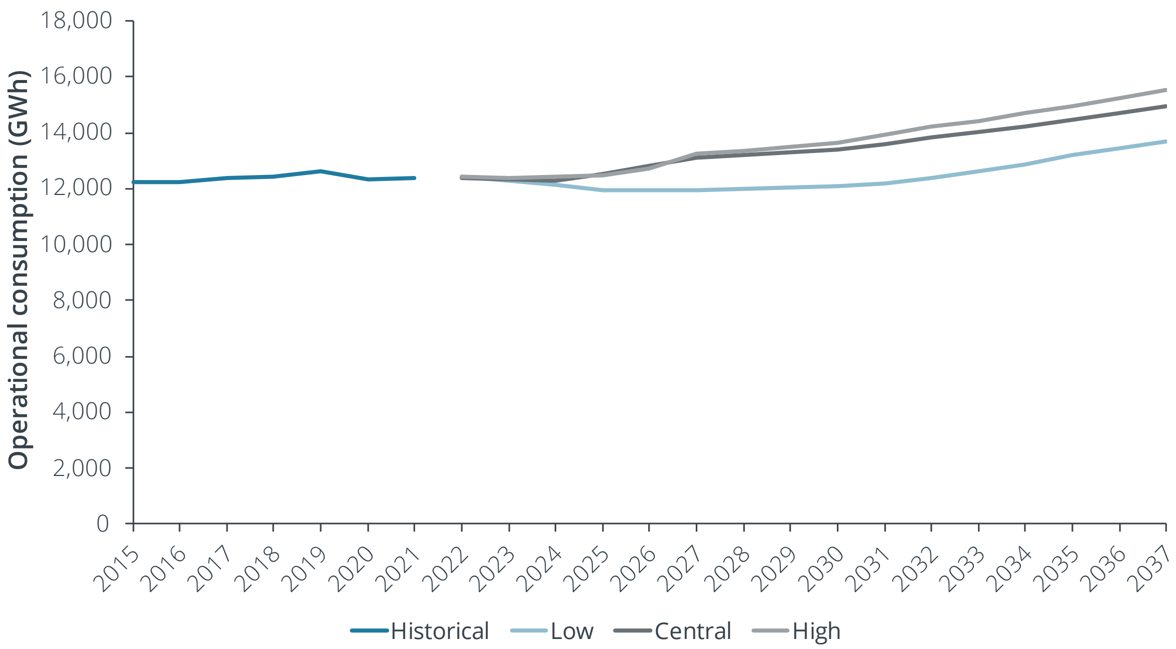
New technologies have an important influence on consumption

The results presented above were based on AEMO's Step Change scenario. We conducted two sensitivities to test the impact of changes in these assumptions:

- A low case based on AEMO's Progressive Change scenario
- A high case based on AEMO's Strong Electrification scenario.

The results of the sensitivities for invoiced consumption are presented in **Figure 65**, **Figure 66** and **Figure 67** below.

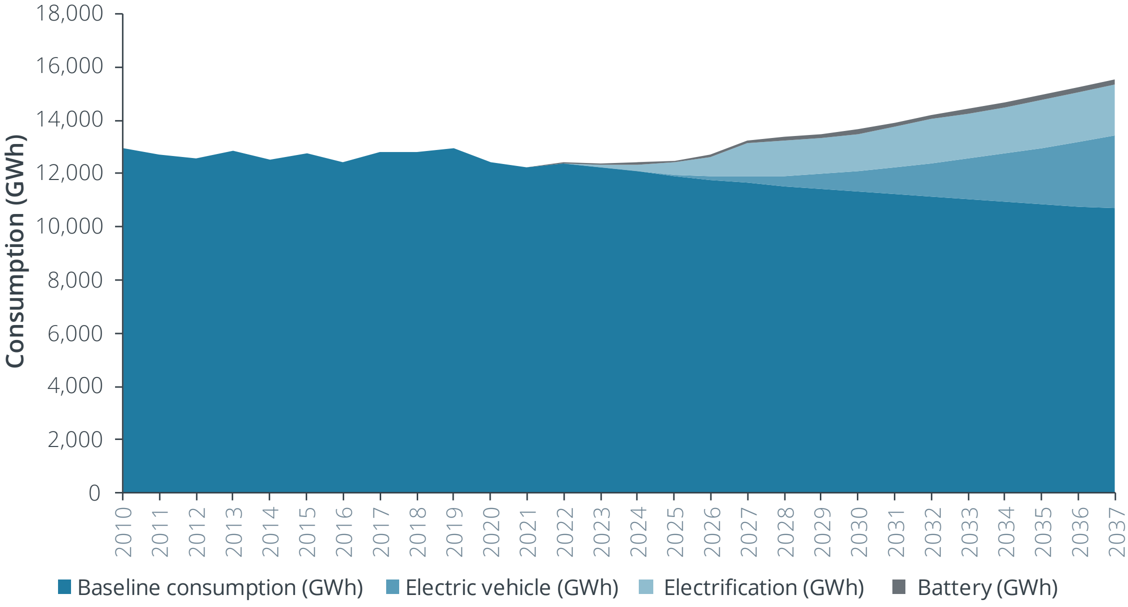
Figure 65: Invoiced consumption compared across scenarios



Source: Frontier Economics analysis

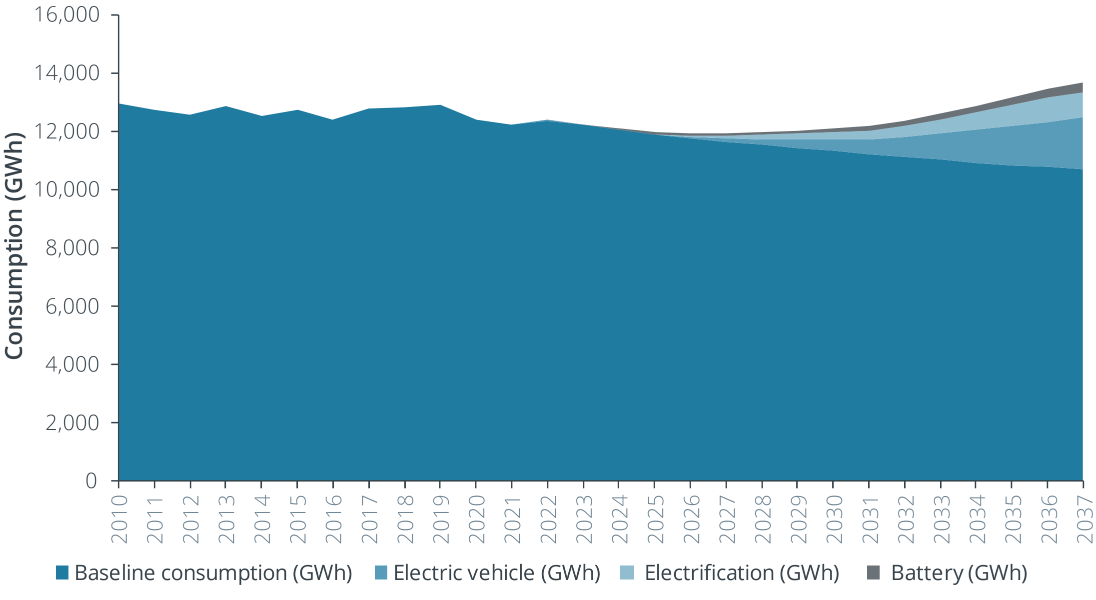
The analysis shows that compared to the central case, the low case results in consumption 8.4% lower by the end of the forecasting period and the high case results in consumption that is 4.2% higher by the end of the forecasting period. As for the TNI and ZSS consumption sensitivities, this is primarily driven by the impact of changes to PV on underlying demand, the contribution of electrification and the rate of EV uptake.

Figure 66: Invoiced consumption: high new technologies case



Source: Frontier Economics analysis

Figure 67: Invoiced consumption: low new technologies case



Source: Frontier Economics analysis

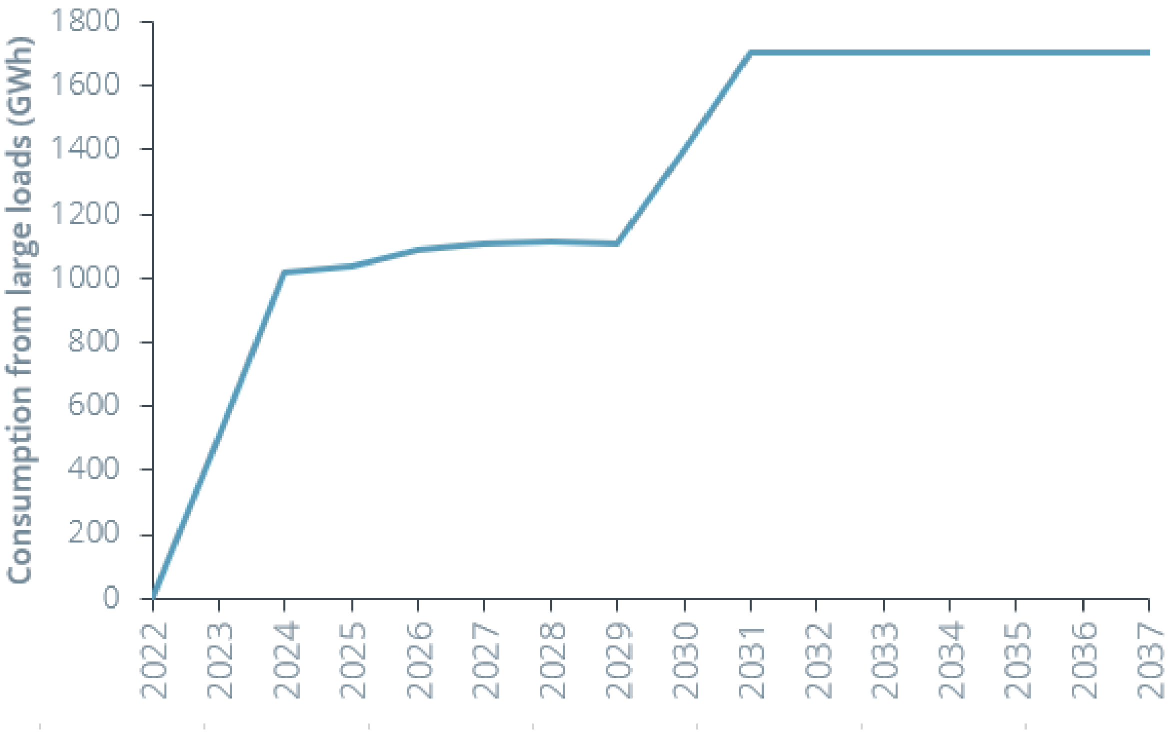
Large loads have the potential to add a significant amount to consumption

Accurately forecasting large loads is not straightforward given the uncertainty associated with the size and timing of large loads and the scope for double counting with load increases embedded in consumption forecasts. To address these concerns we did not include potential large loads in the central case, but undertook a sensitivity to assess the effect of large loads.

We obtained estimates of future large loads from Essential Energy. We used the connection capacity of future large loads as well as an assumed profile shape (business load or mining/flat load) to calculate the annual consumption of each large load. As illustrated in **Figure 68** forecast large loads are estimated to contribute an additional 1,000GWh per annum by 2025, increasing to over 1,500GWh by the early 2030s. This represents a very significant increment to Essential Energy's consumption. **Figure 69** shows the additional contribution to invoiced consumption from new large loads, including the proposed Special Activation Precincts in Wagga, Forbes and Moree.

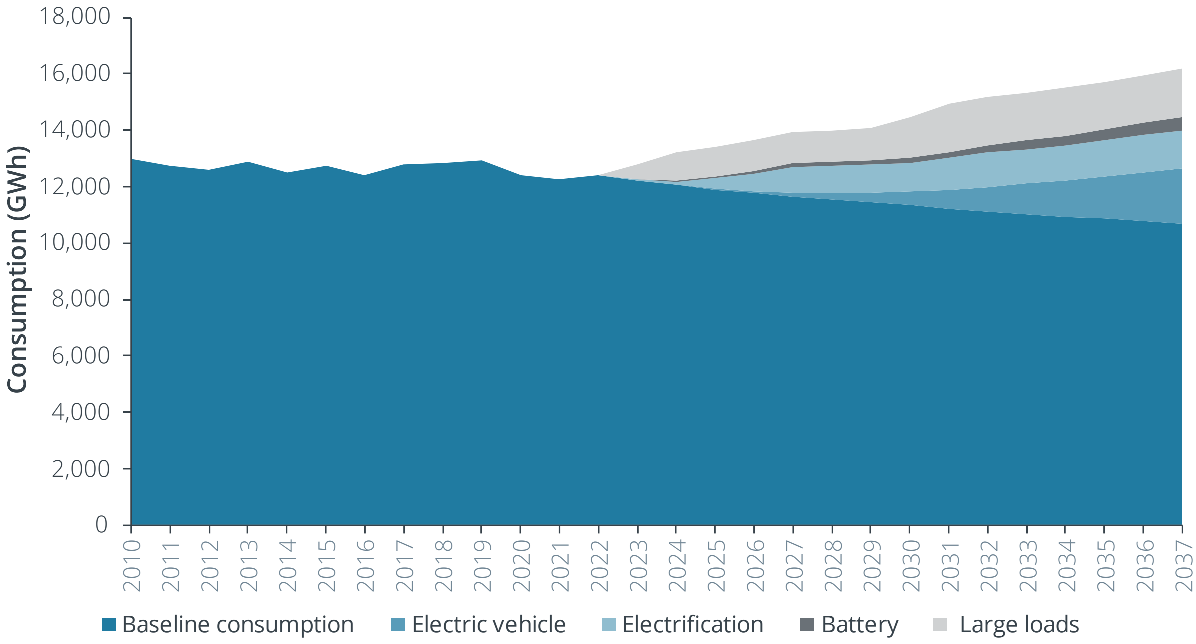
Large loads could to increase invoiced consumption by a significant 1,702 GWh or 11.4% by 2037.

Figure 68: Forecast large loads (including Special Activation Precincts)



Source: Frontier Economics analysis of Essential Energy data

Figure 69: Invoiced consumption including new large loads (including Special Activation Precincts)



Source: Frontier Economics analysis

Population growth has been strong in Essential Energy's service area; more rapid population growth will drive more rapid growth in consumption

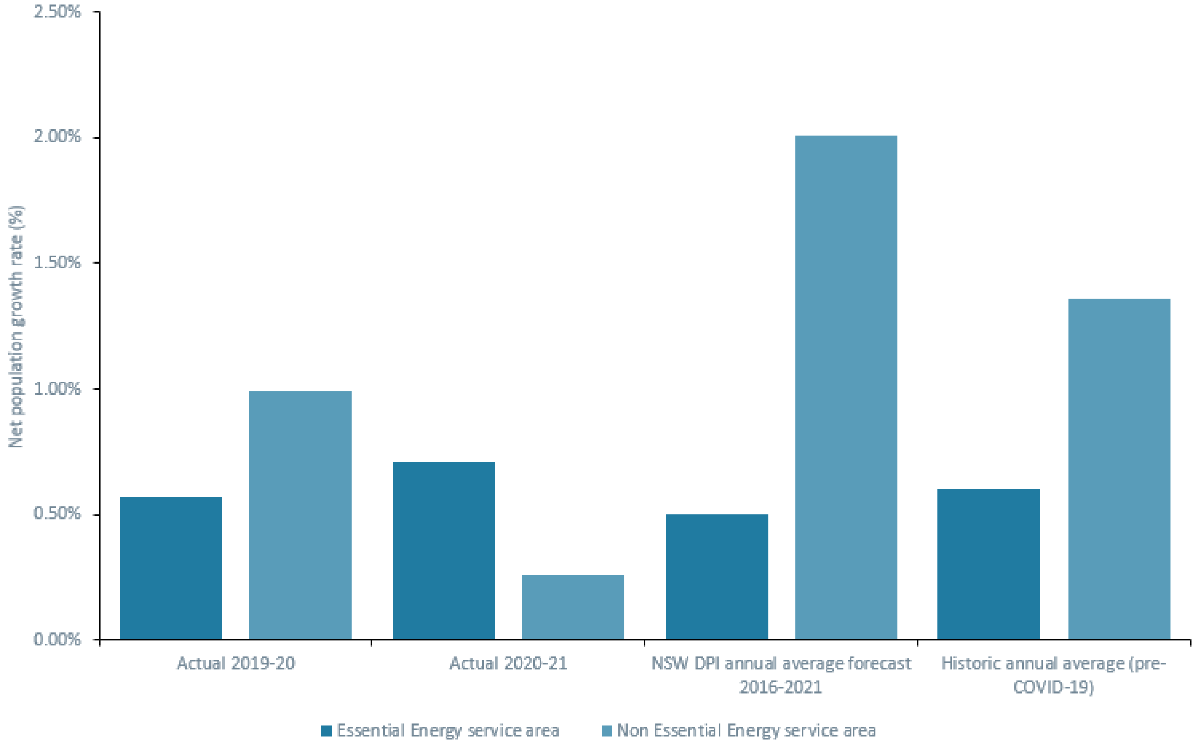
There is qualitative evidence of increasing regionalisation of Australia's east coast population during COVID-19. However, trends in Essential Energy's customer numbers have remained relatively steady over the last two financial years. Essential Energy are interested to explore the potential impact of regionalisation on consumption.

We considered the impact of COVID-19 on the NSW population and its distribution between Essential Energy's service area and those areas outside Essential Energy's service area by examining ABS population data at the LGA level. The analysis shows evidence of consistent population growth in Essential Energy's service area, compared to a considerable slowing in population growth for the rest of NSW.

In particular:

- Population growth in Essential Energy's service area was slightly higher than forecast for both 2019/20 and 2020/21, but broadly consistent with historical average
- Population growth in the rest of the state slowed to around half that forecast in 2019/20 and around a quarter of that forecast in 2020/21
- Population growth in the rest of the state has historically been and is forecast to be higher than that in Essential Energy's service area. This trend was reversed in 2020/21 when the population growth rate for Essential Energy's service area exceeded that for the rest of the state
- Total NSW population has been increasing; however, COVID-19 reduced the population growth rate of NSW significantly, primarily through a reduction in interstate and overseas migration.

Figure 70: Population growth in Essential Energy's service area

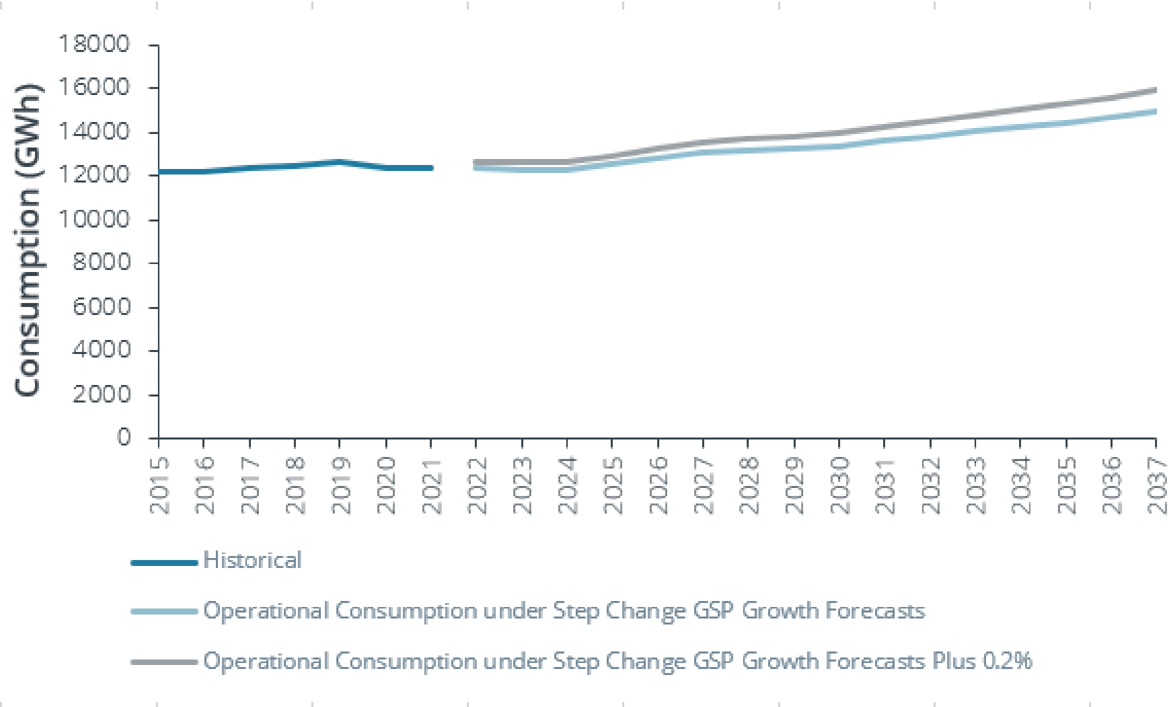


Source: ABS, DPIE

There is limited evidence to suggest the pandemic will result in a sustained change in population growth rates across Essential Energy's service area. Nevertheless, we tested the potential impact of a change in population on Essential Energy customer numbers and demand.

GSP was used to test this sensitivity as GSP and population usually move together. For the purpose of this sensitivity, we instead use an assumed GSP growth rate of 2.2%, an increase of 0.2% on the 2% forecasts adopted for the central case. The results of our analysis are presented in **Figure 71**. The analysis demonstrates that the increase in GSP growth rate is associated with a 4.2% increase in invoiced consumption by 2037.

Figure 71: Population growth sensitivity



Source: Frontier Economics analysis

5.3 Invoiced maximum demand

This section details the data, methodology and results regarding forecasts for invoiced maximum demand, up until the 2037 financial year.

We provide the following forecasts up to the 2037 financial year:

- Invoiced maximum demand for each customer segment (e.g., LV Small Business Demand, HV Demand etc) and tariff class (e.g., BHND1CO, BLND1CO), including export tariffs
- For each customer segment and tariff, the consumption allocated to each billing component e.g., Off Peak, Shoulder, Off-Peak.
- We forecast the effect of new technologies i.e., Electric Vehicles, Electrification and Batteries on future invoiced maximum demand, according to three possible scenarios for the uptake of these technologies.

5.3.1 Data and methodology overview

Essential Energy provided Frontier Economics with monthly maximum demand data by tariff category and billing component over the period from July 2008 to December 2021. The values represent, for each month and tariff category, the sum of the maximum demands (maximum half hour period) for each customer. This is non coincident maximum demand as the maximum demand for each customer can occur in different half hour periods. Unlike invoiced consumption, the monthly series did not need to be aggregated to the annual year which gave a larger sample size for forecasting. The data otherwise did not require any major cleaning or outlier detection.

In the same way as the invoiced consumption forecasts, invoiced maximum demand is forecast on a per connection basis. Therefore, multiplying the per connection demand forecasts by the projected number of customers presented in **Section 5.1** gives a forecast of invoiced maximum demand for each customer class.

Several econometric models were tested for modelling maximum demand per connection, based on a time trend, month dummy variables, PV generation, and in log terms. We determined that the most appropriate model was a linear model based on a time trend and month dummy only. Using the selected model, the maximum demand is forecast across the relevant period.

Given that the objective of this analysis it to estimate maximum demand, the impact and timing of new technologies, including electric vehicles, battery energy storage systems and electrification, profiles is particularly relevant. To account for their impact on invoiced maximum demand, we take the profiles developed in **Section 3** and scale them down to the customers on demand tariffs and apply them as a post model adjustment.

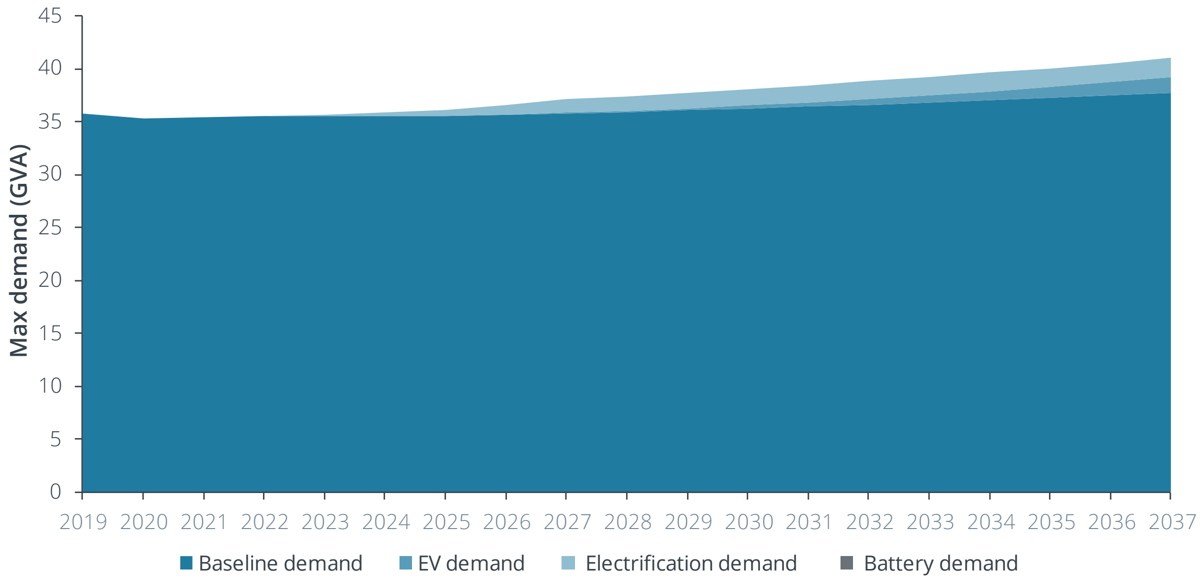
The results of this analysis are presented in **Section 5.3.2**. In addition, we also considered several sensitivities relating to new technology assumptions, presented in **Section 5.3.3**.

5.3.2 Results

The forecasts of maximum invoiced demand are shown in **Figure 72** and the effect of new technologies is shown separately. Maximum demand is forecast to grow 15.4% from 35.5 GVA in 2021 to 41.0 GVA in 2037. By 2037, electric vehicles and electrification are forecast to be adding 1.42 GVA and 1.8 GVA to maximum invoiced demand, respectively. The impact of batteries on reducing invoiced maximum demand is minimal, since it is assumed that most behind-the-meter batteries will be installed by residential customers, who are typically not on demand tariffs.

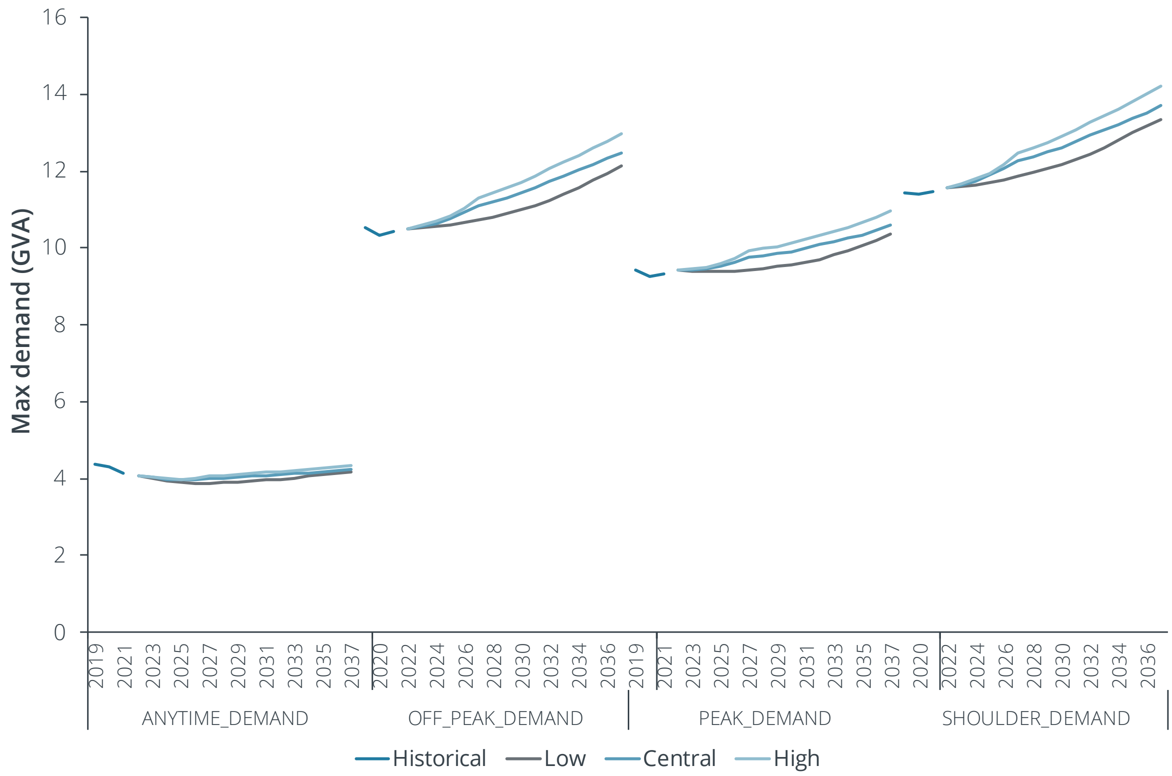
Figure 73 shows the maximum invoiced demand forecasts by each of the billing components. The forecasts for off-peak demand and shoulder demand are growing at a faster rate than for peak demand, reflecting the charging profiles of new technologies. On the other hand, forecast maximum demand for anytime demand tariffs are fairly flat and even falling slightly in the short term.

Figure 72: Maximum Invoiced Demand Forecasts



Source: Frontier Economics

Figure 73: Maximum Invoiced Demand by Billing Component



Source: Frontier Economics

5.3.3 Sensitivities

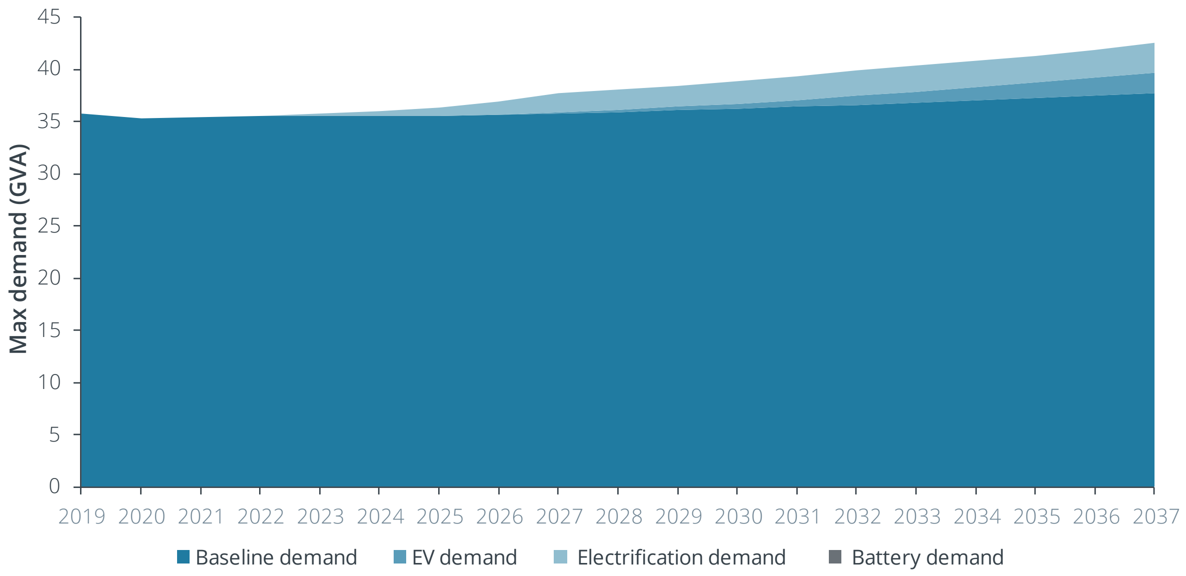
The results presented in section 5.3.2 are based on AEMO's Step Change Scenario.

We conducted two sensitivities to test the impact of changes in these assumptions:

- A low case based on AEMO's Progressive Change scenario
- A high case based on AEMO's Strong Electrification scenario.

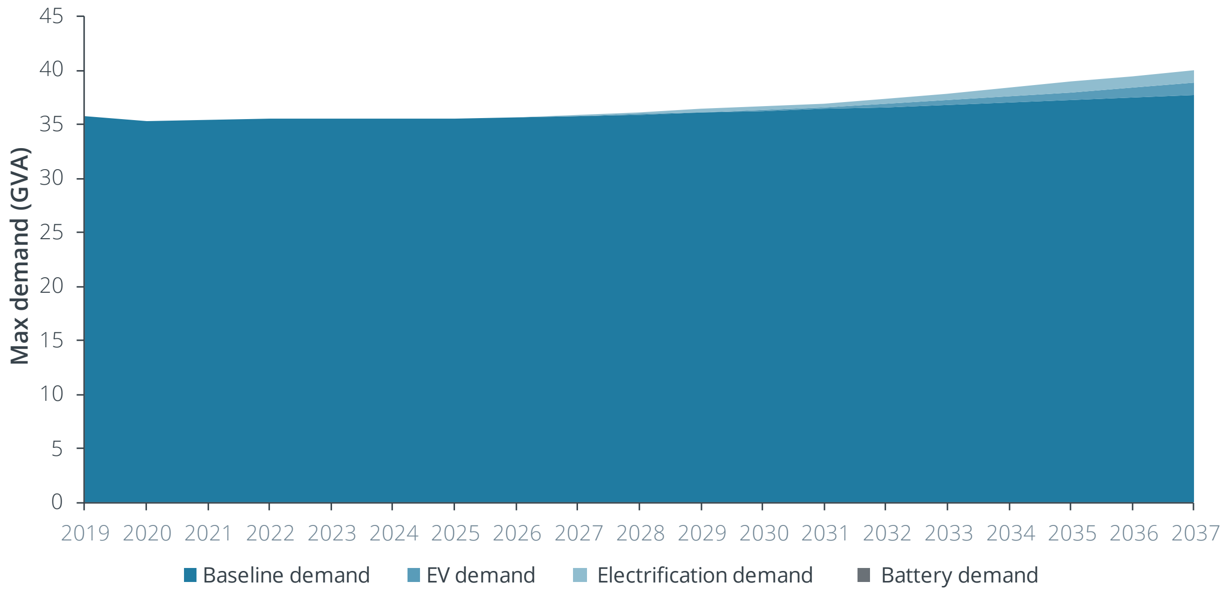
The results of the sensitivities for invoiced maximum demand are presented in **Figure 74** and **Figure 75**. The analysis shows that compared to the central case the low case results in maximum demand 2.4% lower by the end of the forecasting period (40.0 GVA vs 41.0 GVA). This occurs from slower uptake of electric vehicles and slower electrification. The high case results in maximum demand that is 3.6% higher by the end of the forecasting period (42.5 GVA vs 41.0 GVA). This occurs from faster uptake of electric vehicles and faster electrification.

Figure 74: Maximum Invoice Demand: high new technologies case



Source: Frontier Economics

Figure 75: Maximum Invoiced Demand: Low new technologies case



Source: Frontier Economics

6 Minimum and maximum demand

This section details the maximum and minimum demand forecasts for each Bulk Supply Point (BSP) and Zone Substation (ZSS), up until the 2037 financial year.

For each ZSS and BSP as well as the Essential Energy network, we provide the following forecasts up to the 2037 financial year:

- The 10%, 50%, and 90% Probability of Exceedance (POE) values for maximum and minimum demand, for summer and winter months separately.
- The half hour interval in which the maximum and minimum demands will occur

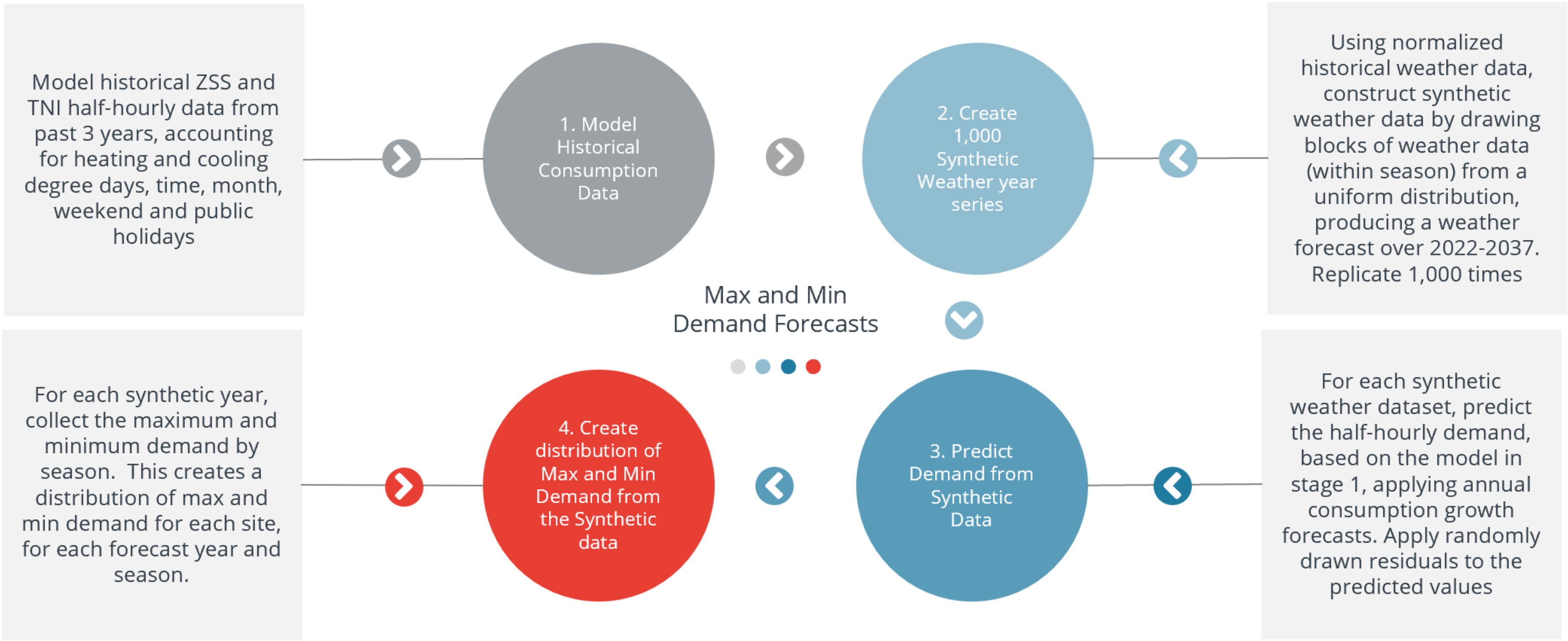
Further detail on the data and methodology used to generate the forecasts is provided in **Appendix C**.

6.1 Data and methodology overview

In calibrating the minimum and maximum demand models, we used the half hourly TNI and ZSS load data, as well as the weather data described in **Section 4.1**.

Minimum and maximum demand are inherently rare occurrences that take place at extreme points in the year. To forecast the probable interval in which an extreme value will take place, we need to establish an approximate distribution of minimum and maximum demand values. **Figure 63** presents a high-level summary of the approach taken to forecast maximum demand for each TNI and ZSS (site).

Figure 76: Minimum and maximum demand forecasting methodology



Source: Frontier Economics

The min-max demand forecasts are calibrated using econometric models of the historical consumption data. For each site we tested several models separately by season, accounting for weather variables, time and day characteristics, and for each site we selected the model which demonstrated the best statistical fit and economic interpretation. The resulting models were a combination of quadratic and linear weather normalised models. For some sites and seasons however, the resulting models were sufficiently poor in fit to not be useful. These sites underwent a different forecasting methodology, which is detailed below.

For the sites with appropriate econometric models, 1000 simulations of synthetic weather data were developed, using a sampling method of 20 years of historical data. The model was then applied to this synthetic weather data, producing 1000 years' worth of fitted half-hourly consumption data. Residuals were then sampled from the econometric model and applied to the fitted data (with the constraint that underlying consumption cannot be negative).

For the sites where an econometric model could not accurately capture the variability in consumption level, 1000 simulations of synthetic data were generated by sampling directly from the historical underlying demand data. From this stage this synthetic demand data follows the same methodology as other sites.

For each simulation, a growth rate is applied to expand the synthetic years across the period 2022-2037, using the annual forecast growth rates described in **Section 4.2**. After expanding the underlying demand across the forecast period, the impact of rooftop PV, embedded generation, batteries, EVs and electrification are included, producing a final demand estimate for each year, for each simulation.

The minimum and maximum final demand is then extracted from each simulation, year, season, and site. The resulting distribution of minimum and maximum demand results are presented in **Section 6.2**. These estimates provide the site-specific maximum and minimum demand values, which may not be coincident.

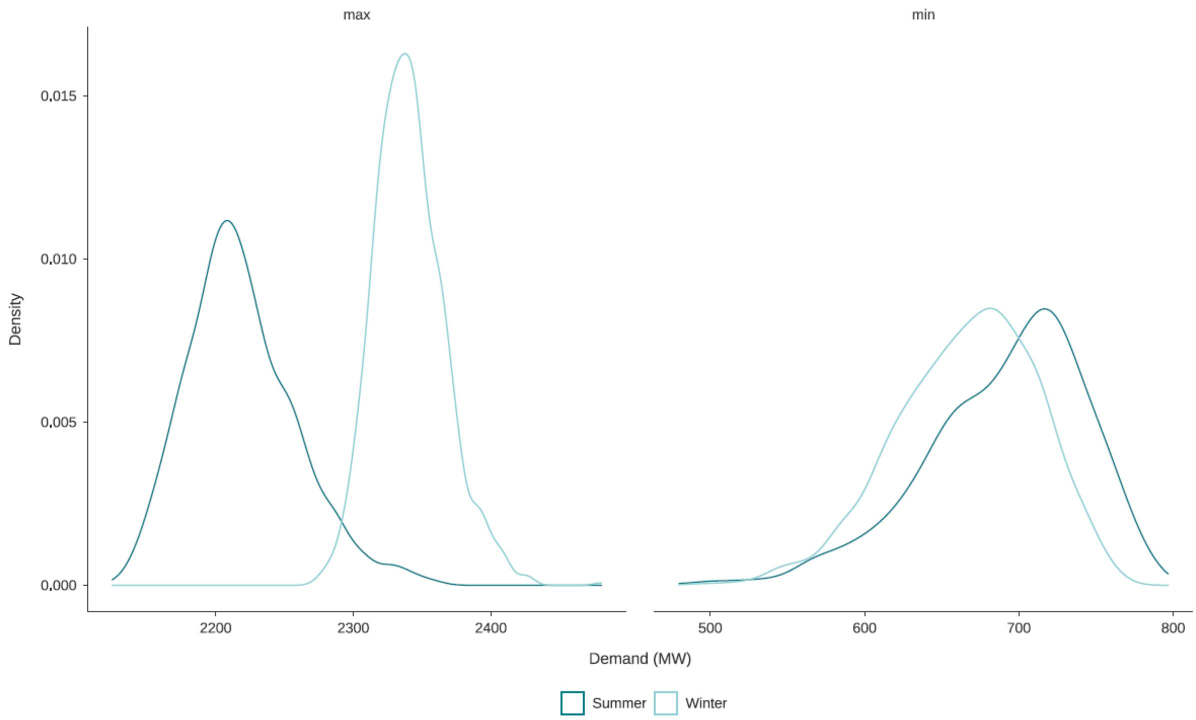
To estimate minimum and maximum aggregate demand, we require that the aggregate demand be assessed for all half hour intervals across each year. The 1000 fitted, or sampled, years previously described (generated for each site) are therefore aggregated to create 1000 synthetic years of final demand across the network. From this sample an aggregate growth rate and profile for PF, and new technologies is applied. For each simulation and year within the resulting dataset, the maximum and minimum demand are selected. The resulting distribution of coincident aggregate minimum and maximum is presented in Section 6.2 for the Central case.

We present the results of the new technology Low and High scenarios in Section 6.3.1. Two sensitives were also considered, applying a hydrogen load to minimum demand (Section 6.3.2), and a profile of large load (Section 6.3.3).

6.2 Results

The resulting distribution of minimum and maximum network demand for 2022 (before performing post model adjustments) is presented in **Figure 77**. The simulated base years have maximum demands which are concentrated around the median of 2,042 MW in winter and 1,904 MW in summer, significantly higher than the average minimum loads of 881 MW in winter and 577 MW in summer. These results are consistent with the historical data which showed that demand was often highest in winter. Across the 67 TNIs modelled, an average of only 32 were summer peaking in a given year across the forecast period.

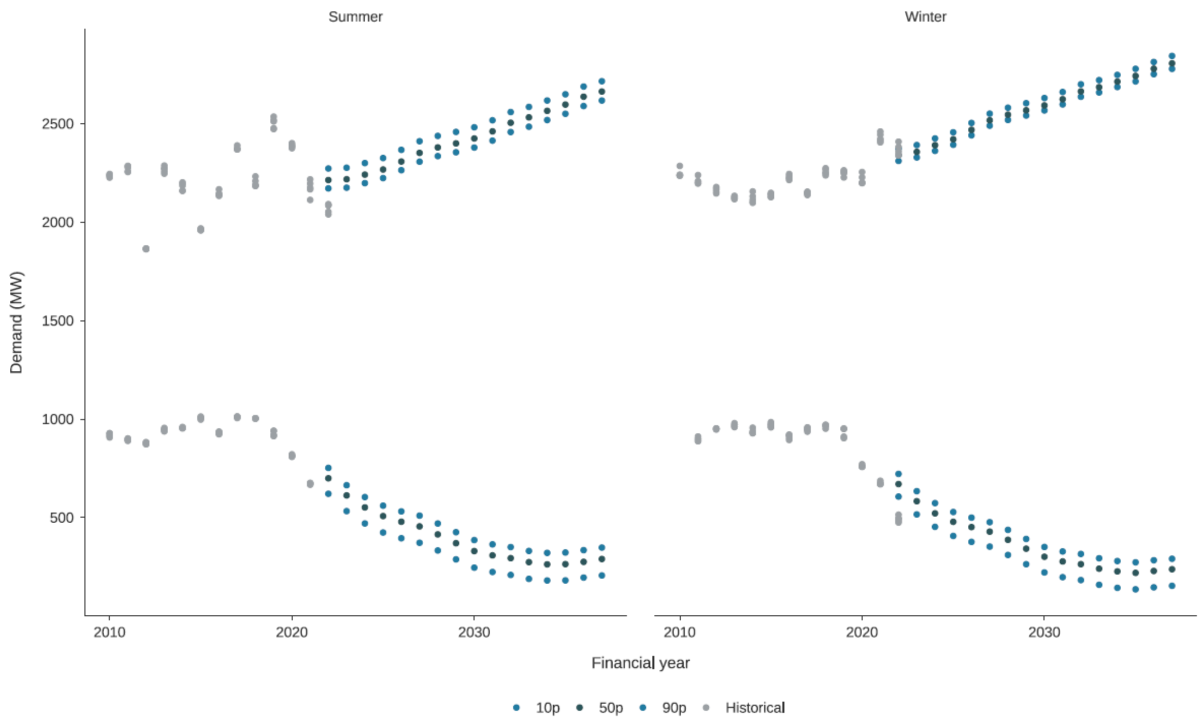
Figure 77: Distribution of minimum and maximum total network consumption forecast for 2022



Source: Frontier Economics analysis

Due to the uncertainty surrounding these estimates, all figures in this section present the POE 10, 50 and 90 of variables of interest. **Figure 78** presents the expected minimum and maximum demand for each season over the full forecast period, compared to the 3 highest (lowest) observations for each financial year in the historical data. Over the period 2022-37 the maximum demand is forecast to increase towards approximately 2,500MW, while the minimum demand decreases towards 0MW.

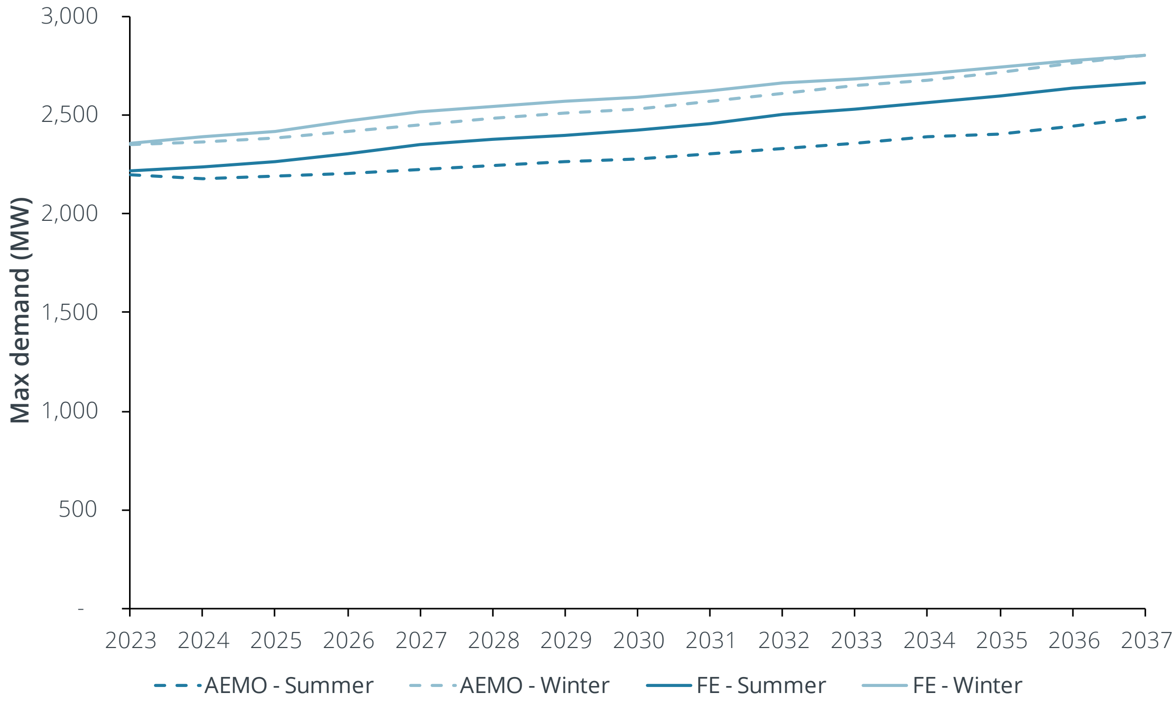
Figure 78: Minimum and maximum total network consumption forecast for 2022-2037



Source: Frontier Economics analysis

The growth in maximum demand, as shown by maximum demand forecast POE50 in **Figure 79**, is closely aligned with AEMO's growth forecasts over the same period, particularly for the maximum demand in winter months.

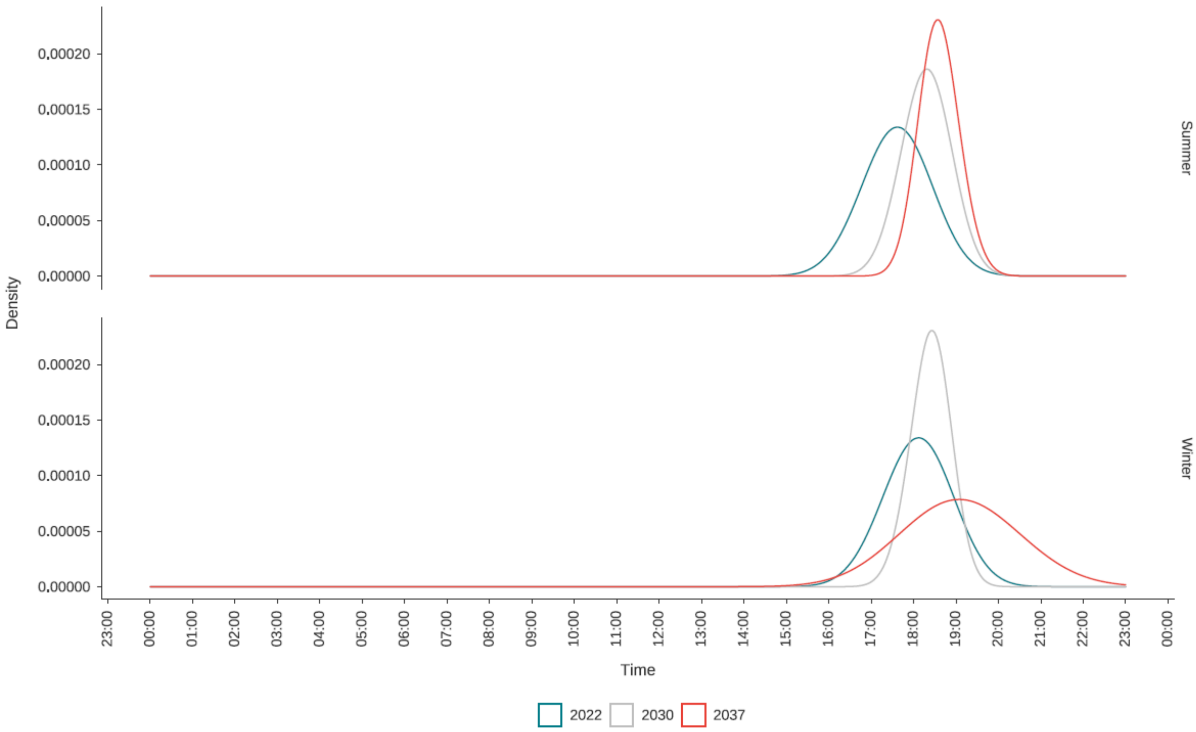
Figure 79: Maximum demand forecasts compared with AEMO growth forecasts



Source: Frontier Economics analysis, AEMO forecast Step change growth rate, ISP 2022

Historically maximum demand has occurred around 6pm in both summer and winter. Figure 80 demonstrates that as rooftop PV capacity and battery uptake increases, the maximum network load is forecast to occur later in the day. By 2037 the peak demand is expected to take place between 6-7pm in summer, and 5-9pm in winter.

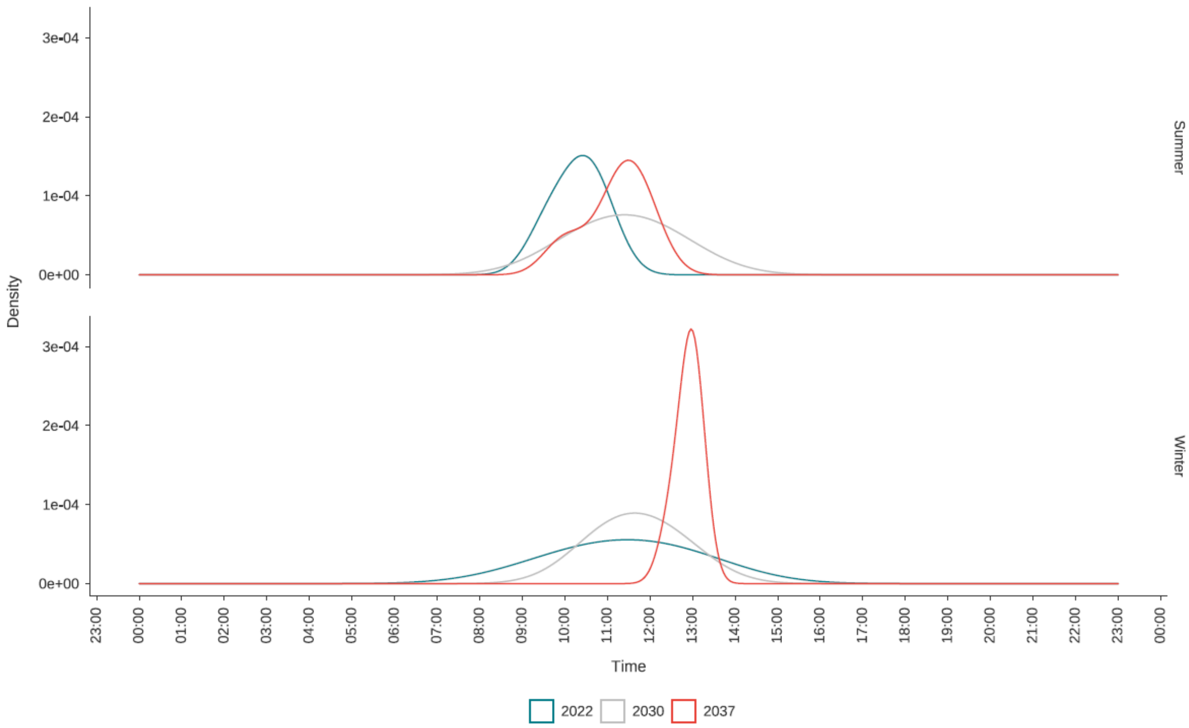
Figure 80: Time distribution of maximum network loads



Source: Frontier Economics analysis

A similar trend is expected for minimum demand in **Figure 81**, as the expected summer minimum shifts from 10am in 2022 to 10am-12pm in 2037. The winter minimum demand in 2022 shows an active period around 9am-1pm The expansion of DER factors will move minimum demand away from the mornings, ultimately concentrating around 1pm by 2037.

Figure 81: Time distribution of minimum network loads



Source: Frontier Economics analysis

6.3 Sensitivities

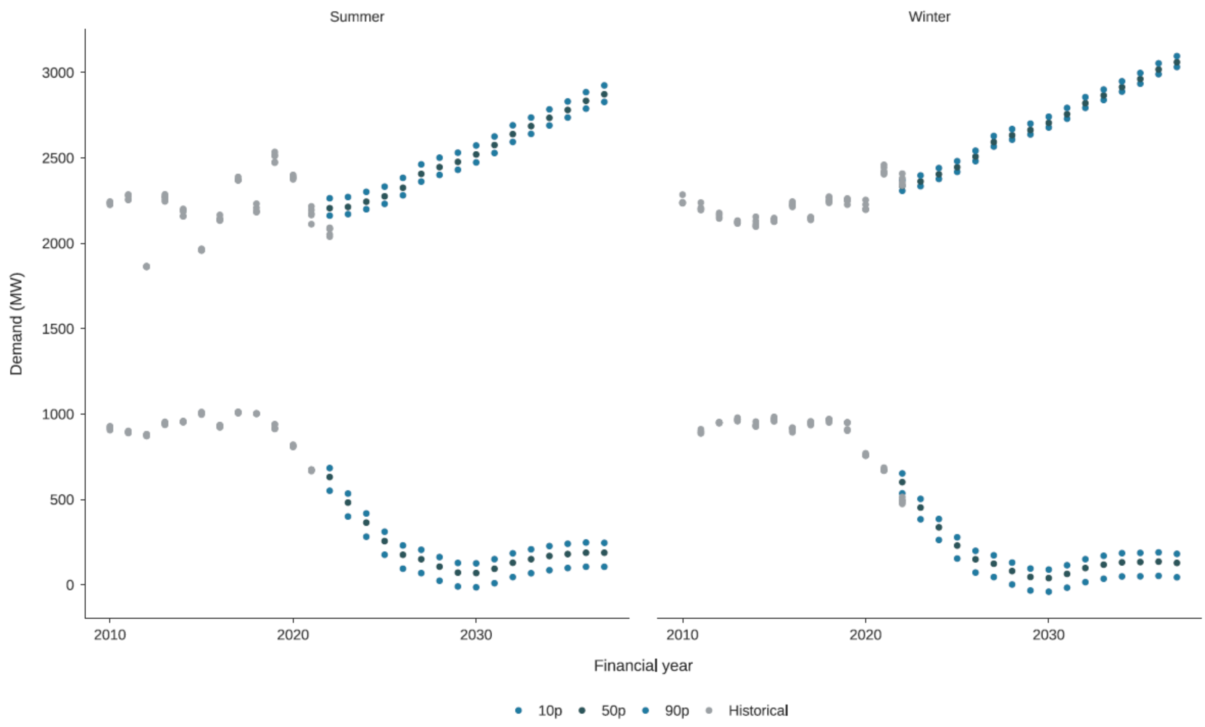
6.3.1 New technologies

We modelled a series of sensitivities to test the impact of changes in underlying assumptions to maximum and minimum demand:

- A low case to test the impact of lower-than-expected growth in consumption and new technologies based on Progressive Change
- A high case to test the impact of higher-than-expected growth in consumption and new technologies based on Strong Electrification

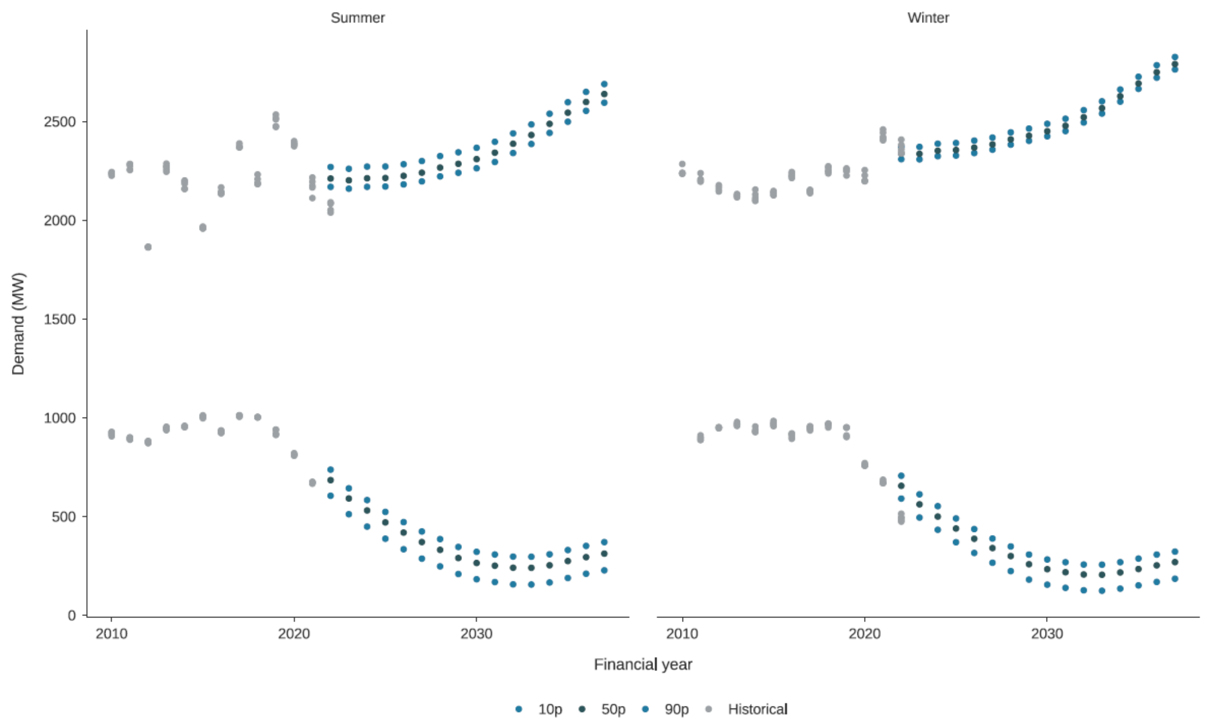
The impact of these changed assumptions on the total network maximum and minimum load forecasts is presented in **Figure 82** and **Figure 83**. The high impact technology case resulting in a significantly faster growth in maximum demand, with winter maximum load approaching 3,000 MW over the forecast period. Similarly, the minimum demand decline towards 0 MW is more rapid compared to the low technology scenario.

Figure 82: High impact of new technologies on forecast network load



Source: Frontier Economics analysis

Figure 83: Low impact of new technologies on forecast network load

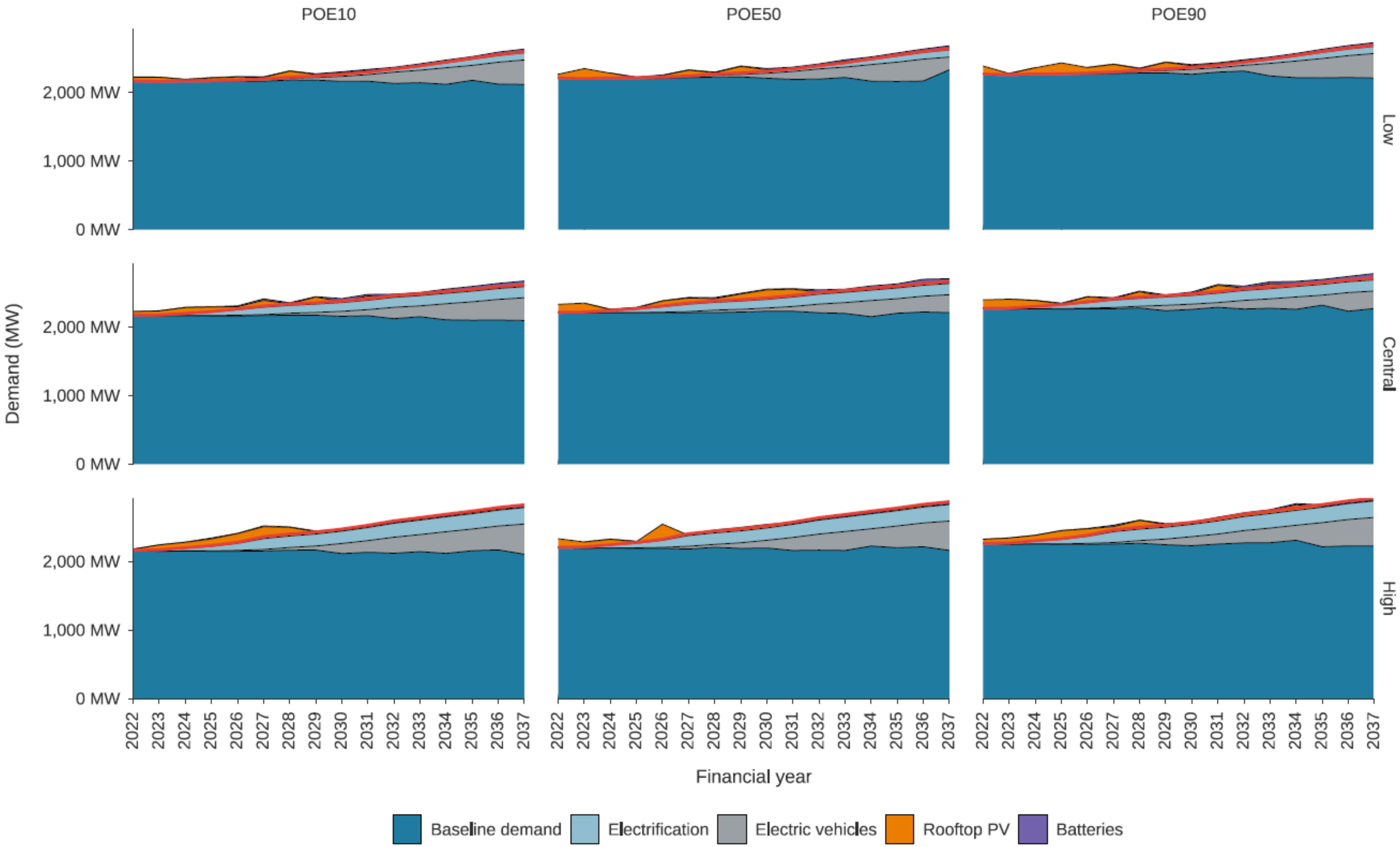


Source: Frontier Economics analysis

Figure 84 and **Figure 85** present the network maximum demand across the three scenarios (central case, high technology impact and low technology impact) broken down into the baseline demand and DER factors. The red dashed line in these figures is the total operational demand experienced on Essential Energy's network. Comparing the POE50 demand instances, the baseline demand is not forecast to grow significantly over time, with most of the increase in maximum demand resulting from the uptake of electric vehicles. Across all scenarios rooftop PV is forecast to have a substantial impact on summer maximum operational demand in the period 2022-2027. In the long run however, this component will not contribute significantly to reducing total maximum demand, as the timing is shifted towards after sundown.

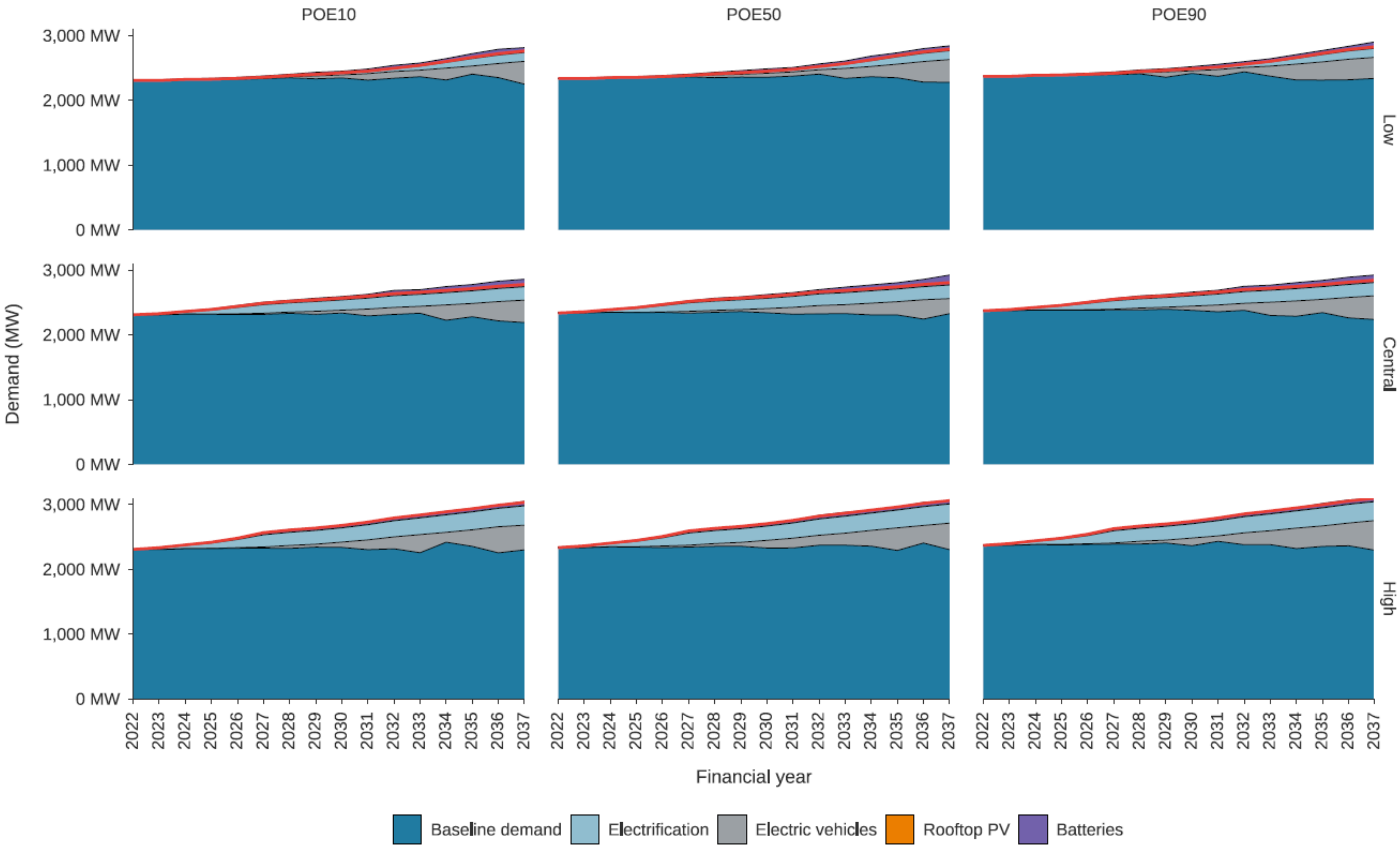
Similar charts are presented for network minimum demand in **Figure 86** and **Figure 87**. The red dashed line in these figures is the total operational demand experienced on Essential Energy's network. The areas below the red line show the impact of technologies which increase minimum demand, while areas above the red line show technologies which decrease minimum demand. As expected, rooftop PV is forecast to decrease minimum demand significantly. Electrification and electric vehicles have differing impacts in increasing minimum demand, depending upon the scenario. Higher uptake of these technologies increases minimum demand more, but the High scenario pairs this higher uptake with a higher uptake of rooftop PV as well.

Figure 84: Contribution of DER factors to forecast maximum summer network load



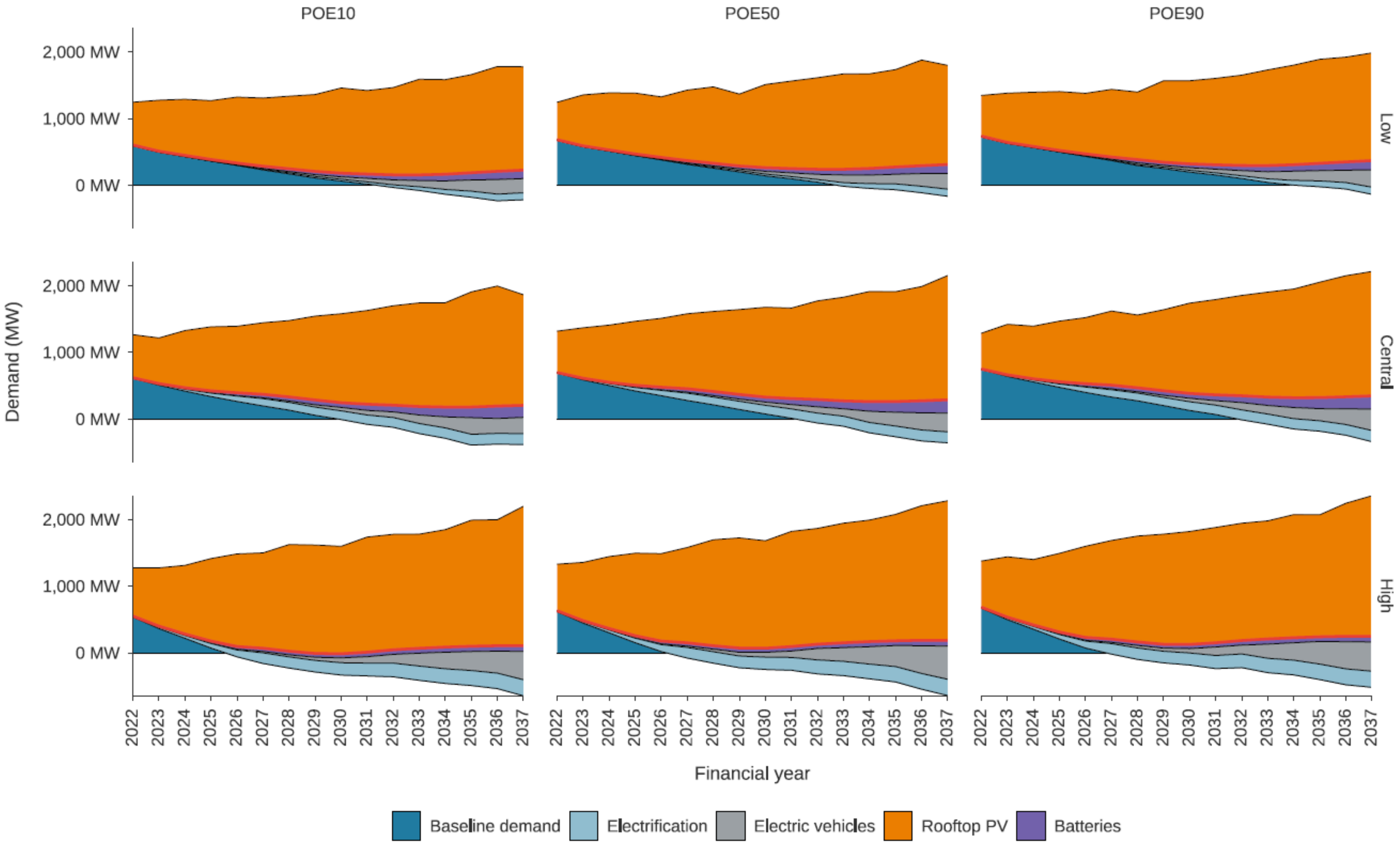
Source: Frontier Economics analysis

Figure 85: Contribution of DER factors to forecast maximum winter network load



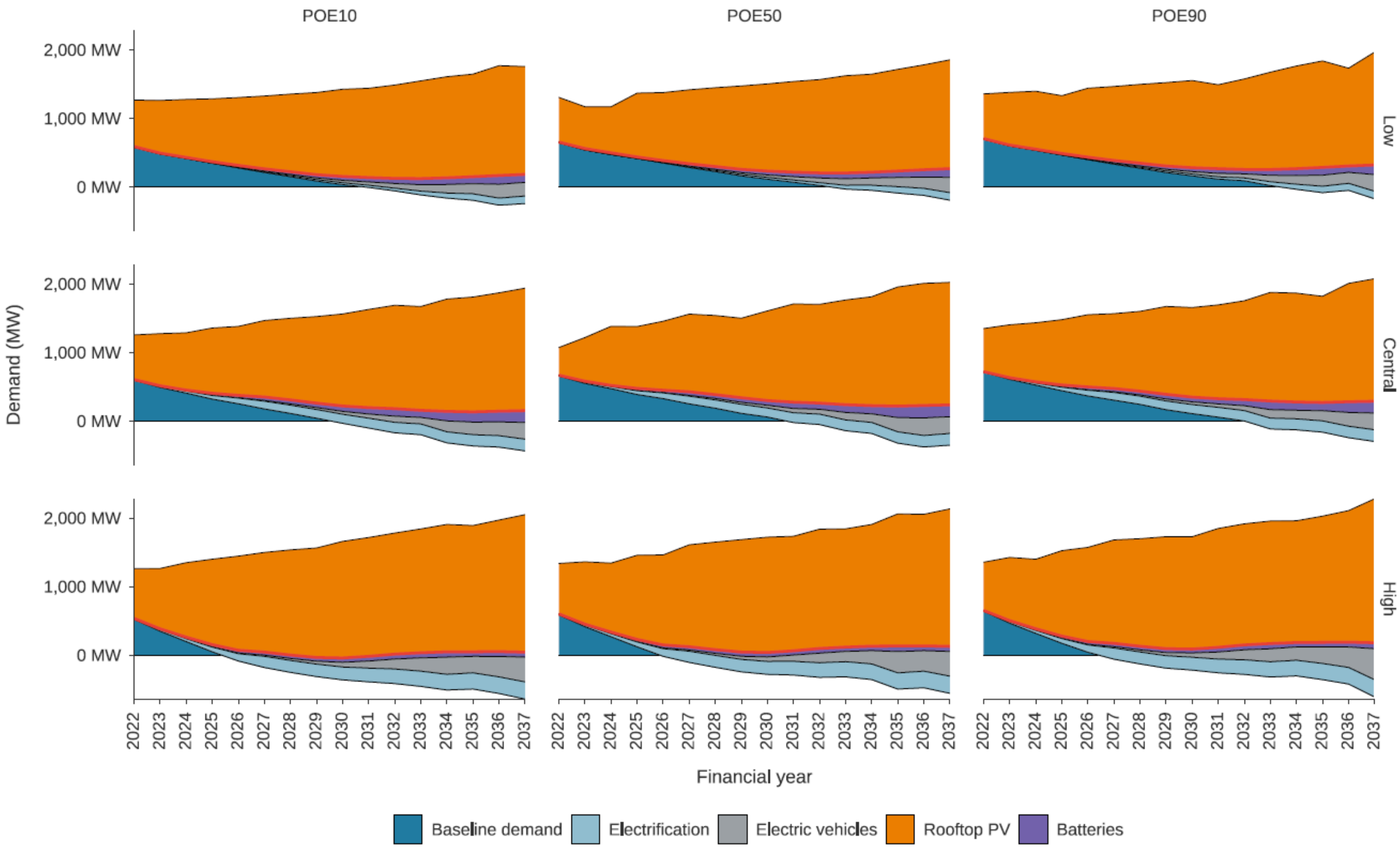
Source: Frontier Economics analysis

Figure 86: Contribution of DER factors to forecast minimum summer network load



Source: Frontier Economics analysis

Figure 87: Contribution of DER factors to forecast minimum winter network load



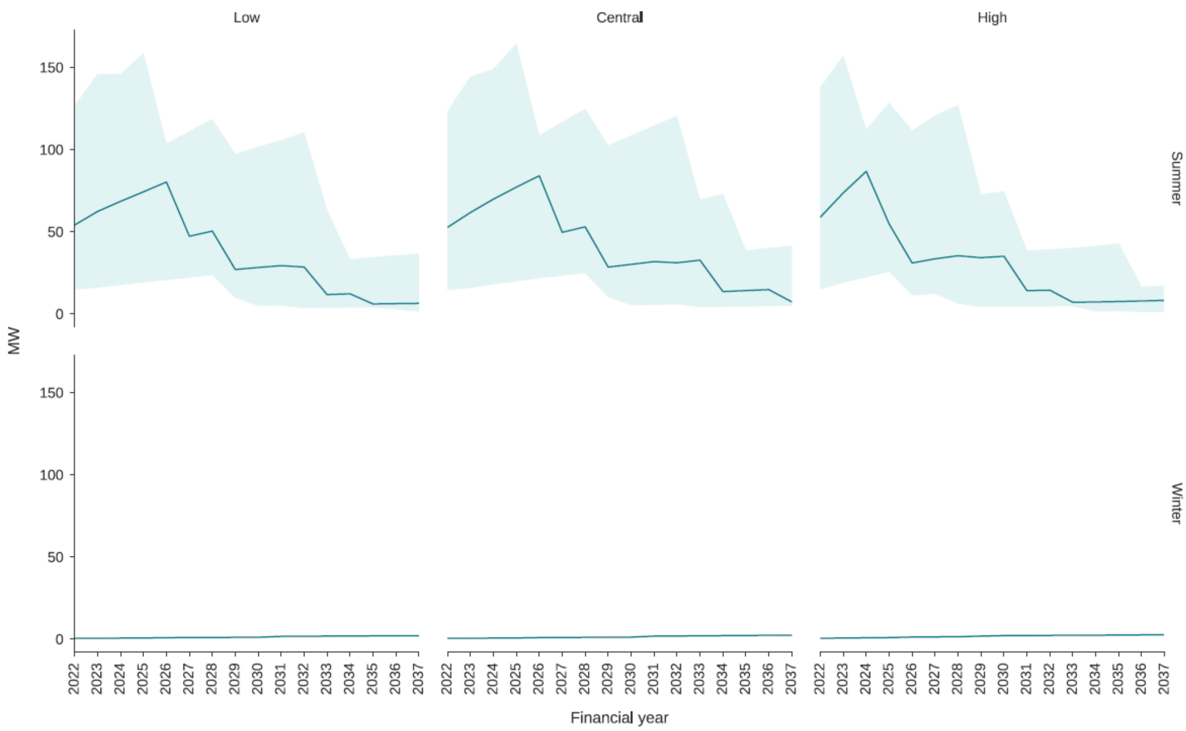
Source: Frontier Economics analysis

Figure 88 through **Figure 95** present the distribution of DER factors contribution to minimum and maximum network demand over the forecast period. The shaded areas reflect the range between POE10 and POE90 of these DER components, as estimated from the 1000 minimum and maximum demand simulated results. The solid blue lines are the POE50.

Rooftop PV

Intuitively, rooftop PV has the highest expected impact on reducing maximum demand during summer months, with little to no impact expected during winter. As rooftop PV is highly variable depending on time of day, this component has a larger range in how it will impact maximum demand. However, we can observe that rooftop PV is expected to decrease in its significance over the forecast period, as maximum demand is pushed later in the evening.

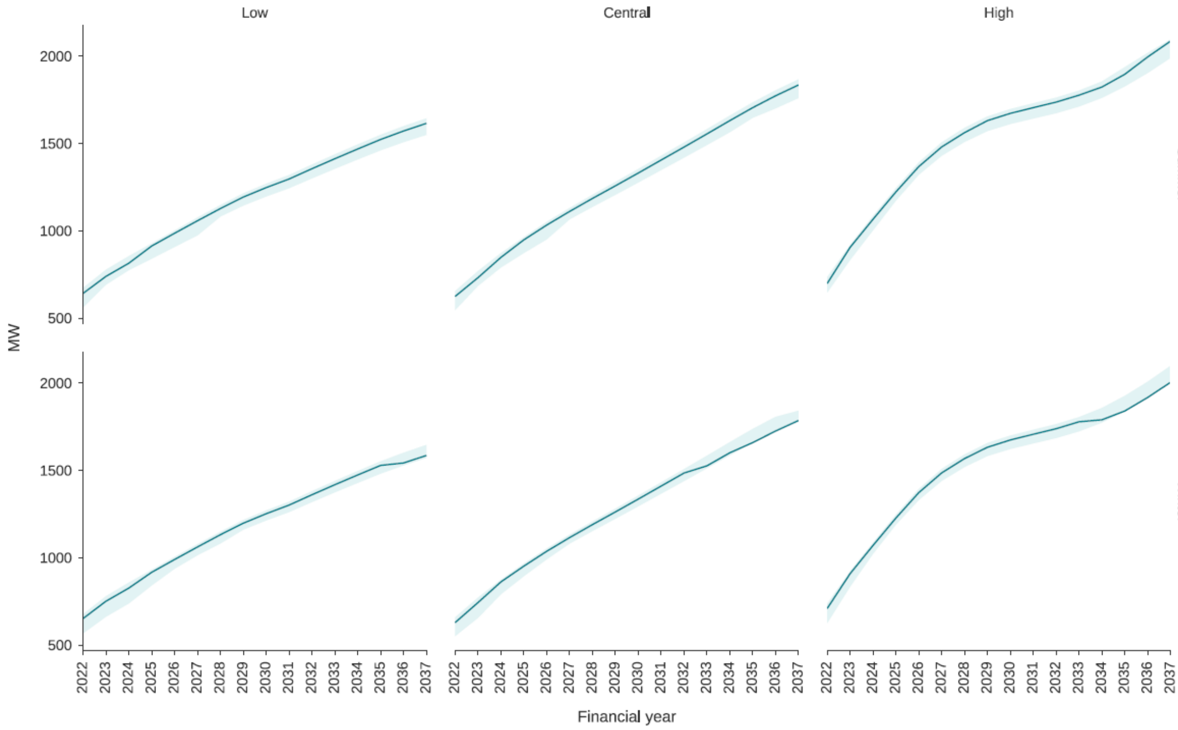
Figure 88: Contribution of rooftop PV to forecast maximum network load



Source: Frontier Economics analysis

Rooftop PV is expected to increase in significance as relates to minimum demand. Over the forecast period rooftop PV is expected to increase its impact on minimum demand from 500 MW of demand, with the POE 10 nearing 2,000MW. This large and increasing role of rooftop PV is consistent with the expected change in time of minimum and maximum demand, as maximum demand is pushed later into the day, and minimum towards the middle of the day, by the emergence of rooftop PV.

Figure 89: Contribution of rooftop PV to forecast minimum network load



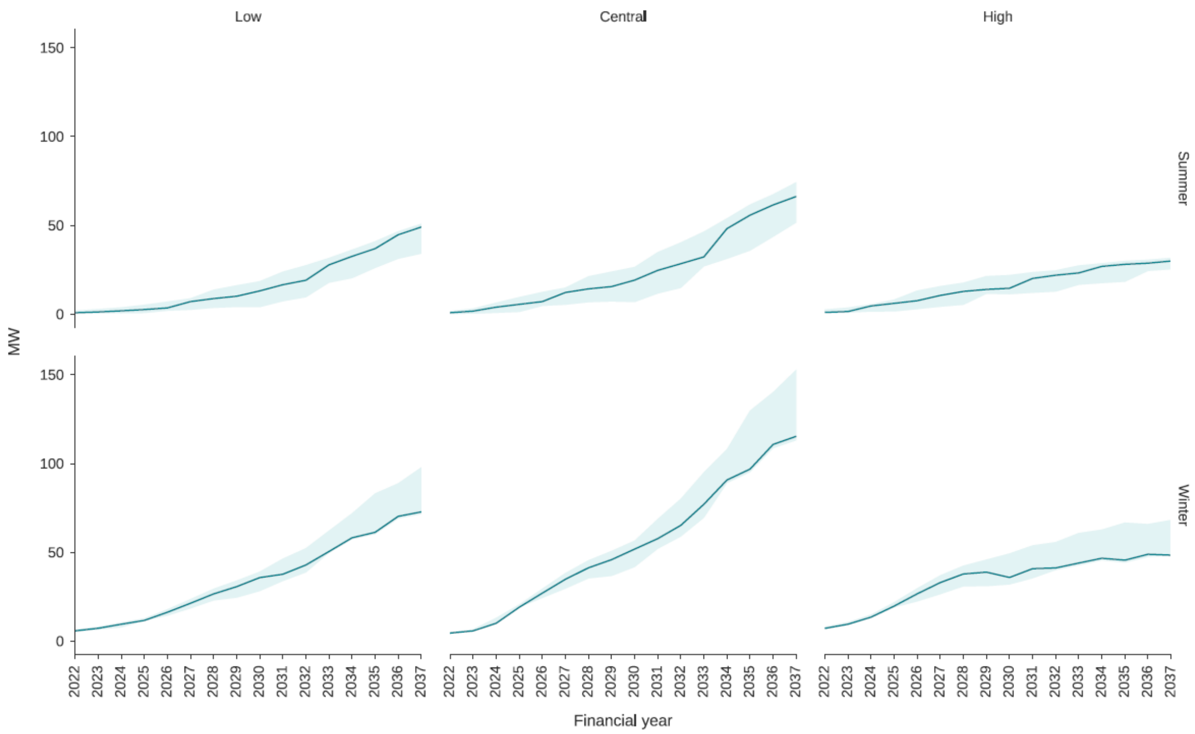
Source: Frontier Economics analysis

Batteries

Batteries do contribute to reducing forecast maximum demand in the near future but have a much larger impact later in the forecast period. This is primarily due to their uptake rate increasing over time, in addition to the maximum being pushed later in the day, when batteries are assumed to discharge more often. It is important to note that in the High case battery uptake is slower, resulting in a smaller contribution to reducing maximum demand.

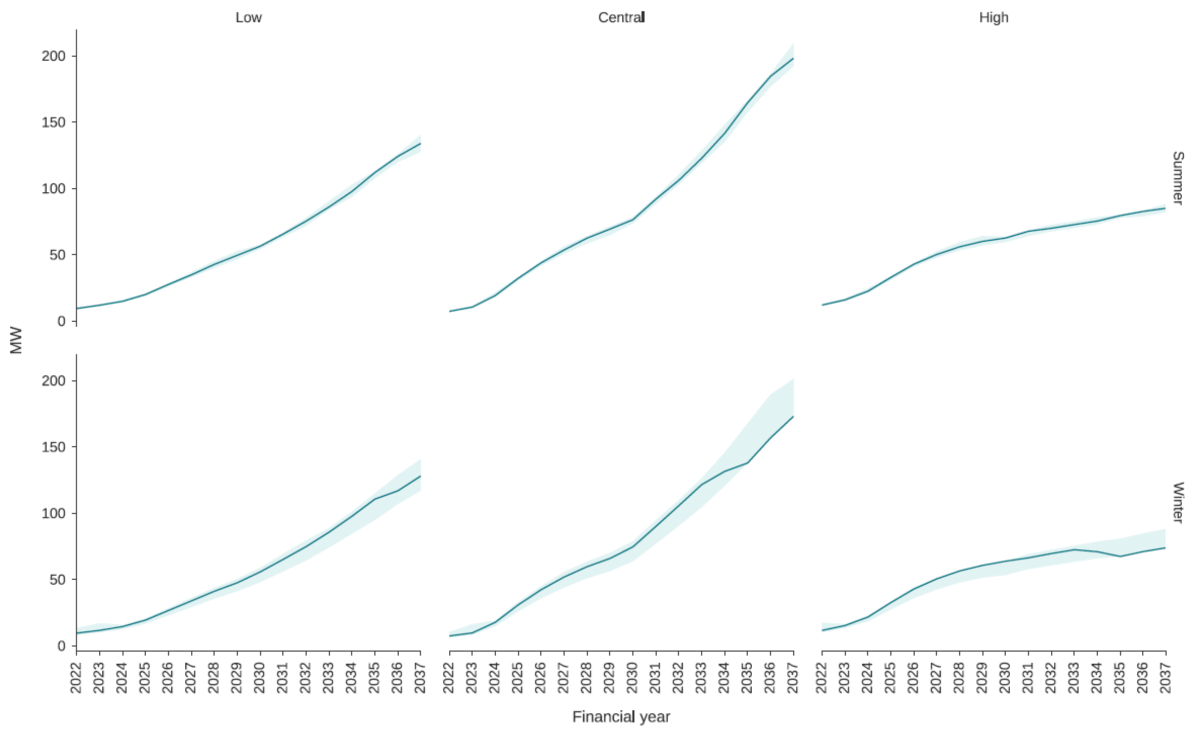
A similar phenomenon occurs for minimum demand, where batteries typically charge. This increases minimum demand, with a high degree of certainty in summer due to the timing of minimum demand. During winter, minimum demand is forecast to shift slightly more often, and so the contribution to increase minimum demand is slightly more variable.

Figure 90: Contribution of batteries to forecast maximum network load



Source: Frontier Economics analysis

Figure 91: Contribution of batteries to forecast minimum network load

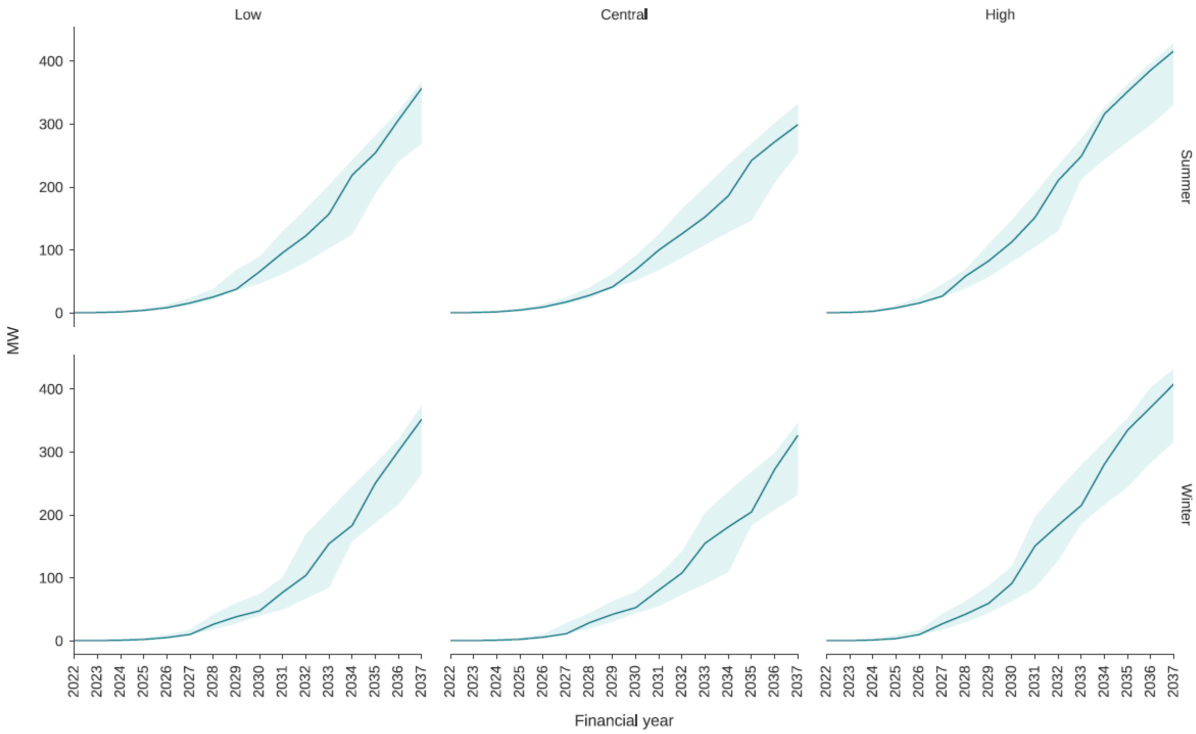


Source: Frontier Economics analysis

Electric vehicles

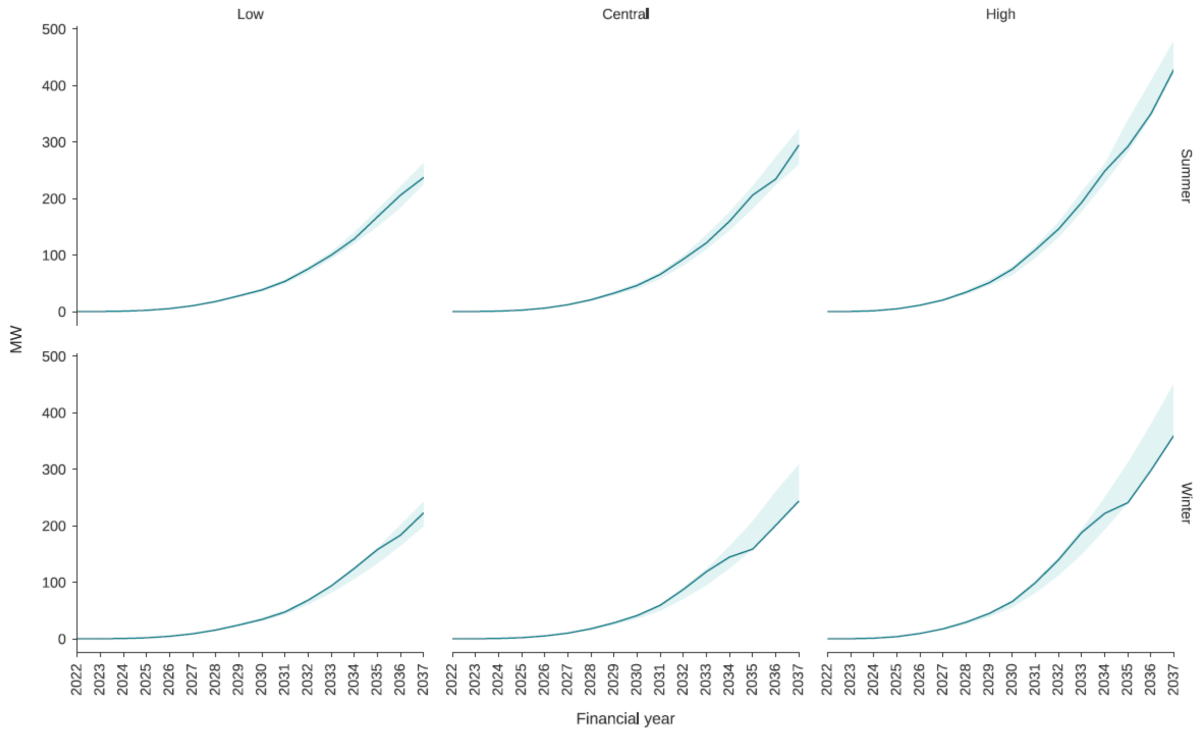
Expected electric vehicle uptake over this period results in rapid growth in energy demand for this purpose, increasing EV's contribution to maximum and minimum demand load over time. Electric vehicles are expected to increase maximum demand more than minimum demand in the early years, due to the expected charging patterns on residential customers using a convenience charging profile. However, as electric vehicle uptake increases, their impact on minimum demand also increases, due to some vehicles being charged to a daytime charging profile.

Figure 92: Contribution of EVs to forecast maximum network load



Source: Frontier Economics analysis

Figure 93: Contribution of EVs to forecast minimum network load

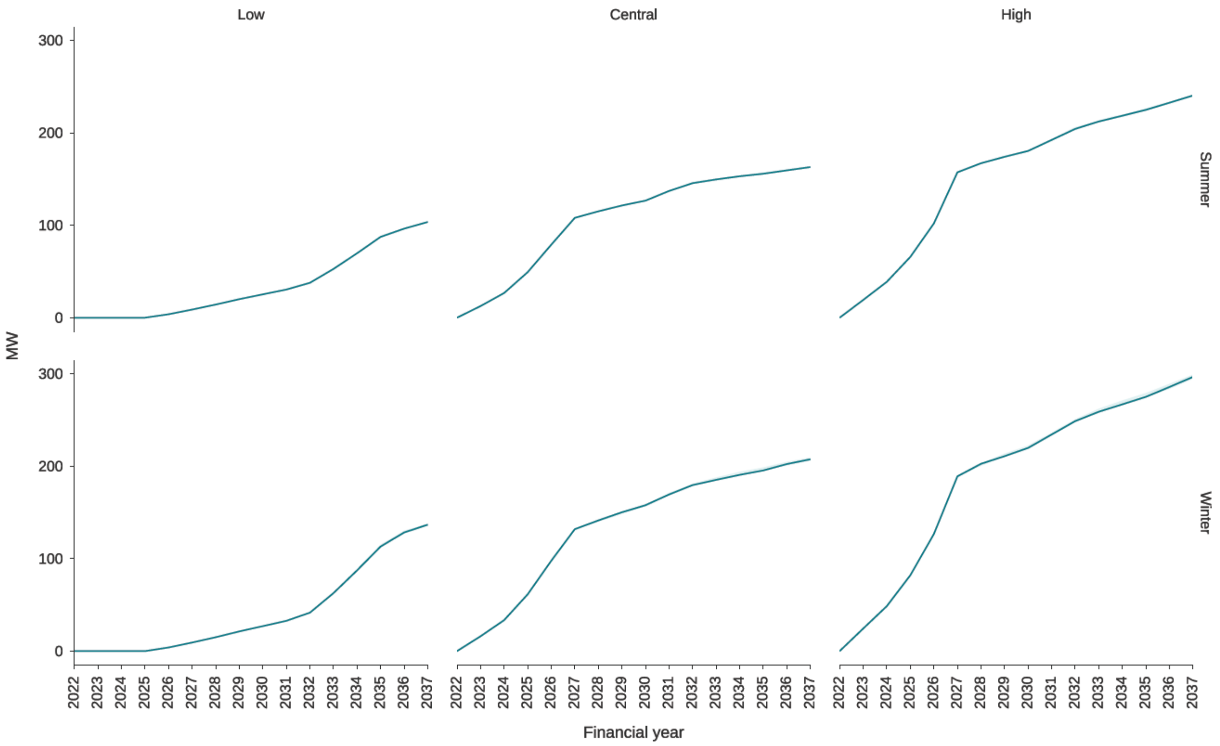


Source: Frontier Economics analysis

Electrification

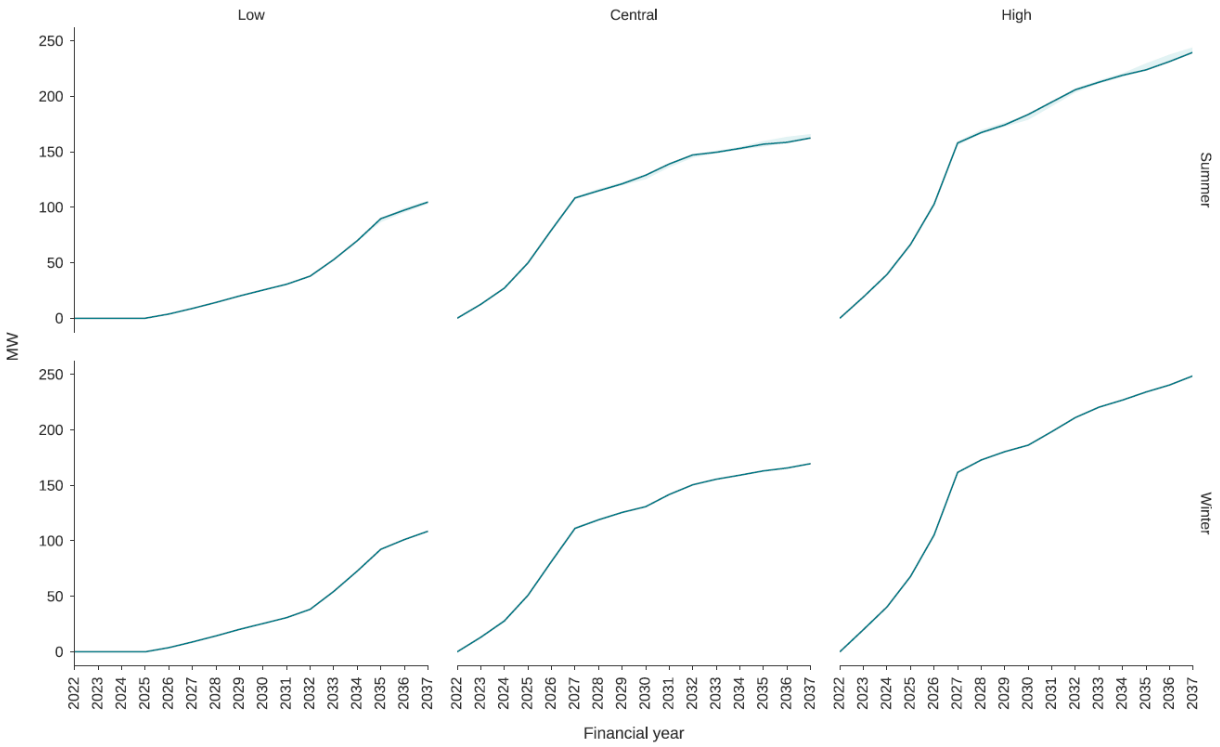
Expected electrification of appliances over this period means that electrification's contribution to maximum and minimum demand is expected to increase substantially over the time period considered. As electrification is not as time varying as batteries and rooftop PV, the expected contribution to minimum and maximum demand is more tightly concentrated, likely approaching 100-200MW by 2037.

Figure 94: Contribution of electrification to forecast maximum network load



Source: Frontier Economics analysis

Figure 95: Contribution of electrification to forecast minimum network load



Source: Frontier Economics analysis

6.3.2 Hydrogen

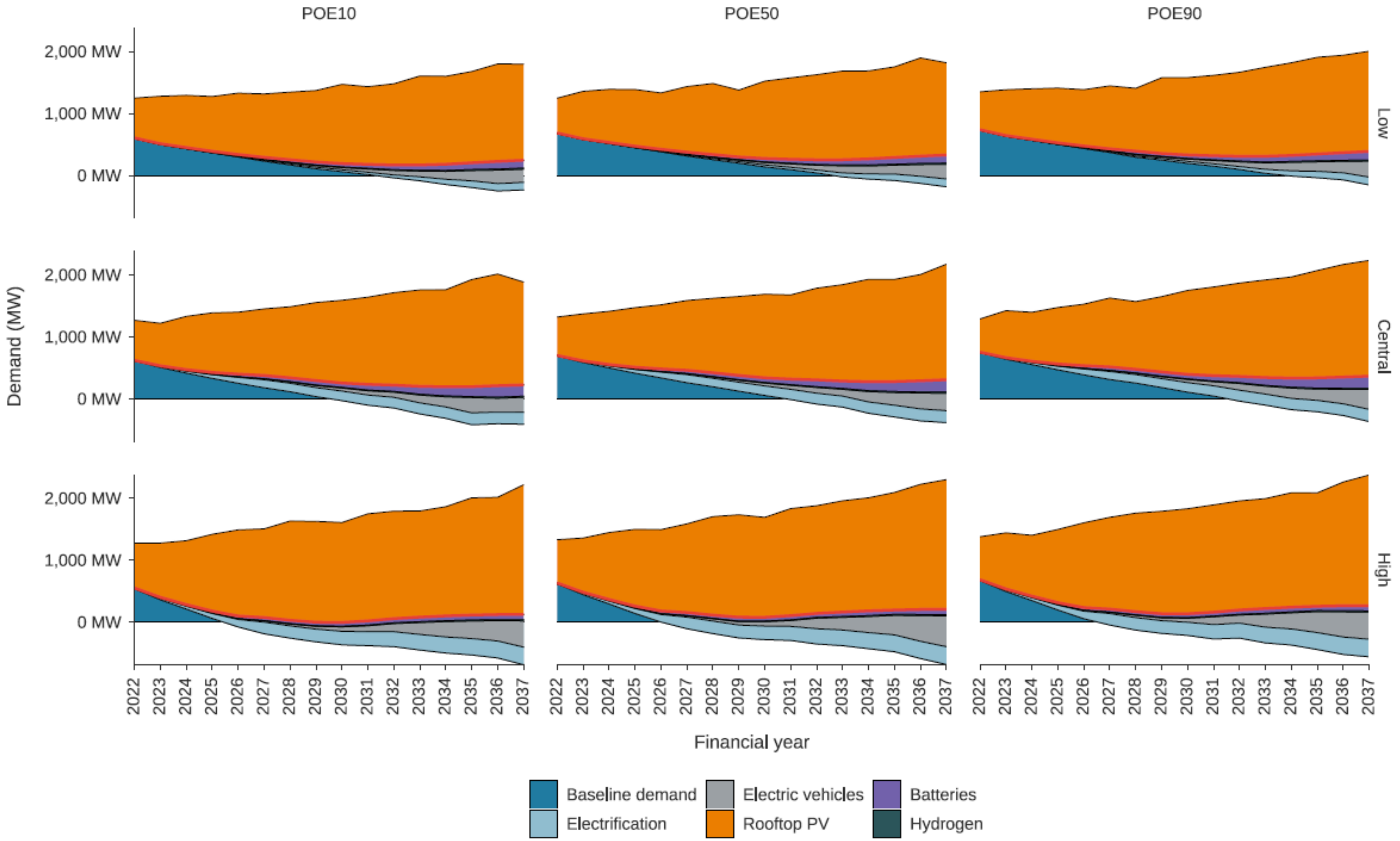
We have undertaken a sensitivity to test the potential impact of demand due to hydrogen electrolysers in Essential Energy's service area. As discussed in Section 2.2 we expect the main impact of the hydrogen electrolyser to be on minimum demand.

Our analysis is based on the NSW hydrogen strategy, which sets a target of 700MW in 2030. We estimate the capacity of electrolysers in NSW, by ramping up linearly from 2024 to the 700MW in 2030 set out in the NSW hydrogen strategy, and assuming this growth continues to 2037. We then estimate the share of electrolysers in NSW within Essential Energy's network area using their share of NSW's business load. Finally, we estimate the capacity of electrolysers which would import from the grid in Essential's network area. We assume 90% of electrolysers within Essential Energy co-located with solar PV, and so would not import from the grid. This is because wholesale prices are typically low when solar PV is generating; meaning when solar is not generating the electrolyser would not be producing, regardless of the network tariff subsidy.

On the basis of these assumptions, we estimate the increase in demand due to hydrogen electrolysers during minimum times is 9MW in 2030 and 17MW in 2037. **Figure 96** and **Figure 97** show the impact of hydrogen on minimum demand within Essential Energy's service area for summer and winter, respectively. On the basis of the assumptions set out above hydrogen has the capacity to reduce minimum demand by 3-4% in 2030 and 8-11% in 2037.[26]

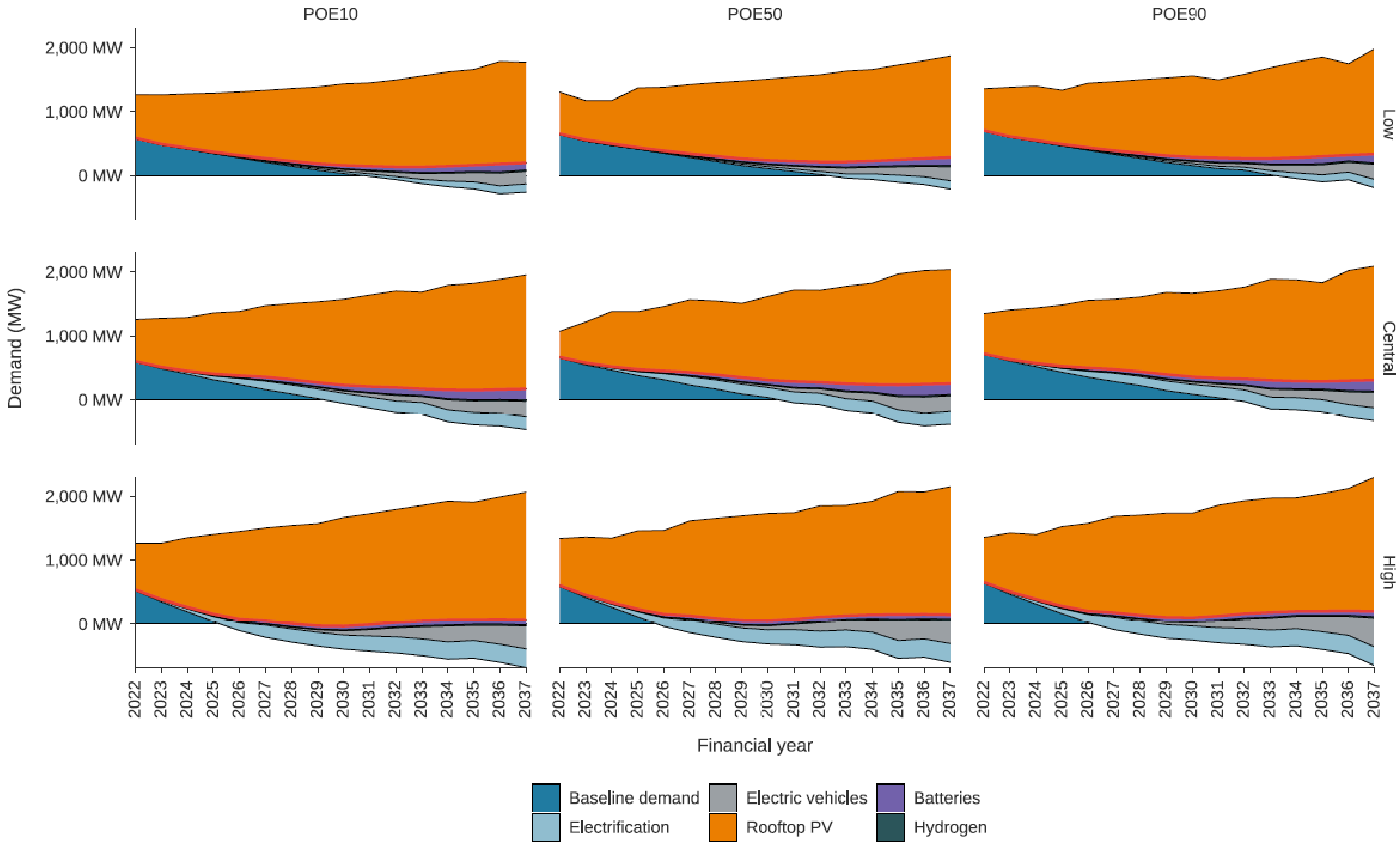
[26] Based on the Central scenario and POE50 minimum demand

Figure 96: Minimum summer final demand with hydrogen



Source: Frontier Economics analysis

Figure 97: Minimum winter final demand with hydrogen



Source: Frontier Economics analysis

6.3.3 Large loads

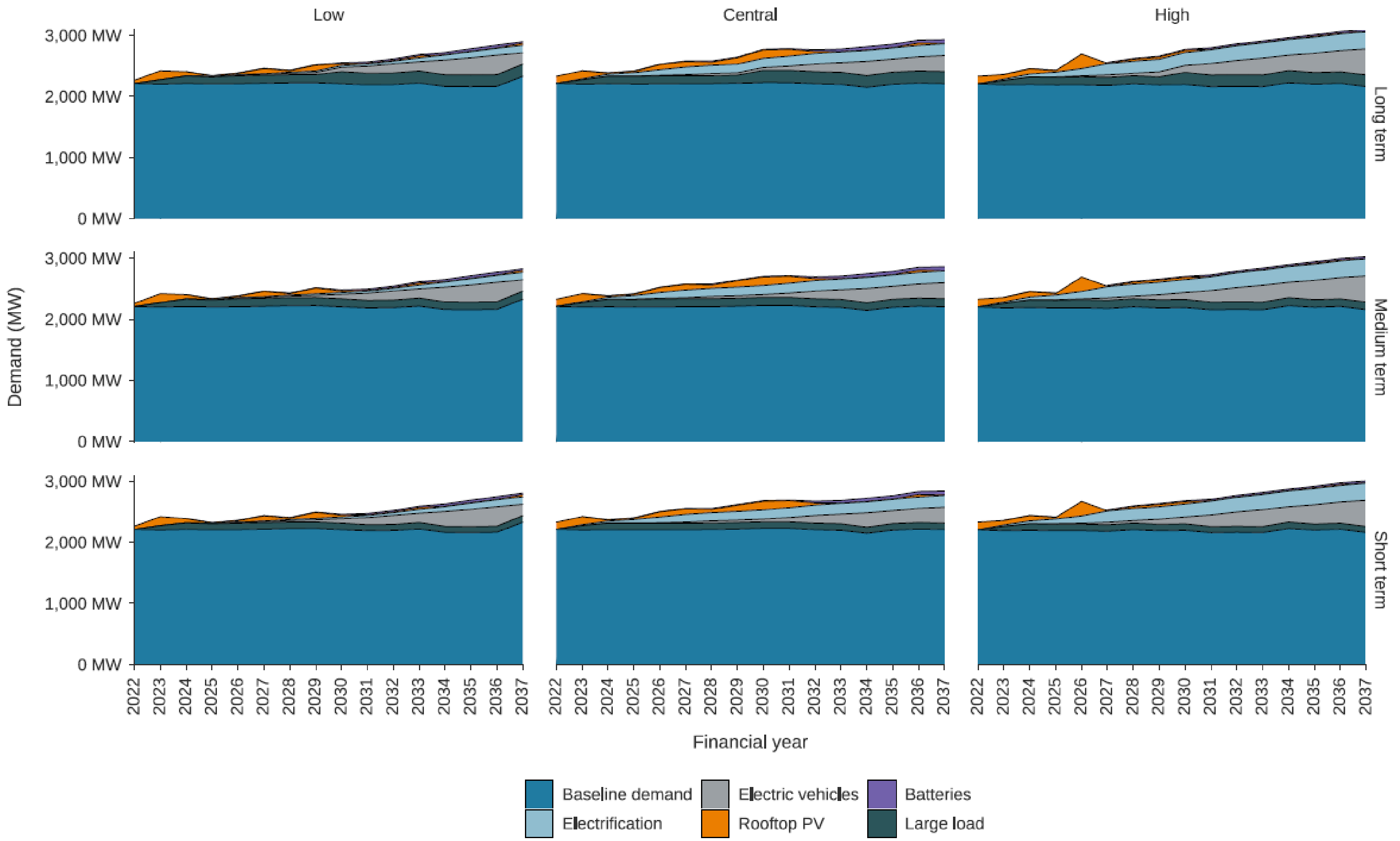
We have undertaken a sensitivity to test the impact of potential new large loads on Essential Energy's network on minimum and maximum demand. This sensitivity is based on estimates of likely future large industrial loads and Special Activation Precincts provided by Essential Energy and presented in Section 5.3.3. A sensitivity of the impact of these large loads on consumption was presented in Section 5.3.3.

On the basis of these assumptions, we estimate the increase in demand is 0-5.4MW in 2022 and 98.3-199MW in 2037. **Figure 98** to **Figure 101** show the impact of large loads on minimum and maximum demand within Essential Energy's service area. The analysis demonstrates potential new large loads have the capacity to:

- Increase minimum demand by 32-66% in 2030 and 37-184% in 2037
- Increase maximum demand by 4-8% in 2030 and 4-7% in 2037.

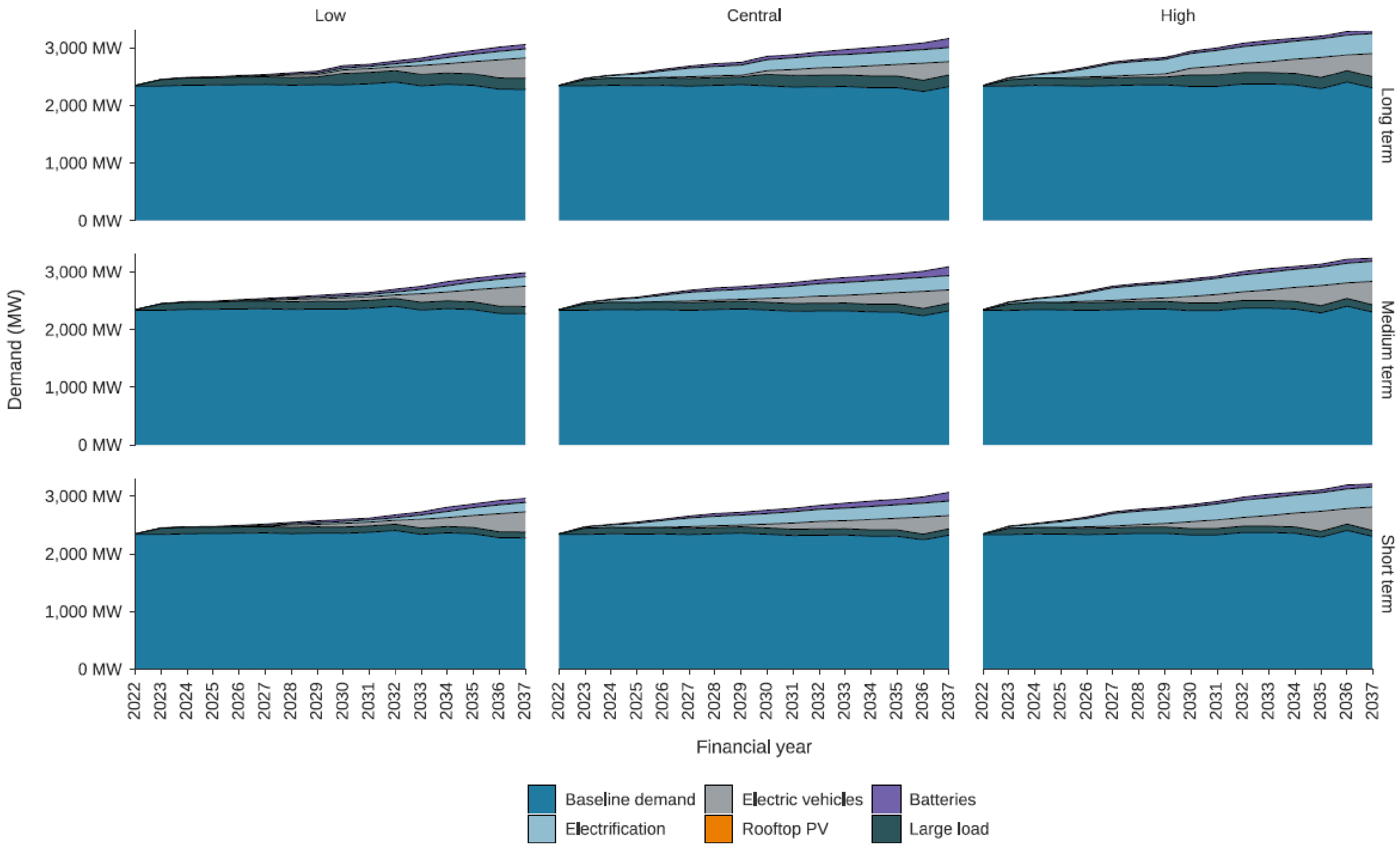
Large loads have the impact to significantly offset the reduction in minimum demand. It is notable the impact of large loads on maximum demand is less material than the impact on consumption (presented in Section 5.3.3), due to the relatively flat nature of these loads.

Figure 98: Maximum summer demand with large loads



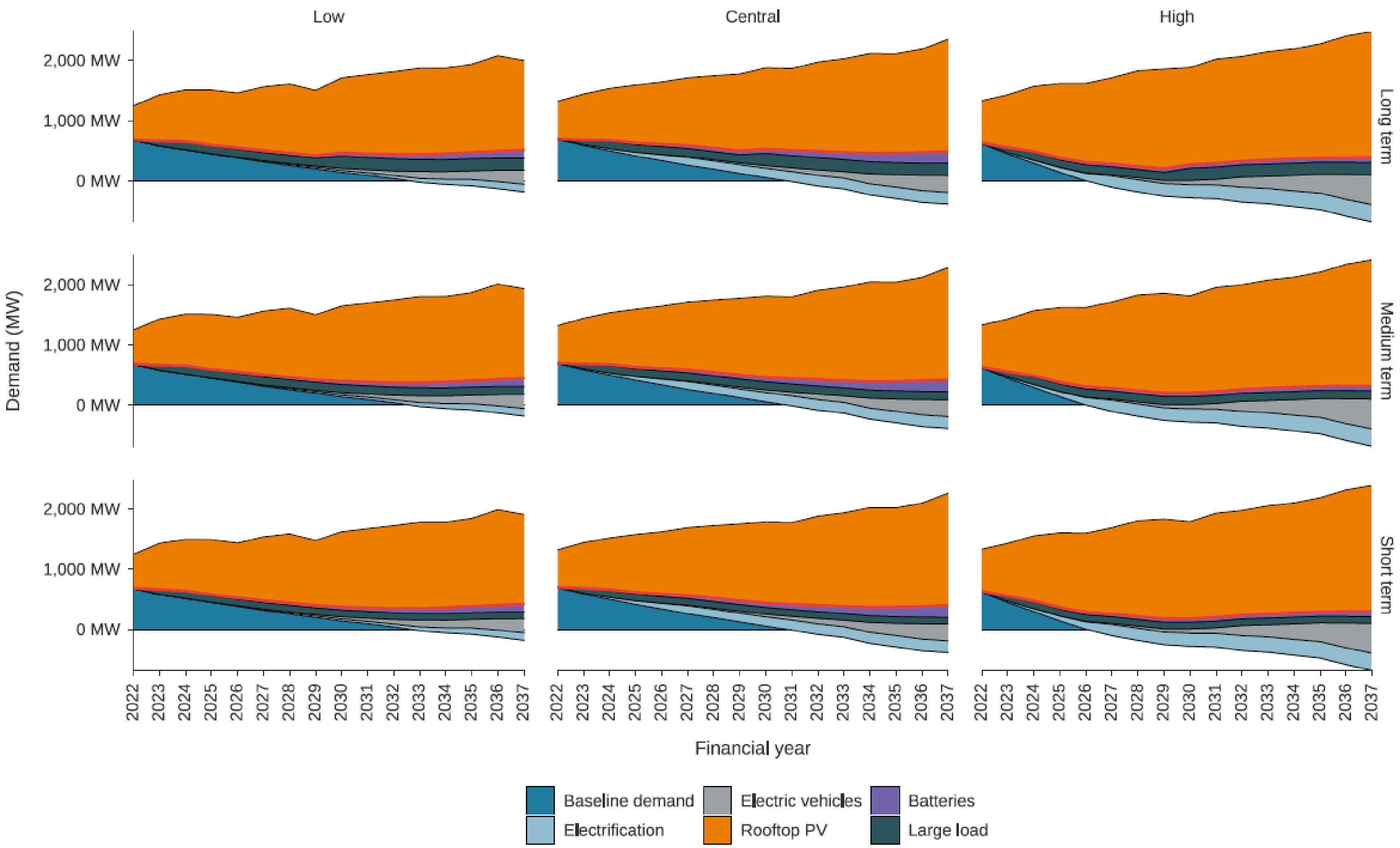
Source: Frontier Economics analysis

Figure 99: Maximum winter demand with large loads



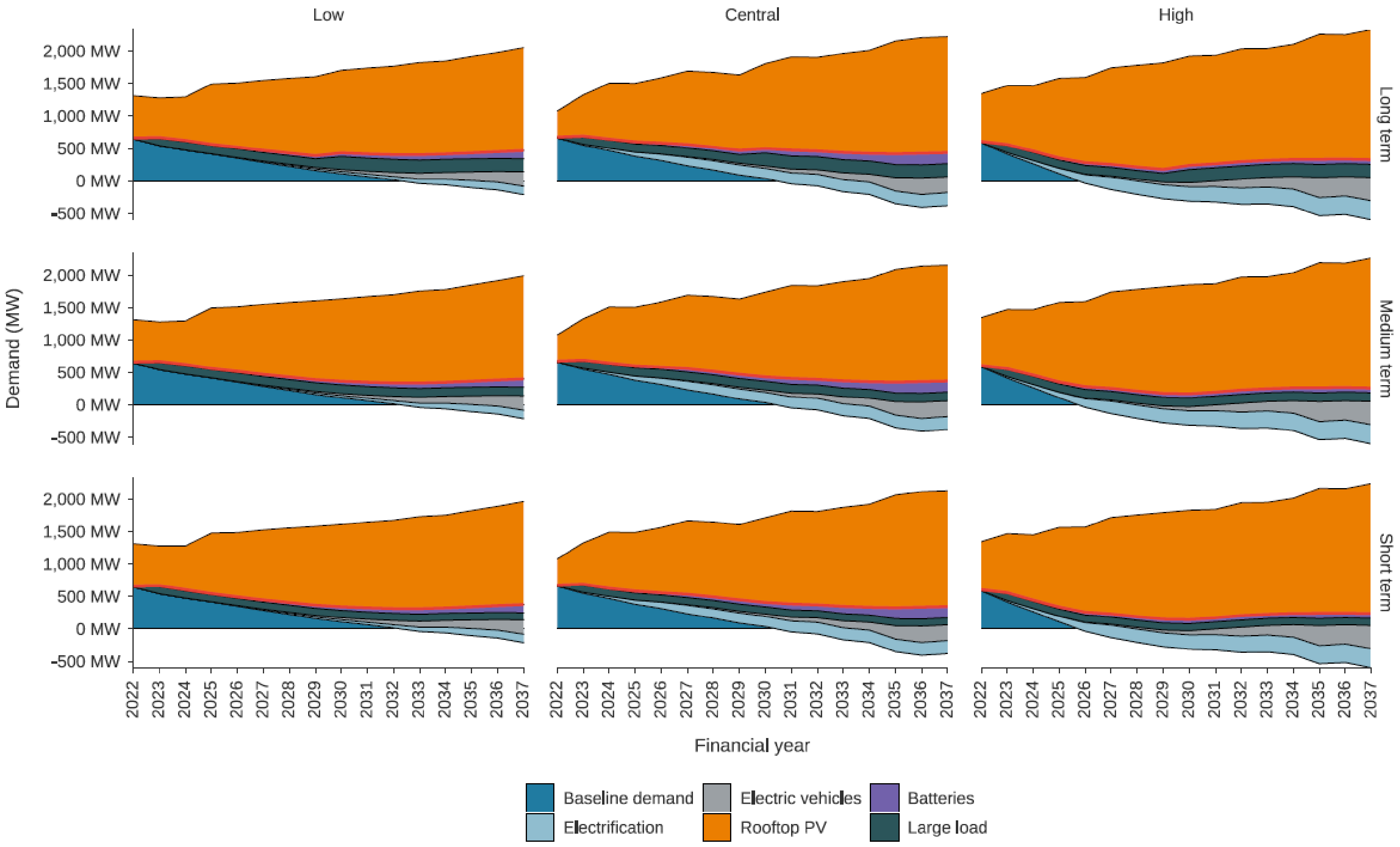
Source: Frontier Economics analysis

Figure 100: Minimum summer demand with large loads



Source: Frontier Economics analysis

Figure 101: Minimum winter demand with large loads



Source: Frontier Economics analysis

A TNI and ZSS consumption data and methodology

Data

TNI and ZSS data

Essential Energy provided Frontier Economics with historical consumption and customer data to inform our analysis:

- Half-hourly demand by TNI over the period from July 2009 to February 2022, which we aggregated to daily to forecast consumption
- Half-hourly demand by ZSS over the period from July 2010 to September 2021, which we aggregated to daily to forecast consumption.

Data cleaning

Our analysis forecasts consumption for the period 2022-2037. As such, TNIs that have been deactivated, or are expected to be inactive during this period, are excluded from analysis. Generation TNIs were also excluded from the forecast of underlying consumption. This leaves a total of 75 TNIs and 348 ZSSs to be modelled.

The consumption data provided by Essential Energy contained half hourly data over a period 2009 to early 2022 at the site level. In preparing this data for analysis there were two forms of cleaning performed:

- Negative ZSS values after accounting for rooftop PV and embedded generation were excluded and from consultation with Essential Energy are assumed to be the result of error.
- Remove periods of inactivity
- Remove outliers that are unlikely to reflect actual consumption

If periods in which a site is inactive are included in analysis this is likely to understate the average consumption. As consumption is unlikely to exactly equal 0 during periods of activity, we assumed that any zero observations are the result of inactivity and are removed from the data set.

From visual inspection we identified 8 sites that were unlikely to have been active during a sufficiently large period to be relevant for our analysis.

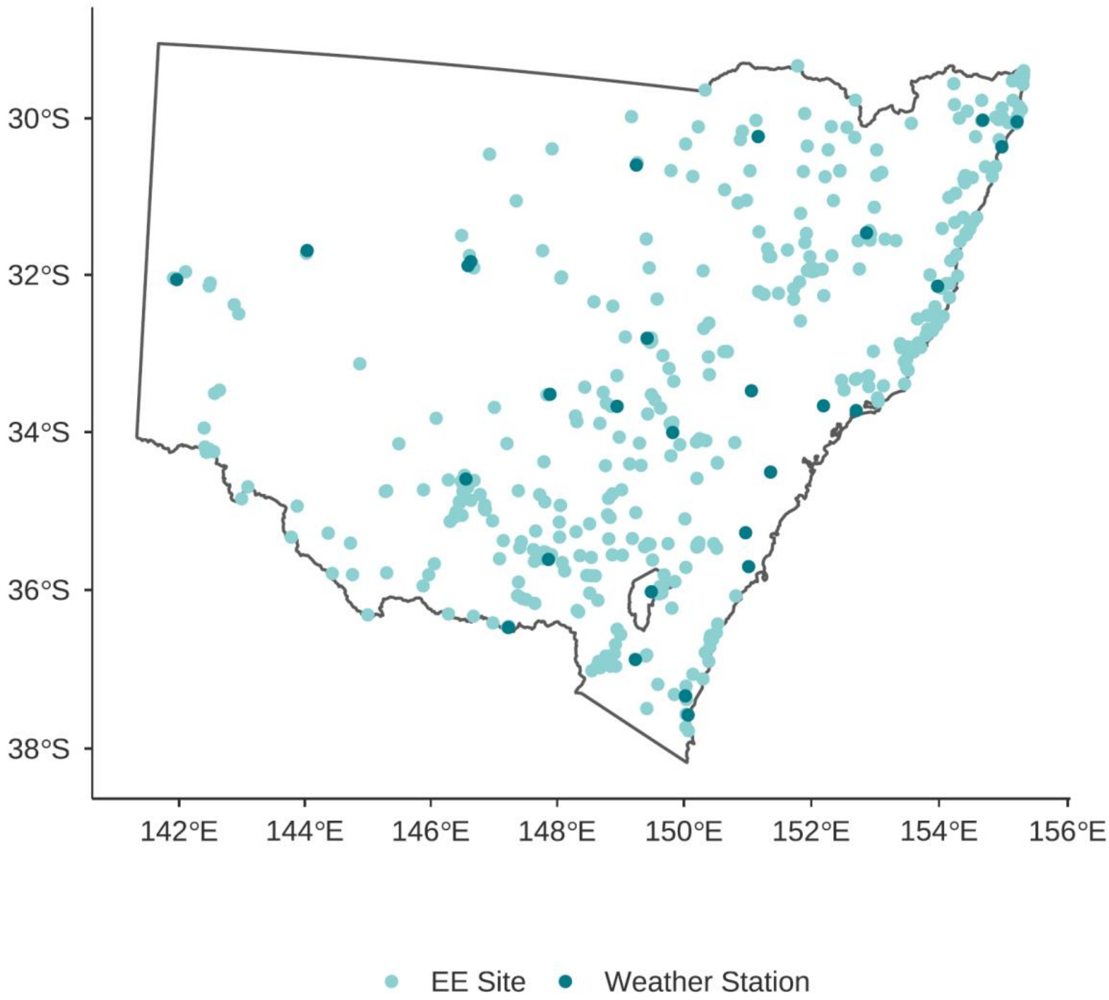
To identify non-zero outliers, the following strategies were employed:

- From a list of known outlier dates provided by Essential Energy, we identified and removed the half hour in which the outlier was likely to occur based on:
  a. Whether the observations were zero
  b. The number of standard deviations away a given load was from the 2-day moving average
- Removed data for periods where cumulative network consumption was above the reported monthly maximum consumption, excluding the three highest consumption sites for that period
- Removed observations that were more than 3.5 standard deviations away from the 2-day moving average load

Weather data

Half-hourly weather data was acquired from the Bureau of Meteorology (BOM). This data reports the half hourly temperature and precipitation of weather stations across NSW. These stations are geo-mapped to the Essential Energy sites to create a profile of weather behaviour over the period July 2001 to January 2022. Due to the extended period of weather data required, only weather stations that have been in operation for this entire period were included, leaving a total of 28 weather stations in the dataset.

Figure 102: Bureau of Meteorology Weather stations mapped to Essential Energy sites



Source: BOM and Essential Energy

Figure 102 presents the location of Essential Energy's TNIs and ZSSs relative to the considered weather stations. These selected stations are sufficiently distributed around the geographic region of NSW, to appropriately capture idiosyncratic as well as systemic changes in weather across the region.

The BOM weather data for this period has many missing data points, which would adversely affect econometric modelling if unaddressed. We employed two methods of interpolating missing weather data based on whether the missing data was continuous across several consecutive periods:

- **For periods of non-consecutive missing data:** Missing data were addressed by taking the average of the immediately preceding and following half hour periods. This relies simply on the assumption that the weather smoothly transitions across a one-to-three-hour interval.
- **For periods of consecutive missing data:** Missing data were addressed by the average of the same time on surrounding days. This methodology preserves the time specific behaviour of temperature but ignore the specific climatic conditions of that day. For example, this assumes that the weather at 4am is more accurately predicted by the weather at 4am on preceding and following days, than by the weather at 4pm on the same day. We believe this assumption to be appropriate.
- **For prolonged periods of missing data:** Where a weather station was presumed to have shut down or inactive, they are excluded from the dataset.

Methodology

Figure 103 provides an overview of the forecasting methodology adopted for TNI and ZSS. We weather normalised the data before testing a series of time-series models and identifying an appropriate model using a combination of visual inspection and model statistics. We then used these models to generate forecasts, before making post-model adjustments for new technologies.

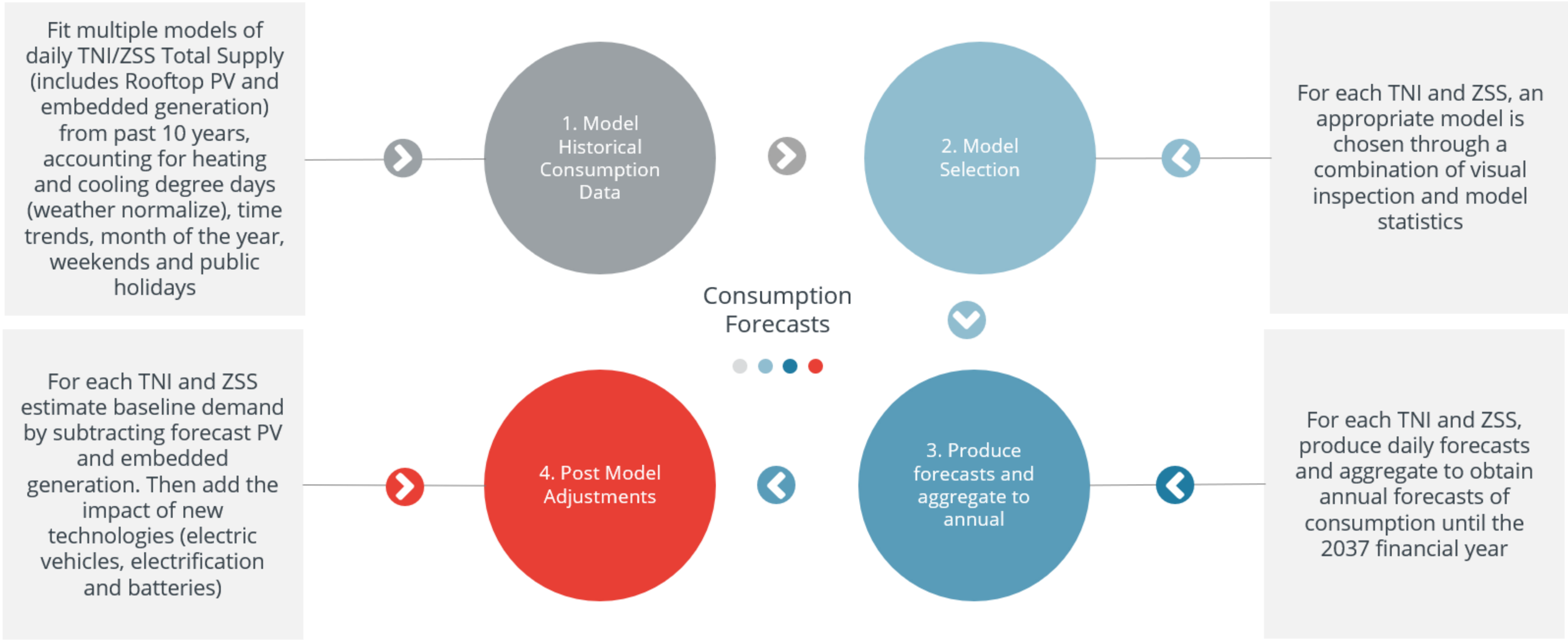
We tested a series of models for economic drivers for TNI and ZSS, consistent with our approach for invoiced consumption. However, given the importance of local characteristics at each TNI or ZSS we found trend-based models consistently generated a better fit. Our consumption forecasts for TNI and ZSS are therefore based on a time series approach.

Once the best model has been selected, predictions of the weather normalised electricity consumption values for each past year can be made by

- Evaluating the model at the long-term average values of the weather variables in the model, and;
- Adding the estimated residual term.

If we only do step (1) in the above procedure, the resulting prediction is referred to as the 'fitted' weather normalised value for electricity consumption in each year. The difference between 'weather normalised' and "fitted weather normalised' electricity consumption is whether the residual term is included in the predicted value. Fitted weather normalised values for electricity consumption are typically considerably smoother over time.

Figure 103: TNI and ZSS forecasting methodology



Source: Frontier Economics

Modelling historical daily data

In assessing the appropriate model for consumption forecasting we considered numerous variables that are likely to drive or influence electricity usage on the daily level. These include:

- Month
- Weekend / weekday status
- Public holiday

In addition, we considered model specifications that could reflect the relationship between electricity consumption and two characteristics of interest:

- Weather
- Time trends

This section will elaborate on their inclusion in the resulting models.

While estimating our econometric models, we weather normalised the electricity consumption data for TNIs and ZSSs. Weather normalisation removes the year-to-year fluctuations in the consumption data due to differences in weather from year to year. The aim of weather normalisation is to predict what consumption would have been in each historical year if the year had experienced temperatures and weather during the year that reflect an average year.

Electricity is used for both heating in winter and cooling in summer. To capture the dependence of electricity consumption on low temperatures, a heating degree day (HDD) variable was created, which is of the form:

$$\text{HDD} = \max(\text{HDD Critical Temperature} - T, 0)$$

where:

- T is the average daily temperature; and
- HDD Critical Temperature is the temperature at which electric heaters are typically turned on to start heating.

Similarly, to capture the dependence of electricity consumption on high temperatures, a cooling degree day (CDD) variable was created, which is of the form:

$$\text{CDD} = \max(T - \text{CDD Critical Temperature}, 0)$$

where:

- T is the average daily temperature; and
- CDD Critical Temperature is the temperature at which electric air conditioners are typically turned on to start cooling.

The HDD and CDD critical temperatures used were 17.0 and 19.5 respectively, based on AEMO 2020 regional estimates, which have the greatest predictive power of demand models.[27]

[27] AEMO, Electricity Demand Forecasting Methodology Information Paper, August 2020, pg. 49

To determine the dependence of electricity consumption on weather, we regressed annual electricity consumption by each TNI and ZSS using the following econometric models. The consumption drivers refer to the calendar variables described above.

Simple Consumption Drivers Model:

$$\text{Total daily electricity consumption (MW)} = \alpha + D \times \text{Consumption drivers} + \text{residuals}$$

Linear Weather Consumption Model:

$$\text{Total daily electricity consumption (MW)} = \alpha + \beta_1 \times \text{HDD} + \beta_2 \times \text{CDD} + D \times \text{Consumption drivers} + \text{residuals}$$

Quadratic Weather Consumption Model:

$$\text{Total daily electricity consumption (MW)} = \alpha + \beta_1 \times \text{HDD} + \beta_2 \times \text{CDD} + \beta_3 \times \text{HDD}^2 + \beta_4 \times \text{CDD}^2 + D \times \text{Consumption drivers} + \text{residuals}$$

Electricity consumption is highly dependent on weather, as such the simple consumption drivers model failed to capture the variation in demand over time.

The quadratic weather model was intended to capture the non-linear response of electricity consumption to changes in average daily temperature, however these variables were not shown to be consistently statistically significant, nor did they contribute significantly to the model fit. As these variables were unlikely to improve our forecasting and were excluded from consideration. Therefore, these models were not used to product forecasts.

Identifying model specification for time trends

In our analysis, two simple models were considered:

Non-Trended Weather Consumption Model:

$$\text{Total daily electricity consumption (MW)} = \alpha + \beta_1 \times \text{HDD} + \beta_2 \times \text{CDD} + D \times \text{Consumption drivers} + \text{residual}$$

Trended Weather Consumption Model:

$$\text{Total daily electricity consumption (MW)} = \alpha + \gamma \times \text{time} + \beta_1 \times \text{HDD} + \beta_2 \times \text{CDD} + D \times \text{Consumption drivers} + \text{residual}$$

Whether a trend was appropriate for inclusion was based on visual inspection of both the historical data and the preliminary forecasts and included the trend variable if it was appropriate and realistic. Overall, 44 TNIs and 93 ZSSs were determined to require a trend component to the model.

Forecasting

For each TNI and ZSS, 12 years of historical data are used to calibrate the model for forecasting. For the forecast period we have set the average daily temperature (T) to the historical average over the period 2009-2021. This normalised the impact of weather on electricity to produce a stable average estimate of consumption across the forecast period.

Post model adjustments for battery, EV, and electrification

Profiles for battery and EV usage, as well as projected electrification are based on the data in described in **Section 3**.These are aggregated to daily levels and applied to forecasts after weather normalisation.

B Invoiced consumption and maximum demand data and methodology

Customer numbers

Data

Customer number data

Essential Energy provided Frontier Economics with historical monthly customer numbers by tariff category over the period from July 2008 to January 2022. Due to the 3-month billing cycles that appear in the invoicing data, the monthly series is aggregated to the financial year for model fitting. The data otherwise did not require any cleaning before model fitting.

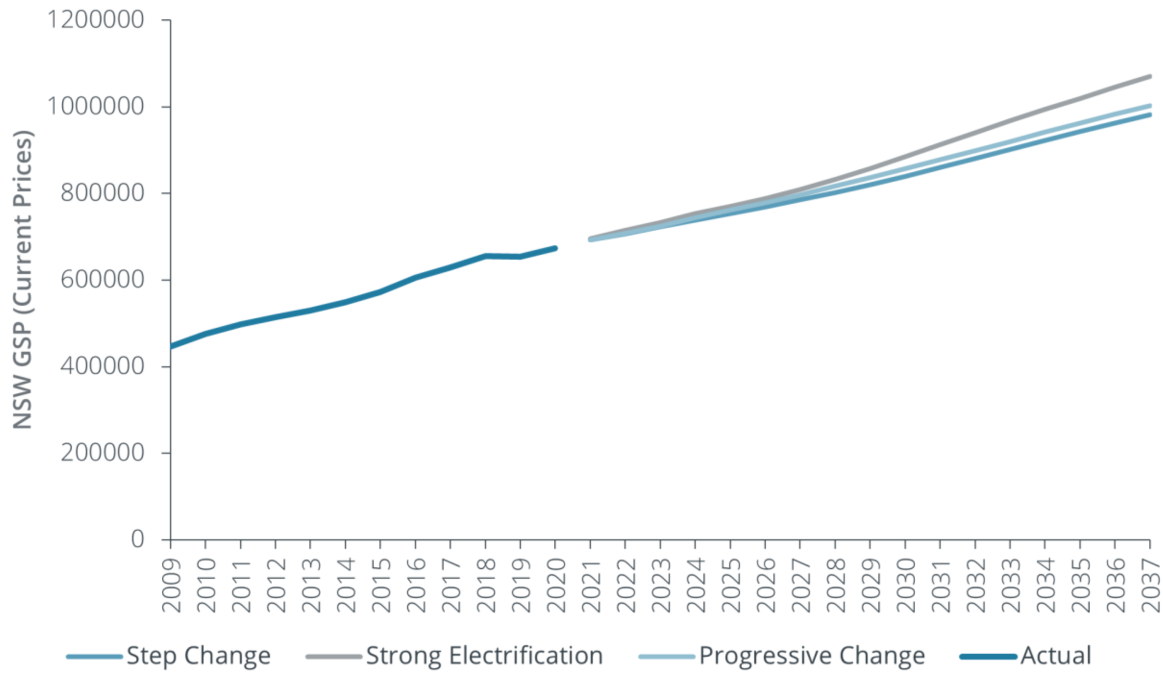
Long-term drivers

This section discusses the long-term drivers of demand that were found to be significant in our analysis.

Gross state product (GSP)

Electricity consumption is a function of economic activity, which is measured as gross state product. Gross state product is a measure of a state's output, calculated as the sum of value added from all industries in the state. GSP for NSW was taken from the ABS and is based on current prices. **Figure 104** presents historical and forecast GSP over the modelling period.

Figure 104: Historical and forecast GSP

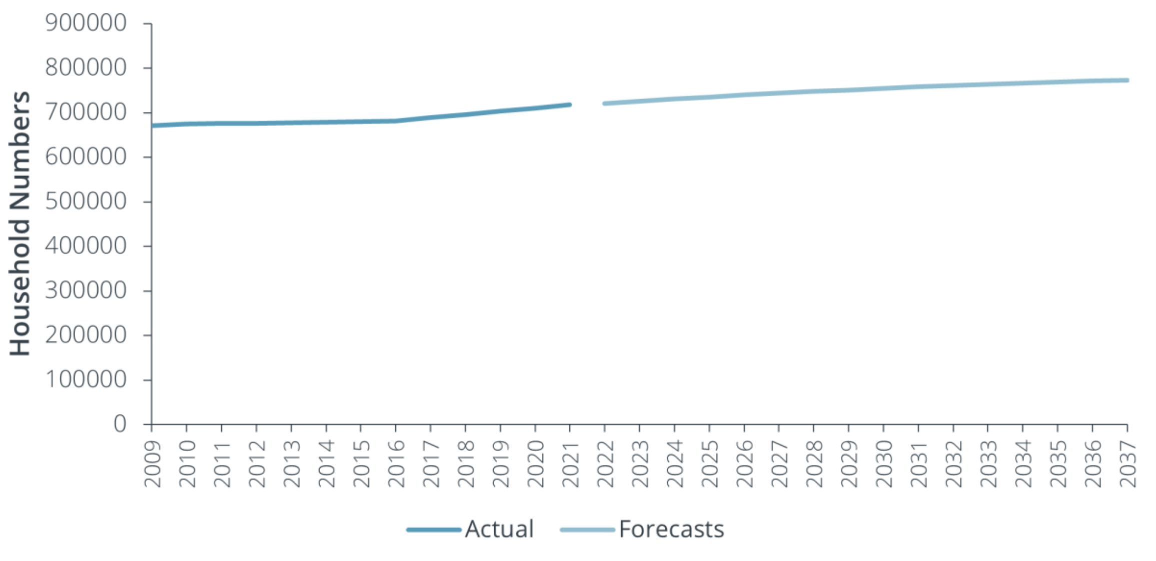


Source: AEMO 2022 ISP

Dwelling data

The number of households was identified as a key driver of residential customer numbers and consumption through the forecasting period. Historical data was obtained from the Australian Bureau of Statistics. The NSW Department of Planning, Industry and Environment forecast household projections were adopted. These inputs are shown in **Figure 105**.

Figure 105: Historical and forecast households



Source: ABS and DPIE

Methodology

For each customer type we considered both a short-term time series model and a long-term causal model:

- **Short-term time series model:** Time-series models are generally accepted to be more applicable in short-term forecasting.[28]
- **Long-term causal model:** We developed a causal model to reflect the macroeconomic drivers understood to have a material impact on customer numbers, including population, electricity prices and gross state product.

We selected the models that provided the best fit for each customer category and blended these models to develop forecasts over the forecasting period.

To derive the preferred forecasting models for forecasting customer numbers, we estimated a wide range of different specifications of the models using different combinations of time trends and economic drivers, which included gross state product, and dwelling numbers. The full list of variables investigated can be found in **Table 3**. We tested a range of specifications, including different combinations of variables, levels and changes, logs, and lags.

[28] Chase, C, 2009, Demand-Driven Forecasting: A Structured Approach to Forecasting. John Wiley & Sons, Inc., Hoboken, New Jersey.

Once the models with different combination of independent variables were estimated, several criteria were used to select the preferred models. An initial set of candidate models was identified based on the adjusted R squared, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) measures. The signs and magnitudes of the coefficients of the chosen models were then checked, to ensure the models produced reasonable estimates of the variables in question. Finally, the significance of the estimate of any coefficients were examined. If the model had an unreasonable estimate for an economic driver, an incorrect sign or an insignificant coefficient estimate then this model was discarded and the models re-ranked. This process was completed until a model was found with reasonable and significant elasticities and coefficients.[29]

Once the preferred model for each customer segment has been identified, forecasts can be produced. Forecasts for dwelling numbers were constructed from ABS/DPI data while forecasts for GSP came from AEMO.

Table 3: Consumption drivers investigated in our modelling

Driver	Description	Source
Household numbers	Historical household numbers	Australian Bureau of Statistics
Real Gross State Product	Historical measure of value adding in the NSW, in real terms	Australian Bureau of Statistics
Electricity prices	An index of the price that customers have paid historically	Australian Bureau of Statistics
Heating degree days (HDD)	An indicator of how cold a year is	Frontier Economics calculations using Bureau of Meteorology data
Cooling degree days (CDD)	An indicator of how hot a year is	Frontier Economics calculations using Bureau of Meteorology data

Consistent with best practice forecasting, including AEMO's methodology, the models were selected to produce forecasts that vary by customer type.

Business customers

We developed both trends based (short term) and economic driver models (long term) of business customers. In the short term, business connections were estimated as a function of a time trend while in the long-term were estimated as a function of gross state product (GSP).

Business Customers – Short Term Model

$$\text{Business customer numbers} = \beta_0 + \beta_1 \times \text{trend} + \text{residual}$$

Business Customers - Long Term Model

$$\text{Business customer numbers} = \beta_0 + \alpha \times \text{GSP} + \text{residual}$$

[29] Given the small sample sizes for these estimations, the level of statistical significance used to select a variable was 10%.

We combined these forecasts for each customer category, adopting a weighting method consistent with AEMO's demand forecasting methodology. This involves adopting an equal weighting of 50% for combing the short term and long-term models in the first forecast year, reducing the contribution of the short-term component to 25% in the second forecast year, 12.5% in the third forecast year and 0% thereafter.[30]

Residential consumption

Residential connections did not exhibit a strong relationship to economic drivers and was estimated as a trend. Specifically, prices and GSP were shown to be insignificant variables.

Trended Residential Consumption Per Connection model:

$$\text{Residential consumption per connection} = \beta_0 + \beta_1 \times \text{trend} + \text{residual}$$

Customer numbers were estimated as a function of dwelling numbers, which reflect the residential building stock.

Residential Customer Numbers Model with Dwellings:

$$\text{Residential customers} = \beta_0 + \gamma \times \text{dwellings} + \text{residual}$$

Invoiced consumption

Data

Consumption data

Essential Energy provided Frontier Economics with historical monthly invoiced consumption by tariff category over the period from July 2008 to January 2022. Due to the 3-month billing cycles that appear in the invoicing data, the monthly series is aggregated to the financial year for model fitting. The data otherwise did not require any cleaning before model fitting.

Methodology

To forecast electricity consumption a series of econometric models were fitted for consumption per connection and customer numbers by customer type. Consumption per connection was calculated by dividing total consumption in each financial year by the number of connections.

Since the model is specified on a per connection basis, multiplying the forecasts produced by these models by the respective projected customer base then gives forecasts of the total consumption for each respective class. A customer is defined as an electricity connection, which for residential electricity will closely align with the number of households.

For each customer type we considered both a short-term time series model and a long-term causal model:

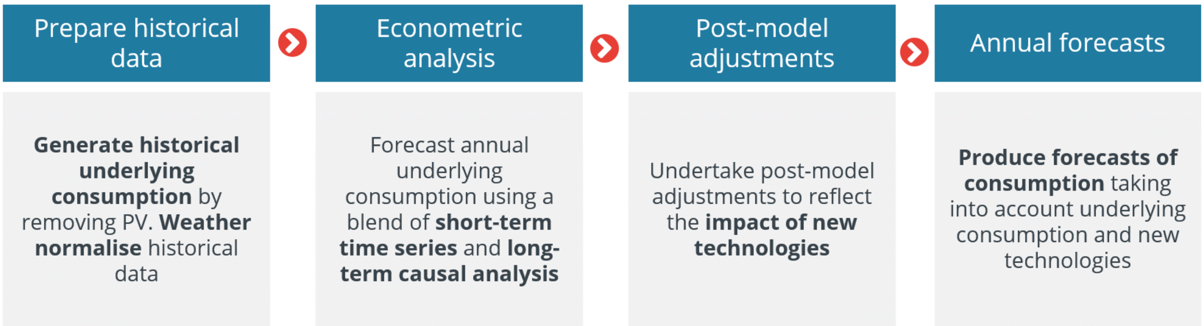
- **Short-term time series model:** A time series model, using either a lag or a time trend
- **Long-term causal model:** We developed a causal model to reflect the macroeconomic drivers understood to have a material impact on consumption, including population, electricity prices and gross state product.

30 AEMO, Electricity Demand Forecasting Methodology Information Paper, August 2020, p19.

Time-series models are generally accepted to be more applicable in short-term forecasting.[31] We used time-series methods to model consumption for each customer type across Essential Energy's network.

We selected the models that provided the best fit for each customer category and blended these models to develop forecasts over the forecasting period.

Figure 106: Consumption forecasting methodology overview



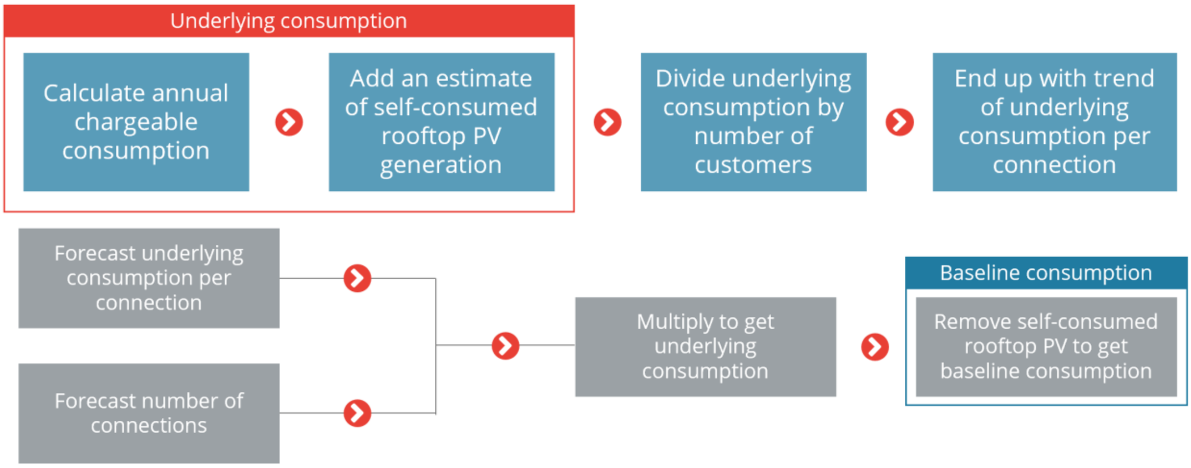
Source: Frontier Economics

Figure 107 and **Figure 108** provide a more detailed overview of the methodology used to forecast invoiced consumption. We use historical data to derive underlying consumption per connection, accounting for rooftop PV and the number of customers. We then forecast underlying consumption per connection and the number of connections to estimate underlying consumption in the future. This is then adjusted to remove forecast PV and calculate baseline consumption. Finally, we add the impact of new technologies including EVs and electrification to calculate consumption.

Our methodology is consistent with best practice forecasting, including AEMO's demand forecasting methodology.

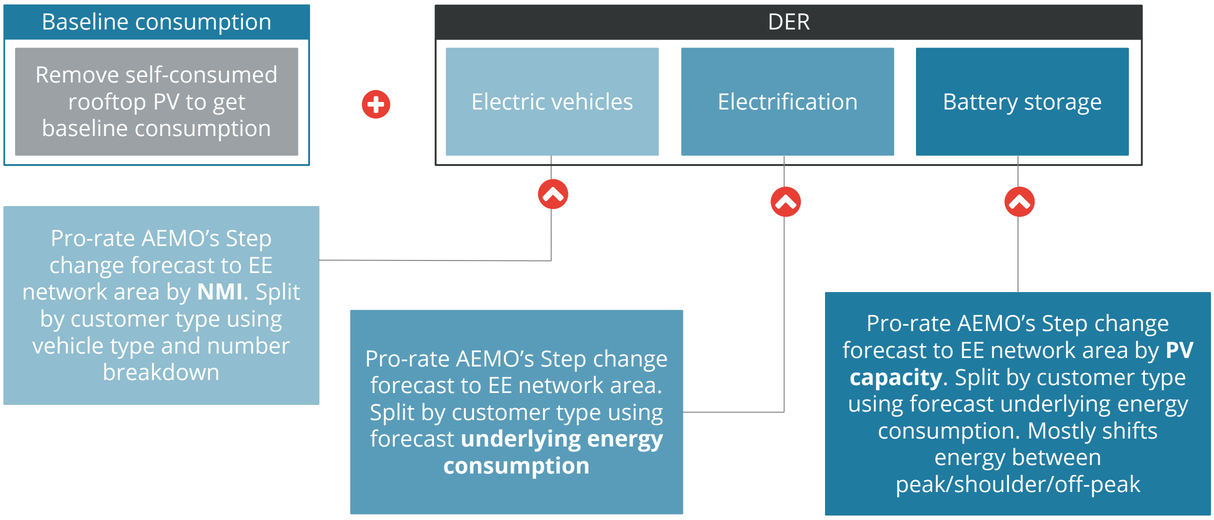
31 Chase, C, 2009, Demand-Driven Forecasting: A Structured Approach to Forecasting. John Wiley & Sons, Inc., Hoboken, New Jersey.

Figure 107: Forecasting baseline invoiced consumption



Source: Frontier Economics

Figure 108: Post-model adjustments to invoiced consumption



Source: Frontier Economics

To derive the preferred forecasting models for forecasting invoiced consumption, we estimated a wide range of different specifications of the models using different combinations of the weather variables and time trends. We tested a range of specifications, including different combinations of variables, levels and changes, logs and lags.

Once the models with different combination of independent variables were estimated, several criteria were used to select the preferred models. An initial set of candidate models was identified based on the adjusted R squared, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) measures. The signs and magnitudes of the coefficients of the chosen models were then checked, to ensure the models produced reasonable estimates of the variables in question. Finally, the significance of the estimate of any coefficients were examined. If the model had an unreasonable estimate for an economic driver, an incorrect sign or an insignificant coefficient estimate then this model was discarded and the models re-ranked. This process was completed until a model was found with reasonable and significant elasticities and coefficients.[32]

Once the preferred model for each customer segment has been identified, forecasts can be produced. Forecasts for dwelling numbers were constructed from ABS/DPI data while forecasts for GSP came from AEMO.

Consistent with best practice forecasting, including AEMO's methodology, the models were selected to produce forecasts that vary by customer type.

Business consumption

We estimated business consumption per connection and multiplied these variables with the business customer numbers to find total consumption. We developed both trend based (short term) and economic driver models (long term) of business consumption.

In the short term, business consumption per connection was estimated as a function of a time trend while in the long-term business consumption per connection was estimated as a function of gross state product (GSP). Weather normalisation variables, i.e., HDD and CDD were tested but were found to have significant impact on consumption at the annual level.

The model specifications are shown below.

Business Consumption per Connection – Short Term Model

$$\text{Business consumption per connection} = \beta_0 + \beta_1 \times \text{trend} + \text{residual}$$

Business Consumption per Connection – Long Term Model

$$\text{Business consumption per connection} = \beta_0 + \alpha \times \text{GSP} + \text{residual}$$

Where the trend controls for general time-varying, unobserved factors that affect electricity usage, such as efficiency gains and price impacts.

We combined these forecasts for each customer category, adopting a weighting method consistent with AEMO's demand forecasting methodology. This involves adopting an equal weighting of 50% for combing the short term and long-term models in the first forecast year, reducing the contribution of the short term component to 25% in the second forecast year, 12.5% in the third forecast year and 0% thereafter.[33]

Residential consumption

AEMO emphasizes the role of demographic factors in driving residential consumption via the customer base. Residential consumption per connection did not exhibit a strong relationship to economic drivers and was estimated as a trend. Specifically, prices and GSP were shown to be insignificant variables.

Weather normalisation variables (HDD and CDD) were also used but showed no significance in modelling per connection consumption. This is likely due to there being not enough variation in HDD and CDD in the historical data (when aggregated to the annual level).

Trended Residential Consumption Per Connection model:

[32] Given the small sample sizes for these estimations, the level of statistical significance used to select a variable was 10%.

[33] AEMO, Electricity Demand Forecasting Methodology Information Paper, August 2020, p19.

$$\text{Residential consumption per connection} = \beta_0 + \beta_1 \times \text{trend} + \text{residual}$$

Customer numbers were estimated as a function of dwelling numbers, which reflect the residential building stock.

Residential Customer Numbers Model with Dwellings:

$$\text{Residential customers} = \beta_0 + \gamma \times \text{dwellings} + \text{residual}$$

Invoiced maximum demand

Data

Essential Energy provided Frontier Economics with monthly maximum demand data by tariff category and billing component over the period from July 2008 to December 2021. The values represent, for each month and tariff category, the sum of the maximum demands (maximum half hour period) for each customer[34]. This is non coincident maximum demand as the maximum demand for each customer can occur in different half hour periods.

Unlike invoiced consumption, the monthly series did not need to be aggregated to the annual year which gave a larger sample size for forecasting. The data otherwise did not require any major cleaning or outlier detection.

Methodology

In the same way as the invoiced consumption forecasts, invoiced maximum demand is forecast on a per connection basis. Therefore, multiplying the per connection demand forecasts by the projected number of customers gives a forecast of invoiced maximum demand for each customer class. The steps involved in the forecasting process are as follows:

- Forecast per connection maximum demand at the billing component level (e.g., Shoulder, Peak, Off-peak) for each customer segment (at the monthly level).
- Multiply per connection forecasts by the customer number forecasts explained in the previous section.

Since the data is at the monthly level, we use the month of the year as a variable in the model as maximum demand is heavily influenced by seasonality[35]. The regression equation used to forecast per connection demand is shown below.

Maximum Demand Per Connection - Model

$$\text{Consumption per connection} = \beta_0 + \beta_1 \times \text{trend} + \sum_{k=1}^{11} \beta_k \times month_k + \text{residual}$$

We tried other models, including fitting in logs and including PV generation as an explanatory variable. These alternations did not improve the model, so we decided to exclude them.

[34] Depending upon the tariff, invoiced maximum demand may be measured in kilovolt amps (kVA) or kilowatts (kW).

We include only 11 month dummy variables as one of the months acts a reference category

New technologies

The uptake of new technologies, including electric vehicles, battery energy storage systems and electrification, will impact a customer's invoiced maximum demand. To account for their impact on invoiced maximum demand, we take the profiles developed in section 3 and scale them down to the customers on demand tariffs. For this process, it is assumed that all industrial and large business customers are on demand tariffs. This means the only customers not on a demand tariff are those residential and small business customers on continuous or time-of-use tariffs.

To pro-rate the profiles down to the tariff level, we use the energy consumption of each tariff to apportion each new technology profile. It was then assumed that, for each time component, the maximum demand occurred for each customer at the same time. The times at which each tariff is assumed to reach its maximum demand is given below in **Table 4** for each tariff period.

Table 4: Contribution times of new technologies

Tariff period	Contribution time
Peak	6pm
Shoulder	3pm
Off-peak	10pm
Anytime	6pm

Source: Frontier Economics

C TNI and ZSS maximum and minimum demand data and methodology

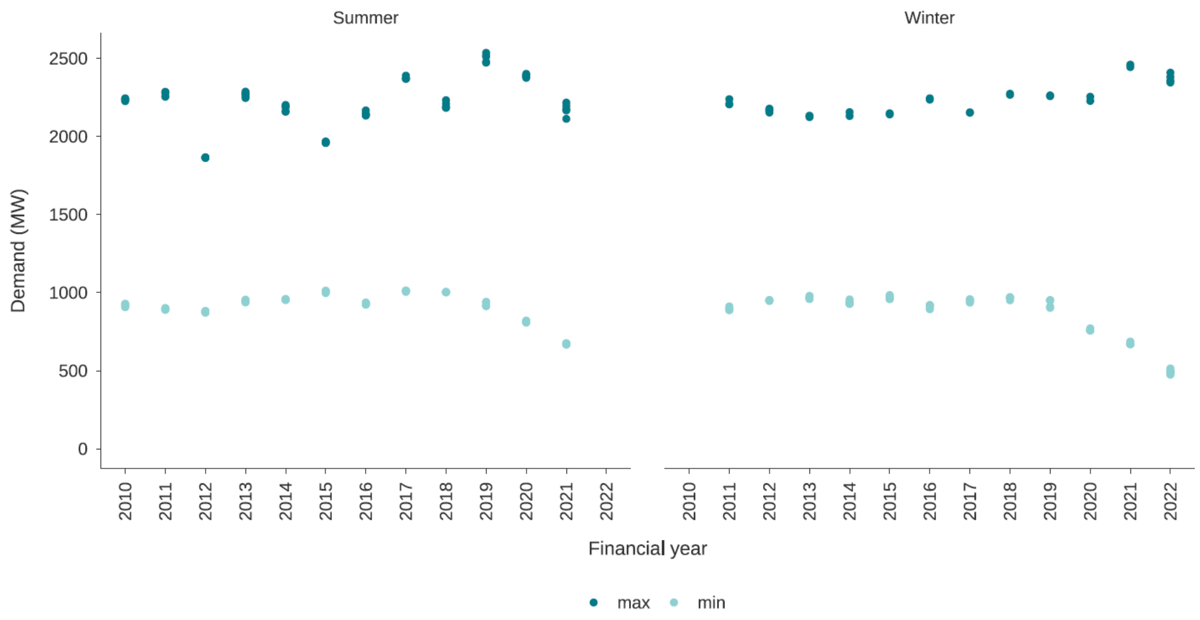
Data

Underlying demand

In calibrating the minimum and maximum demand models, we used the half hourly TNI and ZSS load data described in 0. **Figure 109** presents the five minimum and maximum half hourly load across the Essential Energy network from financial year 2011 to 2022, after the removal of outliers and presumed reporting errors. The minimum demand is less volatile than maximum demand and is showing a significant decline from 2018 in both summer and winter months. The maximum demand is increasing over time but shows a lot of year-on-year variation due to the weather.

Over the historical period analysed maximum demand was not considerably higher in summer months compared to winter months. Of the 80 TNIs for which we have data, in any given year only 40.5-48.1% were summer peaking.

Figure 109: Historical minimum and maximum demand



Source: Frontier Economics' analysis of Essential Energy data

Weather data

The weather data described in Appendix A is employed to both model electricity demand, as well as to construct synthetic weather years.

In our modelling, we have attempted to reflect that electricity usage is affected by both heating in winter and cooling in summer. To capture the dependence of electricity consumption on low temperatures, a heating degree day (HDD) variable was created, which is of the form:

HDD = max(HDD Critical Temperature -T, 0)

where:

T is the temperature at a given half hour; and

HDD Critical Temperature is the temperature at which electric heaters are typically turned on to start heating.

Similarly, to capture the dependence of electricity consumption on high temperatures, a cooling degree day (CDD) variable was created, which is of the form:

CDD = max(T- CDD Critical Temperature, 0)

where:

T is the temperature at a given half hour; and

CDD Critical Temperature is the temperature at which electric air conditioners are typically turned on to start cooling.

These variables are defined for each half hour for each TNI and ZSS based on the normalised BOM weather data from the nearest weather station. The HDD and CDD critical temperatures used were 17.0 and 19.5 respectively, based on AEMO 2019 regional estimates, which have the greatest predictive power of demand models.[36]

Methodology

For electricity, maximum demand is defined as the half hour in the year, or in the winter and summer seasons, with the highest consumption. Minimum and maximum demand are inherently rare occurrences that take place at extreme points in the year. To forecast the probable interval in which an extreme value will take place, we need to establish an approximate distribution of minimum and maximum demand values. This section presents a summary of the methodology used to construct a distribution of forecast minimum and maximum demand values for the period 2022-2037.

Modelling half-hourly demand data

Stage 1 of the min-max demand forecasting requires developing a half hourly model of electricity demand based on historical data, for each ZSS and TNI. We tested several models to maximum the predictive power of the model. All models consider typical demand drivers, including:

- Month
- Time of day
- Weekend / weekday status
- Public holiday status

[36] AEMO 2019, Electricity Demand Forecasting Methodology Information Paper, pg. 44

- HDD and CDD

Although a linear measure of temperature will reflect the expected increases in electricity demand on warm and cold days, this modelling approach may not accurately reflect the non-linear response to temperature changes. We introduce two additional variable types that can be used to capture this response to temperature:

- HDD^2
- CDD^2

We estimate the dependence of electricity demand on these defined variables by regressing electricity consumption by each TNI and ZSS on these consumption drivers in an econometric model. These models are run using the prior three years' worth of data, to prevent structural changes at the site level from driving results.

We considered the following model specifications:

Combined Linear Model:

$$\text{Electricity demand (MW)} = \alpha + \beta_1 \times \text{HDD} + \beta_2 \times \text{CDD} + \omega \times \text{Summer} + D \times \text{demand drivers} + \text{residuals}$$

Seasonal Linear Model:

$$\text{Electricity demand (MW)} = \alpha + \beta_1 \times \text{HDD} + \beta_2 \times \text{CDD} + D \times \text{demand drivers} + \text{residuals, regressed separately for Summer and Winter months}$$

Seasonal Quadratic Model:

$$\text{Electricity demand (MW)} = \alpha + \beta_1 \times \text{HDD} + \beta_2 \times \text{CDD} + \beta_3 \times \text{HDD}^2 + \beta_4 \cdot \text{CDD}^2 + D \times \text{demand drivers} + \text{residuals, regressed separately for Summer and Winter months}$$

The goodness of fit of each model varies by site, however the combined linear model was outperformed by all seasonal models overall. Therefore, this model was excluded from further consideration.

We would expect that the coefficients of HDD and CDD would be positive ($\beta_1, \beta_2 > 0$) and statistically significant (as on heating and cooling days additional electricity is used to control the climate of residential and commercial buildings).

For the variables HDD^2 and CDD^2 the sign of the coefficient does not have an immediately obvious interpretation and must be interpreted jointly with the coefficients of HDD and CDD, and either positive or negative coefficients can be logically explained. For example, as temperature increases residents may be increasingly willing to use their air conditioning to cool their house, resulting in a positive sign of CDD^2. Alternatively, as temperature increases to extreme temperatures, most cooling appliances may be unable to operate more and so there is a diminishing effect of temperature, resulting in a negative sign of CDD^2. As such, we believe it is reasonable to include these variables in the model so long as they improve the performance of the model, and do not result in demand predictions that are overly sensitive to weather changes. As such, the statistical significance of these coefficients will be relevant, rather than their sign.

Note that the response of electricity demand to heating days and cooling days need not be the same. As such, the appropriateness of a linear or quadratic model should be assessed for each HDD and CDD separately. The resulting model may be a hybrid of these approaches.

Therefore, the model used for each TNI and ZSS, for each season, is determined by the following process outlined in Box 3.

Box 3: Model selection process for each TNI and ZSS seasonal model

Step 1:

Run a Seasonal Quadratic Model (including all Consumption driver variables, as well as linear and quadratic weather variables).

- If β_3 or β_4 (the coefficients of the quadratic terms) are both are statistically significant at the 10% level, move to Step 2.
- If either β_3 or β_4 are not statistically significant at the 10% level, remove that variable from the model. If both, remove both. Move to Step 2.

Step 2:

Run the model on the remaining variables.

- If $\beta_1 > 0$, $\beta_2 > 0$ (the coefficients of the linear terms) and both are statistically significant at the 10% level, move to Step 3.
- If either $\beta_1 < 0$, $\beta_2 < 0$ or are not statistically significant at the 10% level, remove that variable from the model. In addition, remove the associated quadratic variable for that weather type (HDD or CDD). If both, remove all weather variables. Move to Step 3.

Step 3:

Run a linear regression model on the remaining variables considered. This can take on the form of a hybrid of the Seasonal Linear and Quadratic models for each of HDD and CDD. **Stop.**

To determine the best model, for each TNI and ZSS the above model selection process was employed. The initial model with a quadratic weather component resulted in linear coefficients and R squared presented in **Figure 110** and **Figure 111**.[37] For many TNIs and ZSSs the initial model specification presented a plausible model for forecasting, fitting the historical data well with economically and statistically significant responses to changes in weather. However, for many sites this model implied a negative relationship between extreme weather and electricity demand, which is likely to be a spurious relationship.

[37] The coefficient estimate for HDD (or CDD) can be interpretated as the unit increase in MW demanded associated with a 1ºC degree decrease (or increase) in temperature below (or above) the threshold temperature for a given site.

Figure 110: Quadratic weather model coefficient estimate for linear HDD and CDD variable

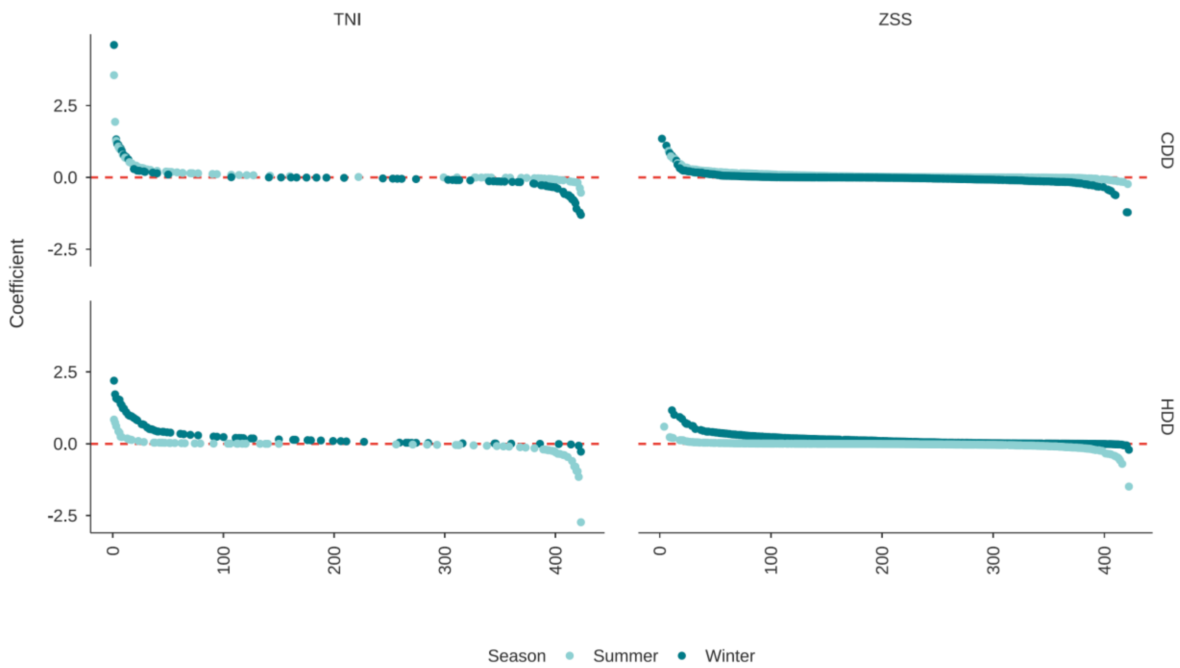
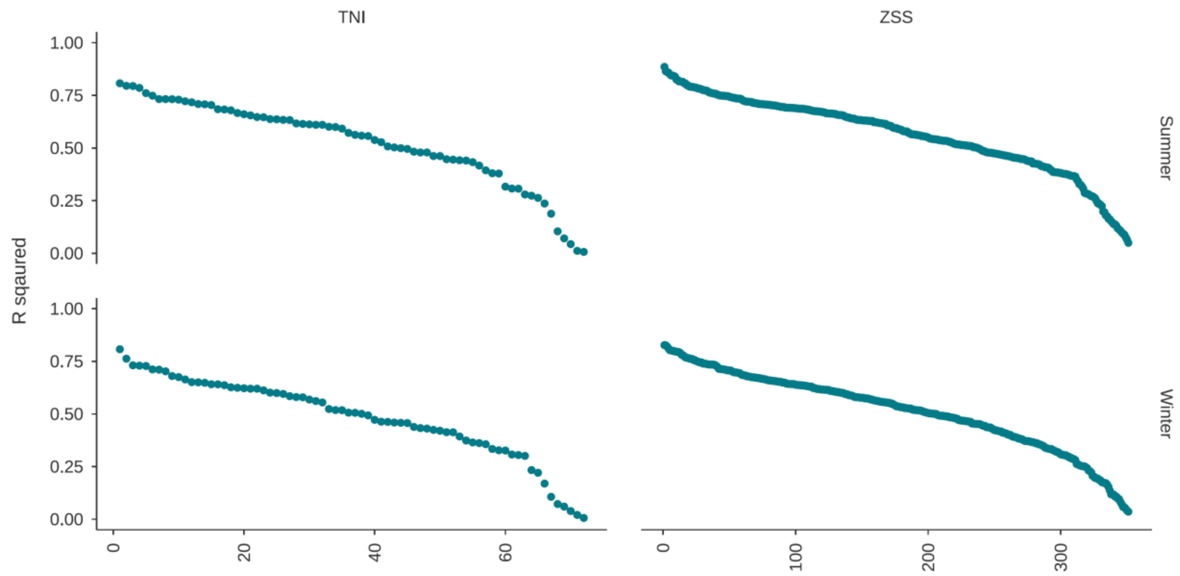
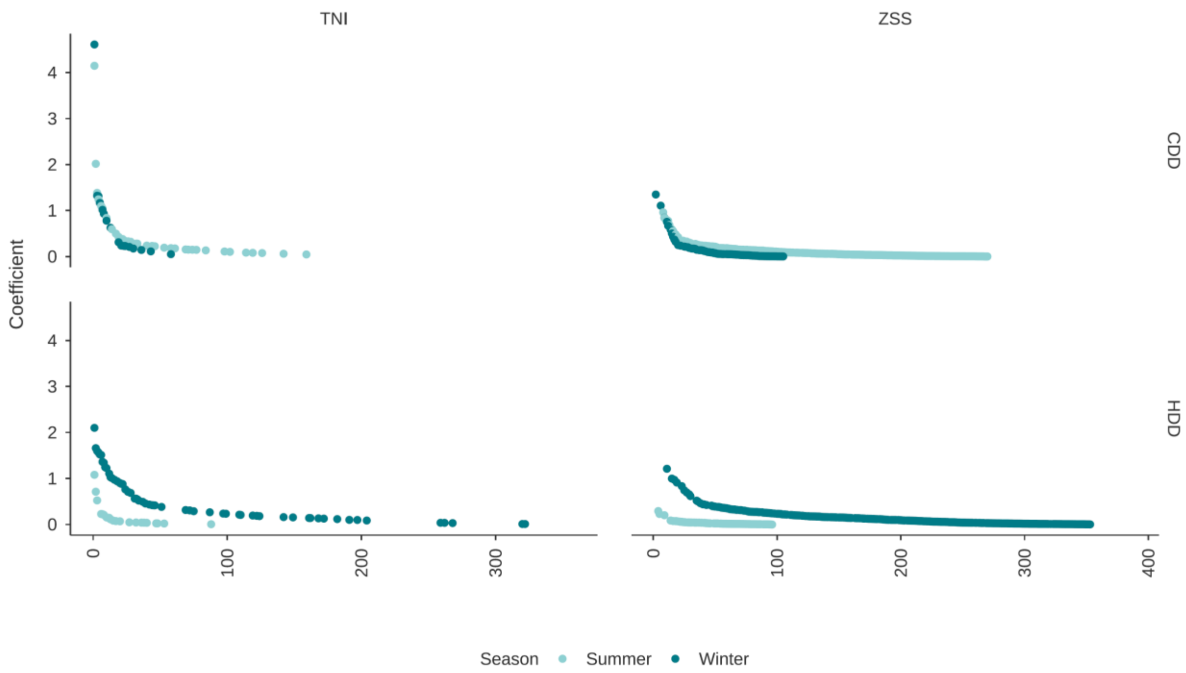


Figure 111: Quadratic weather model fit



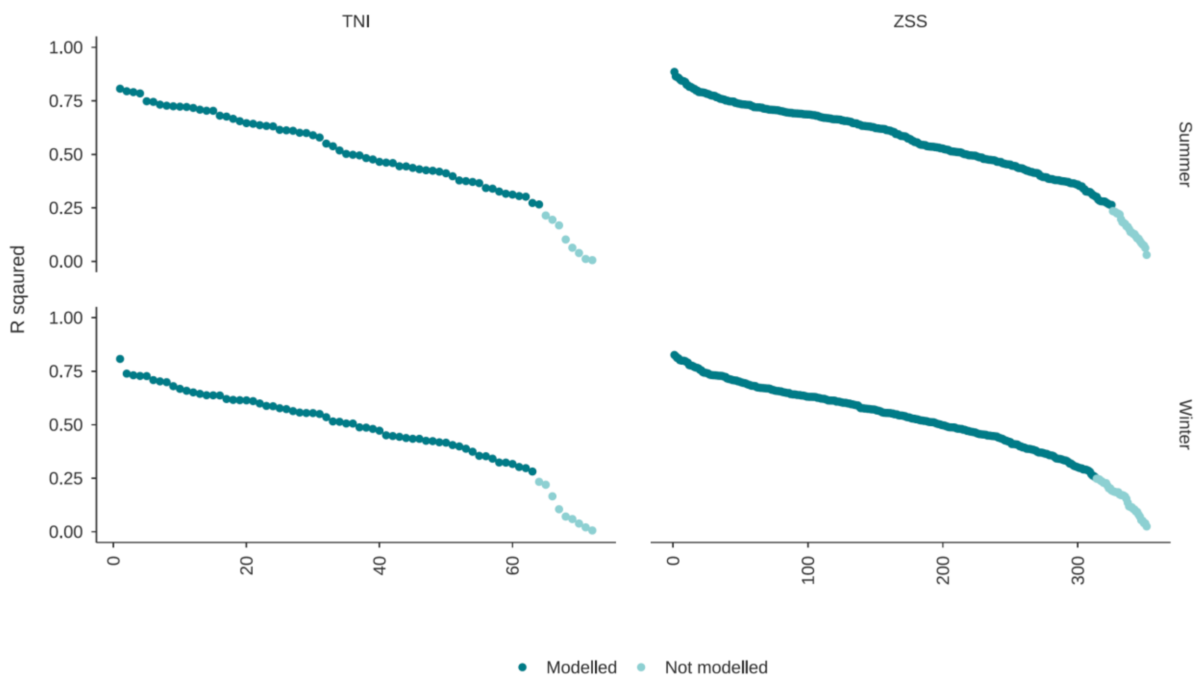
After applying the process described in **Box 3** the interpretability of coefficient estimates improves, as heating degree days were shown to be more significant in winter, and cooling degree days more significant in summer. This improvement in model specification was despite not significant reduction in overall model fit. These results are presented in **Figure 112** and **Figure 113**.

Figure 112: Selected weather model coefficient estimate for linear HDD and CDD variable



Source: Frontier Economics analysis

Figure 113: Selected weather model fit



Source: Frontier Economics analysis

Despite the improved model results, from **Figure 113** it is evident that for some TNIs and ZSSs the model fit is extremely low. For sites with a sufficiently low R^2 (below 0.25) to use the model predictions as a basis of forecasts would be inappropriate and unnecessarily computationally intensive. Therefore, we determine that for the 11 TNIS and 43 ZSSs with a sufficiently small R^2, the forecast minimum and maximum values will be estimated without use of these econometric models. The next section details the approach used to forecast demand for these sites.

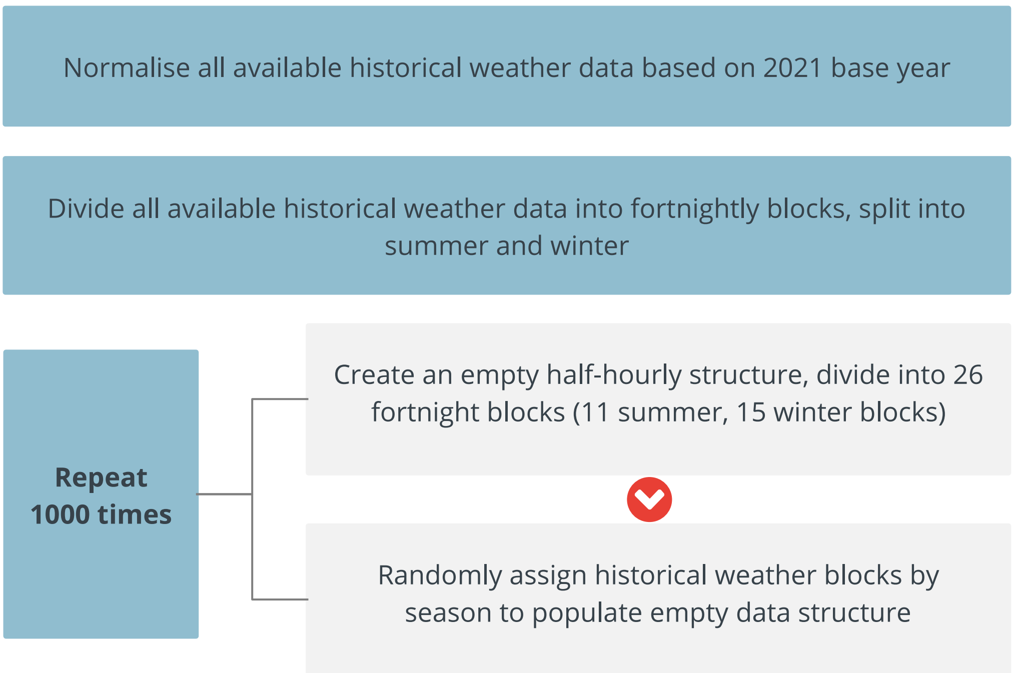
Forecasting minimum and maximum demand

Creating synthetic weather data

Figure 114 presents a high-level overview of the process by which synthetic weather is created for the 28 weather stations. We have used historical data going back to 2001, but to account for changing weather conditions over this time all weather data is normalised such that the mean air temperature for each financial year is adjusted to equal the average in financial year 2021. This is accomplished by a scaling multiple, which preserves zero and negative temperatures.

The 20 years of historical weather data is then segmented into fortnightly blocks, which are attributed to either summer or winter months (where summer is assumed to be November to March inclusive). The fortnights that straddle this seasonal divide are excluded from consideration. The approximately 200 summer and 280 winter fortnights are then randomly assigned to the corresponding seasons in an empty data structure for each of the 1000 synthetic years. These allocations are consistent across all weather stations, such that in a given synthetic year the weather data from the same historical period is used across the Essential energy grid. This consistency is significant due to the correlation of weather events across locations, and their coincident impact on total network load.

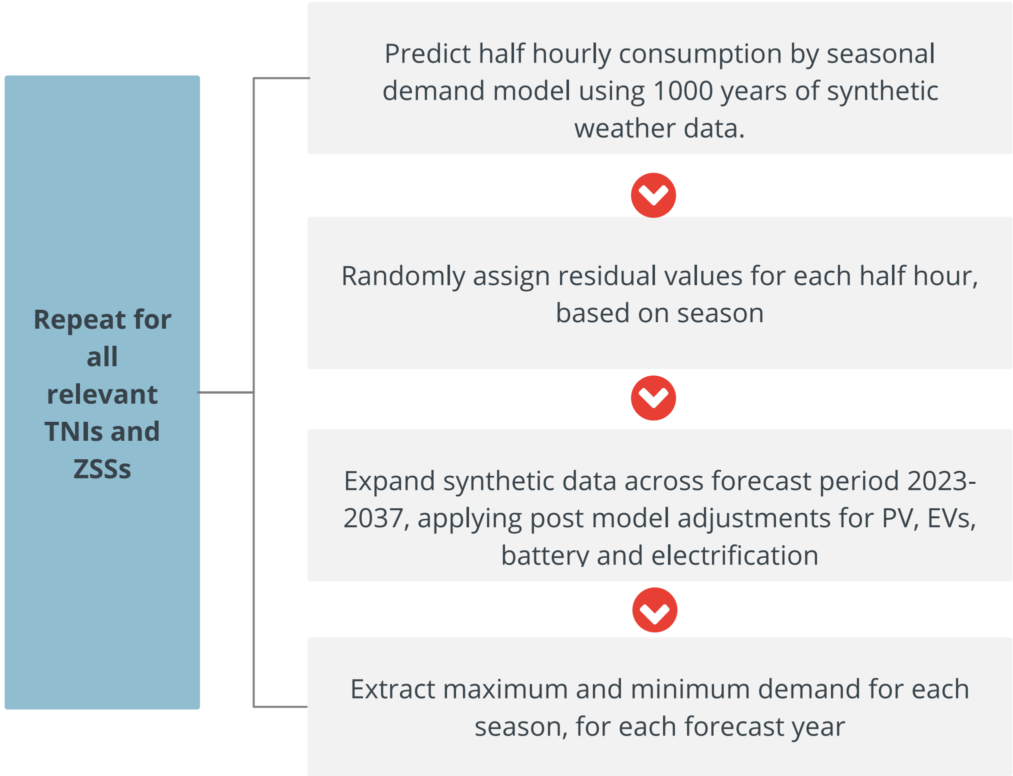
Figure 114: Synthetic weather construction methodology



Constructing synthetic minimum and maximum demand

Figure 115 presents a high-level summary of how TNI and ZSS half-hourly electricity demand is predicted across the 1000 synthetic weather years, adjusted for PV, EV, battery, and electrification, and then used to develop a distribution of maximum and minimum demand.

Figure 115: Maximum and minimum demand methodology using synthetic weather years



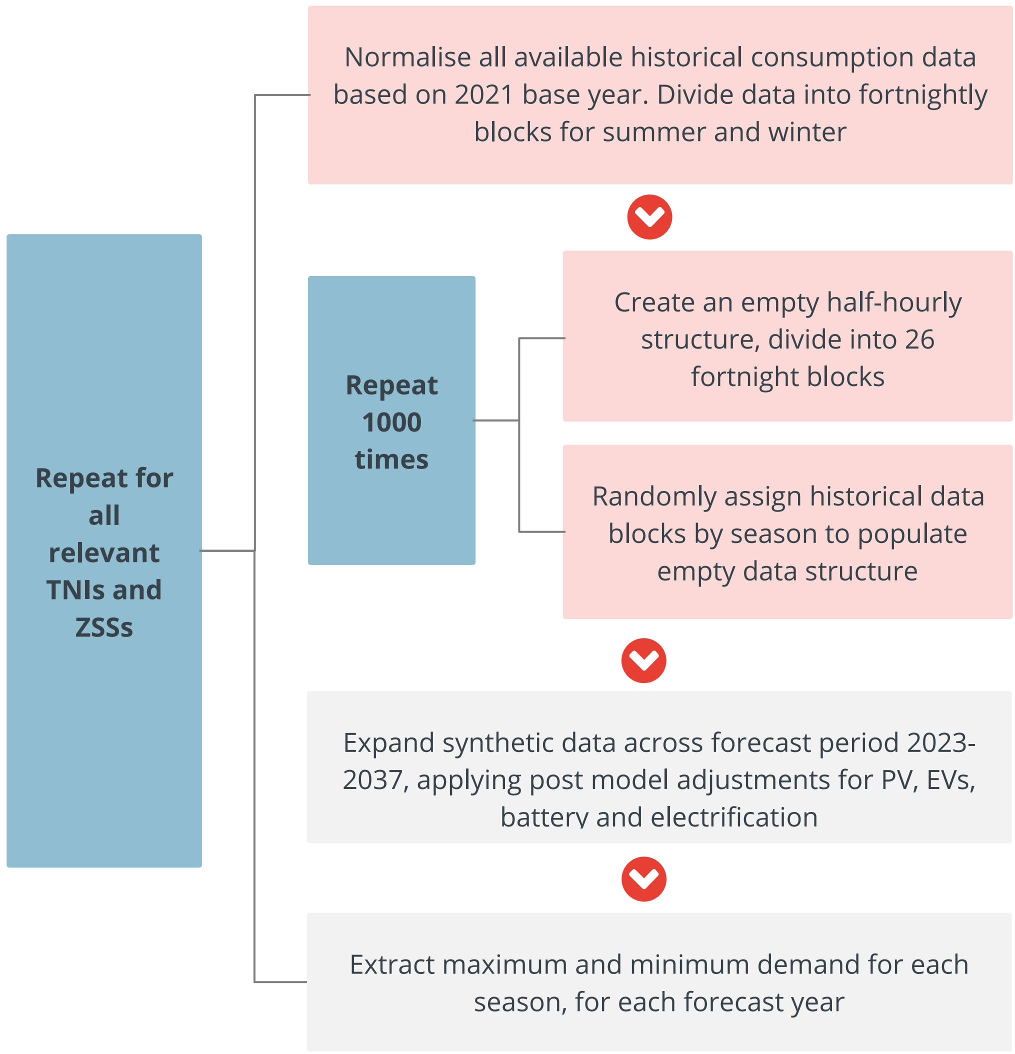
Using the underlying demand models described above, the constructed HDD and CDD, electricity demand is predicted for each half hour over 1000 synthetic years. This initial predicted electricity reflects the mean consumption conditional on time and weather variables and does not reflect any of the randomness of electricity consumption.

To accurately reflect the idiosyncratic nature of electricity consumption, residual values are added to the predicted mean demand. These residuals are drawn from the underlying demand models and are matched by season. The resulting electricity demand therefore has the same distribution as the historical data, adjusted for weather.

TNIs and ZSSs with poor model fit

As discussed above it is evident that for some TNIs and ZSSs the model fit is extremely low. For sites with a sufficiently low R^2 (measure of model fit) to use the model predictions as a basis of forecasts would be inappropriate. We determined that for sites with an R^2 of 0.25 or below the forecast demand should not be modelled, but randomly sampled from the normalised historical data.

Figure 116: Maximum and minimum demand methodology for sites with poor model fit



The historical consumption data is normalised so that the mean value of consumption is equal to the 2021 financial year mean. Only fortnights with less than 5% of observations missing are considered for the synthetic data construction.

Unlike the synthetic weather data described in Appendix A, the historically drawn consumption data does not preserve time consistency between sites. This is done for two reasons:

- **Inconsistent data availability:** Each site's simulated forecast values are drawn from their own historical data. Although data is generally available back to 2009, not all sites have been in continual operation across this period. By removing fortnight periods with large amounts of missing data (over 5%) the set of available periods from which to draw data is very different between sites. To require that all sites have sufficient data for a given data to be included, would substantially limit the set of periods which make up the synthetic consumption data. This could result in misleading and biased results.
- **Assumed lack of correlation:** The synthetic weather data was generated to preserve time consistency as we assume that weather is highly correlated geographically across NSW. For example, a heat wave affecting one station is likely to affect other nearby stations. As weather affects electricity consumption, it is logical that electricity consumption across weather affected areas is likely to be correlated as well, affecting maximum and minimum values.

Sites that are modelled by historical consumption data are so modelled specifically because they are not able to be modelled accurately by weather, or other observed characteristics (as reflected by the low R squared values). As a result, we have assumed that they would not share the same correlation by time as other stations.

Post-model adjustments

At this stage, the predicted demand values do not represent a forecast of future electricity consumption, as it does not account for changes in underlying consumer behaviour, and adoption of new technologies. For the forecasts over 2022-37 to appropriately reflect these changes, post model adjustments are made to account for forecast changes to PV usage, battery adoption, EV usage, and electrification.

The method of developing and applying profiles for PV, batteries, EVs and electrification are explained in Section 3.

Sampled minimum and maximum values

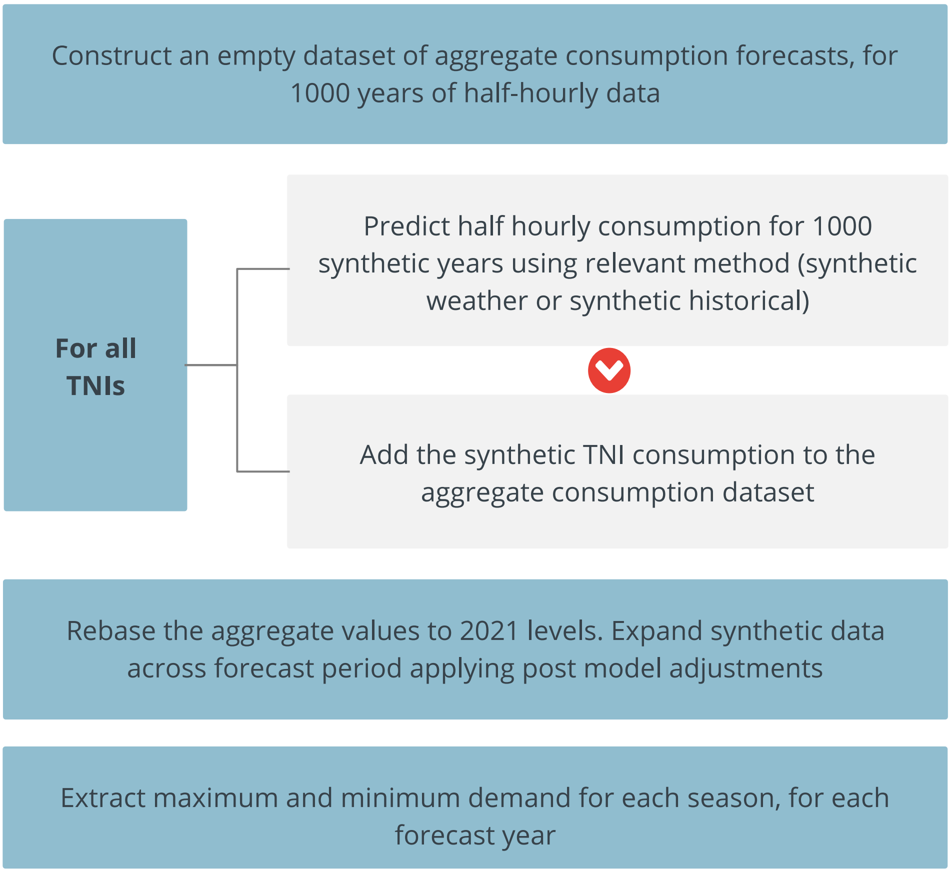
The resulting adjusted demand data consists of 1000 series of half hourly electricity demand data for the period 2022-37, for each TNI and ZSS.

For each synthetic series, the minimum and maximum demand is collected for each season of each forecast year. The resulting four observations are collected from all 1000 synthetic series. For each TNI and ZSS there are therefore 1000 sampled minimum and maximum demand values for each season, for each forecast year

Aggregating for total network load

To estimate the network maximum demand, we interrupt the TNI forecasting processes described in **Figure 115** and **Figure 116**, extracting the fully synthetic consumption data for period 2022 for all 1000 simulations. This process is presented in **Figure 117**.

Figure 117: Total network minimum and maximum demand methodology



Each of these consumption profiles is then added together, to produce 1000 simulations of total network consumption over a year. After this base synthetic network year has been produced, aggregate post model adjustments are applied, accounting for the total rooftop PV, battery and added electrification for each half hour. Similarly, growth rates are applied based on the consumption forecasts presented in Section 4 to create a profile over 15 years. From each simulated year within the forecast period, the maximum and minimum total demand are extracted (for each season).

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