ENDGAME

04/11/2025

A report for Jemena

Demand Forecasting Methodology

DESCRIBE, UNDERSTAND, MODEL, SOLVE

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Sections in this report

→

01
Introduction

We have produced an independent demand forecast for Jemena's network to support their regulatory determination to the AER

Jemena has submitted its proposal for the 2026-2031 regulatory period to the Australian Energy Regulator (AER). However, following this submission, the AER raised concerns regarding Jemena's demand forecasts, and in response, Jemena engaged Endgame to provide an independent assessment of the network's future demand.

Overall, our results align with Jemena's new 2025 forecasts, which are based on another consultant's, Blunomy's, methodology.

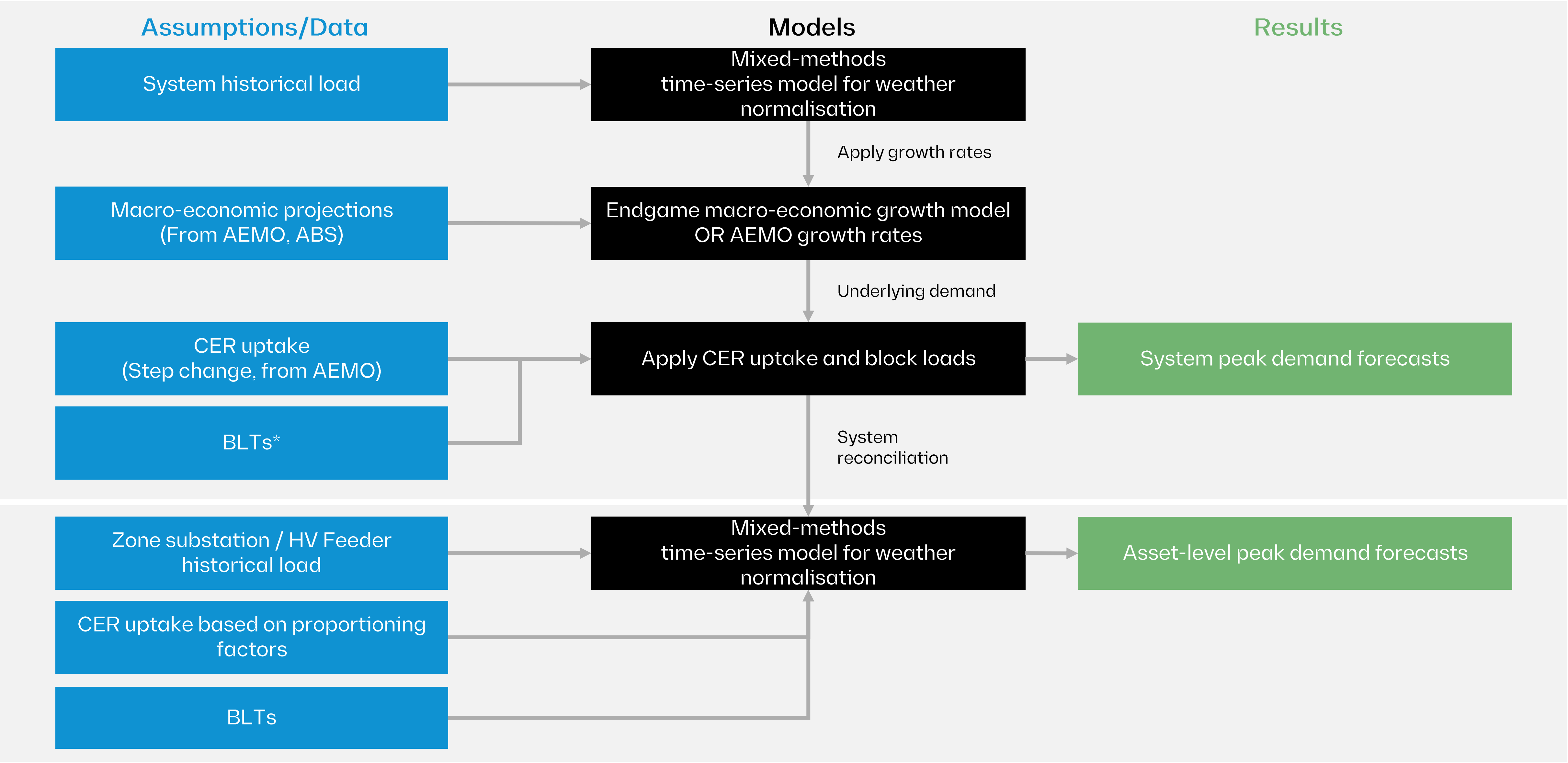
We produced forecasts of Jemena's network, excluding major customers, to demonstrate the robustness of their existing methodology (major customers are separately modelled by Jemena using a probability- and scenario-based approach).

We employed a component-based framework that prioritises simplicity, explainability and reproducibility. This results in two 30-minute granularity time-series consumption forecasts: one using our internal macroeconomic growth rates and the other using AEMO's underlying growth rates. We then take the maximum demand from these traces to derive the final estimate.

The remainder of our report demonstrates this process with the results presented at the end.

02
Methodology

High Level forecasting approach (ex Major Customers)



Underlying macroeconomic growth projections

Long-term electricity consumption can be influenced by macroeconomic factors such as population and income growth. We developed a regression model to capture these trends.

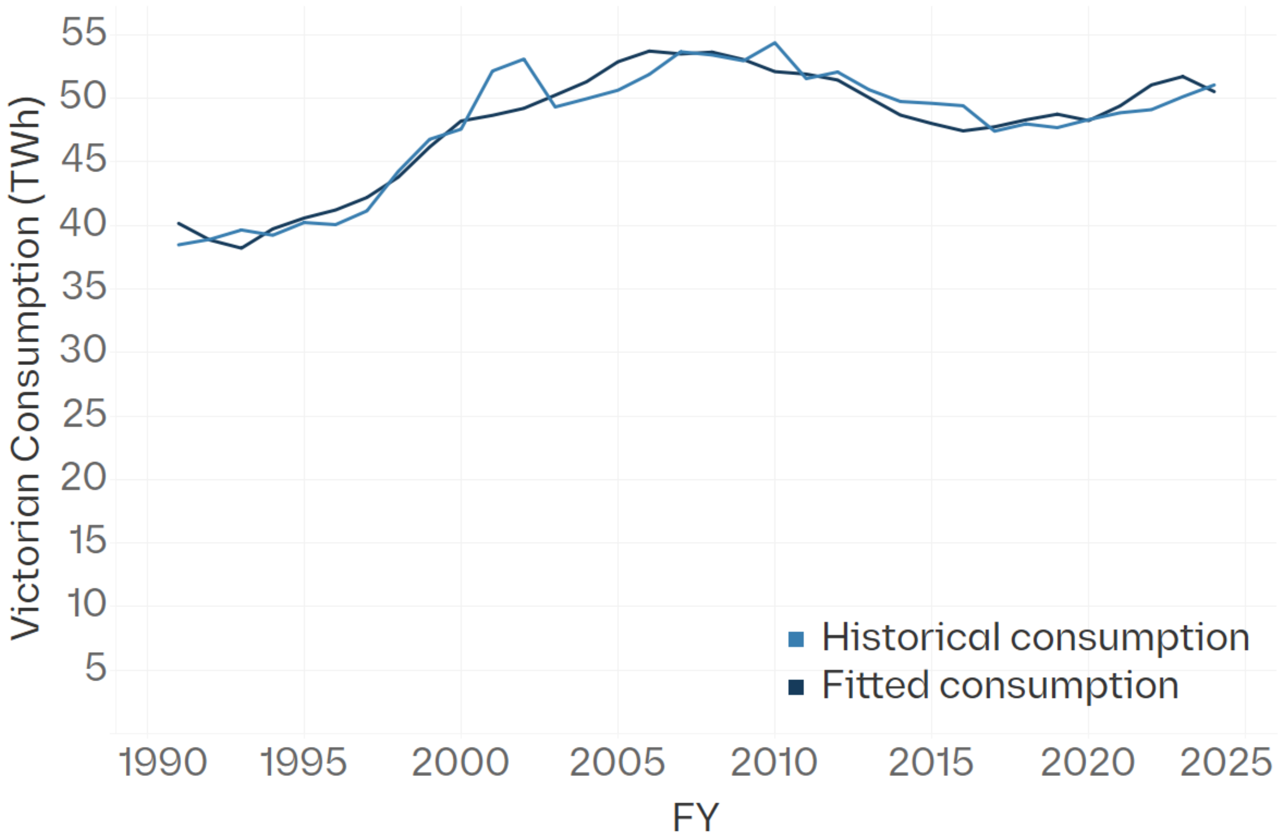
The dependent variable was (log) yearly historical Victorian electricity consumption from DCEEW[1], and the independent variables were (log) gross state product[2] (GSP) and GSP per capita, obtained from the ABS.

We also tested other independent variables, such as price indexes and energy productivity, but encountered multicollinearity and small sample size issues. Therefore, we anchored the model on key drivers of population and GSP, which were statistically significant, producing an Adj. R-squared of 0.9.

Energy efficiency and electrification is captured in overall historical trends as we are focused on the short term, the next 5-10 years. We didn't investigate "changed" behaviours, as AEMO does in its multi-sector modelling. However, we have provided AEMO's assumptions as a sensitivity.

We then used forecasted GSP variables from AEMO's step change scenario[3] and population projections from the ABS medium series[4].

Historical Victorian consumption and econometric model fitted consumption



1: https://www.energy.gov.au/energy-data/australian-energy-statistics
2: https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-state-accounts/latest-release
3: https://www.aemo.com.au/consultations/current-and-closed-consultations/2025-iasr
4: https://www.abs.gov.au/statistics/people/population/population-projections-australia/latest-release

Temperature-dependent demand model (Weather normalisation)

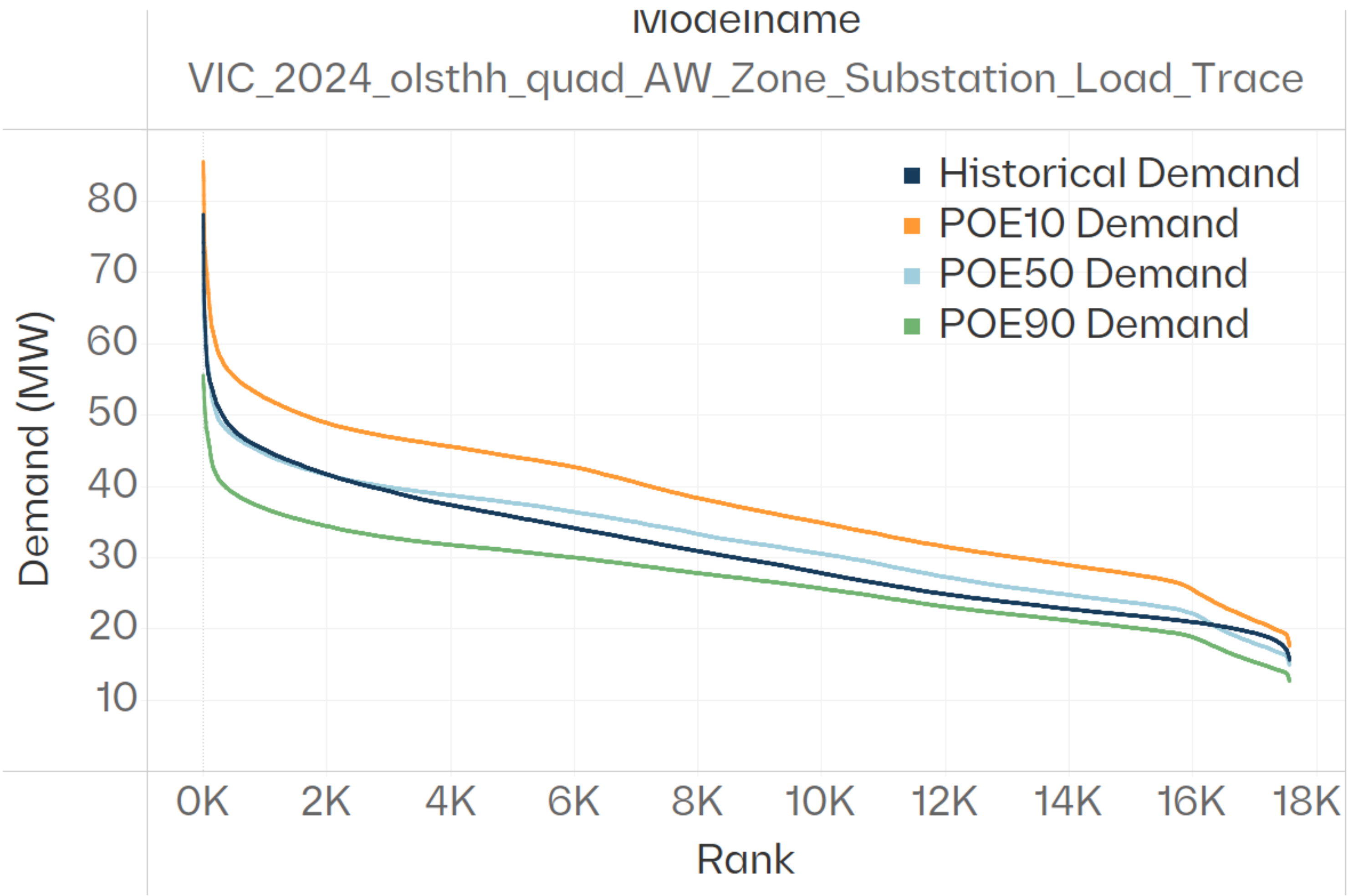
We used NASA's MERRA-2 weather reanalysis dataset[1] to build 30-minute underlying demand projections.

The temperature model is a combined OLS regression with a GEV model fitted on residuals, which assists with predicting extreme values in the distribution, allowing for the estimation of P50, P10 and P90 demand for each 30-minute interval.

The model uses temperature, quadratic, calendar, time, and interaction variables to estimate the relationship between temperature and demand in Jemena's network.

This approach also enables testing the sensitivity of demand to weather years.

Duration curve of 30-minute historical demand, and GEV-adjusted demands for AW ZSS



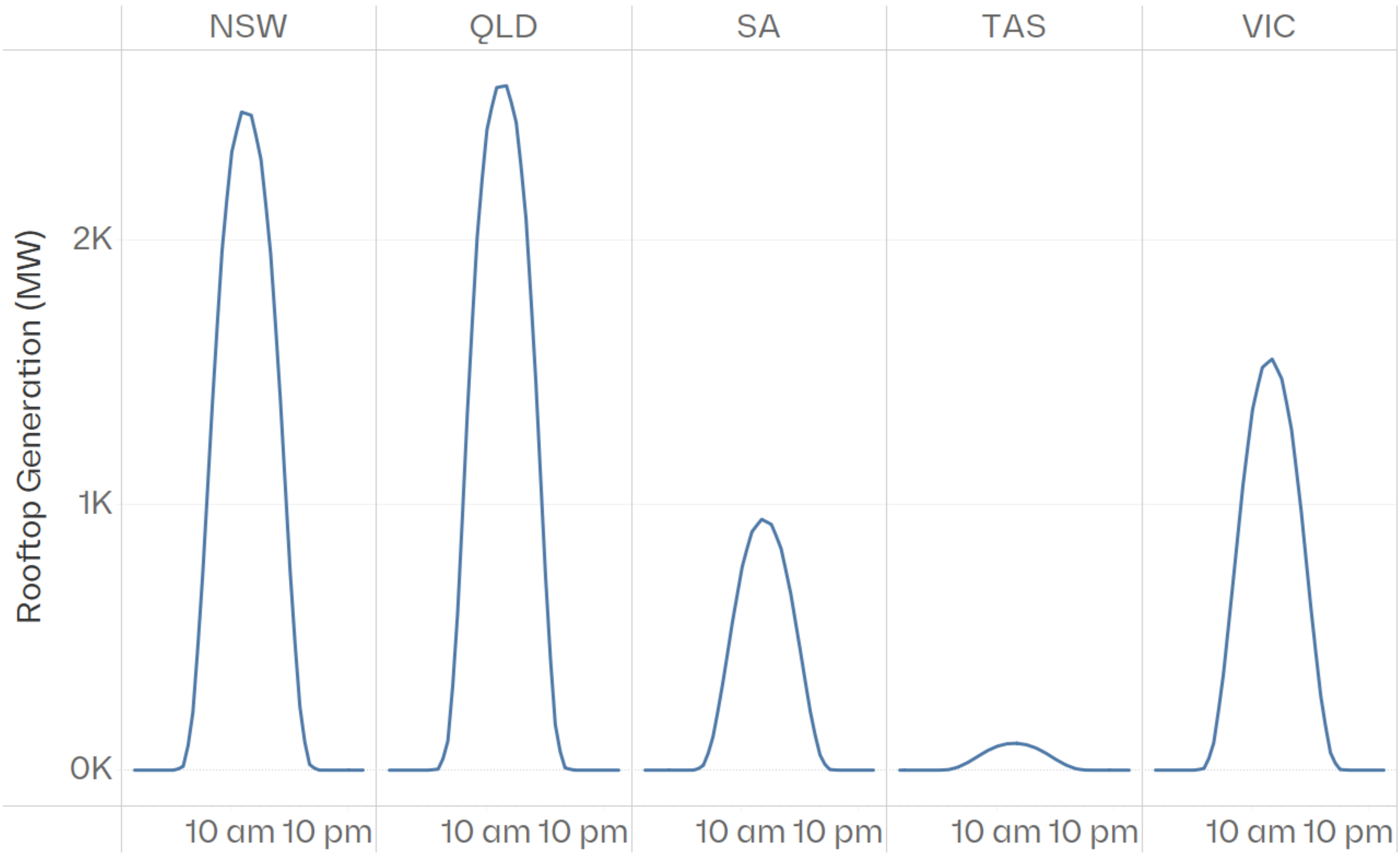
1: https://gmao.gsfc.nasa.gov/gmao-products/merra-2/

PV Treatment

We use a custom model to estimate household rooftop PV. This is done using a Support Vector Regression model with the MERRA-2 data set incorporating solar irradiance, temperature, time and other weather variables. The model is fitted to Victorian historical rooftop PV generation.

For Jemena's entire network, we then scaled down the resulting model based on installed capacity and future rooftop PV uptake.

Historical Rooftop PV traces by state (VIC profiles are selected for JEN forecasts)

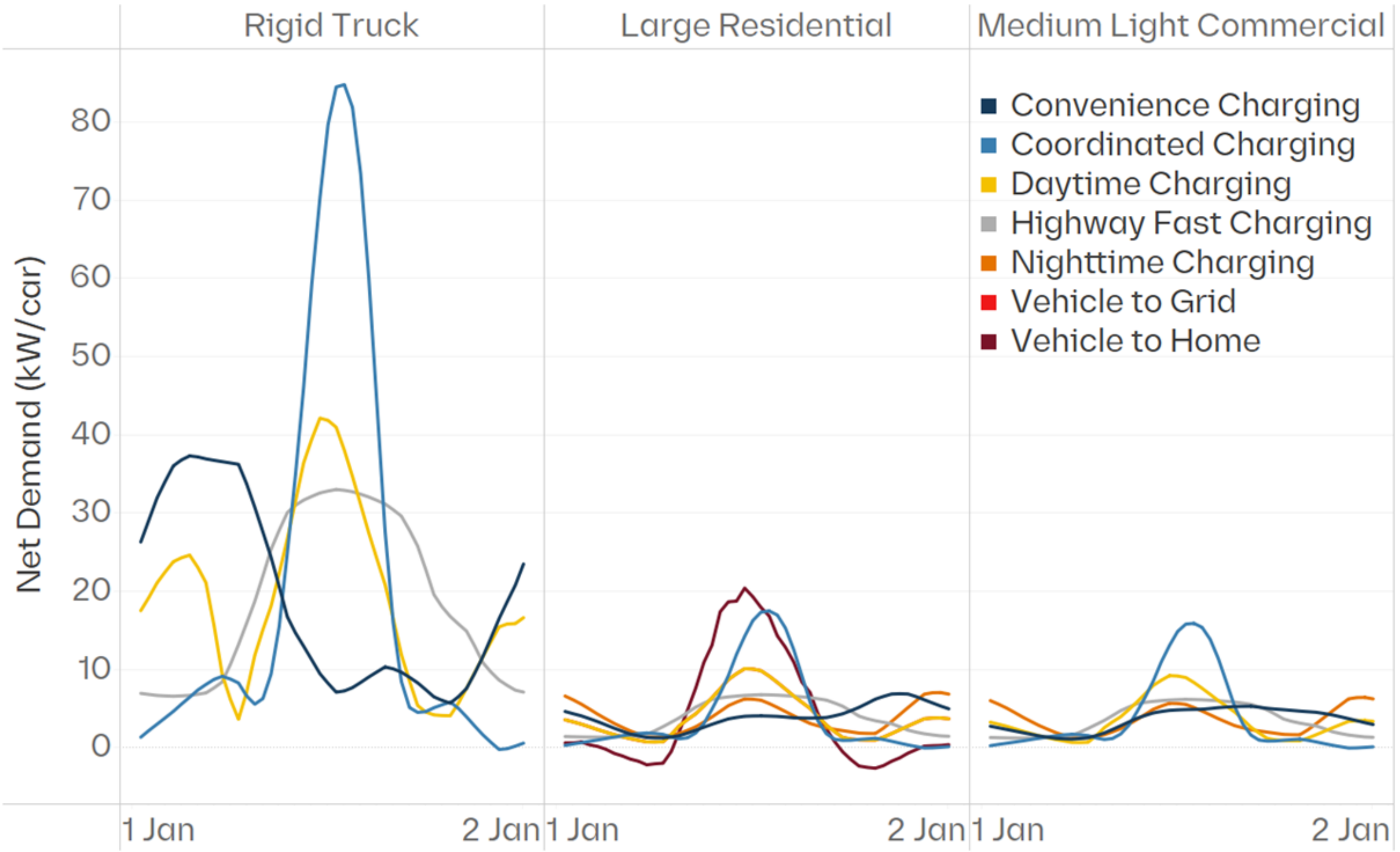


EV and batteries

For the remaining CER, such as EVs and behind-the-meter (BTM) battery energy storage systems (BESS), we used 30-minute profiles and projections from AEMO.

AEMO provides standard daily profiles for different charging behaviours and the composition of behaviour types. These are proportions for each scenario and we used the step change arrangement.

Representative profiles for EVs by charging behaviour (source: AEMO)



CER Proportioning

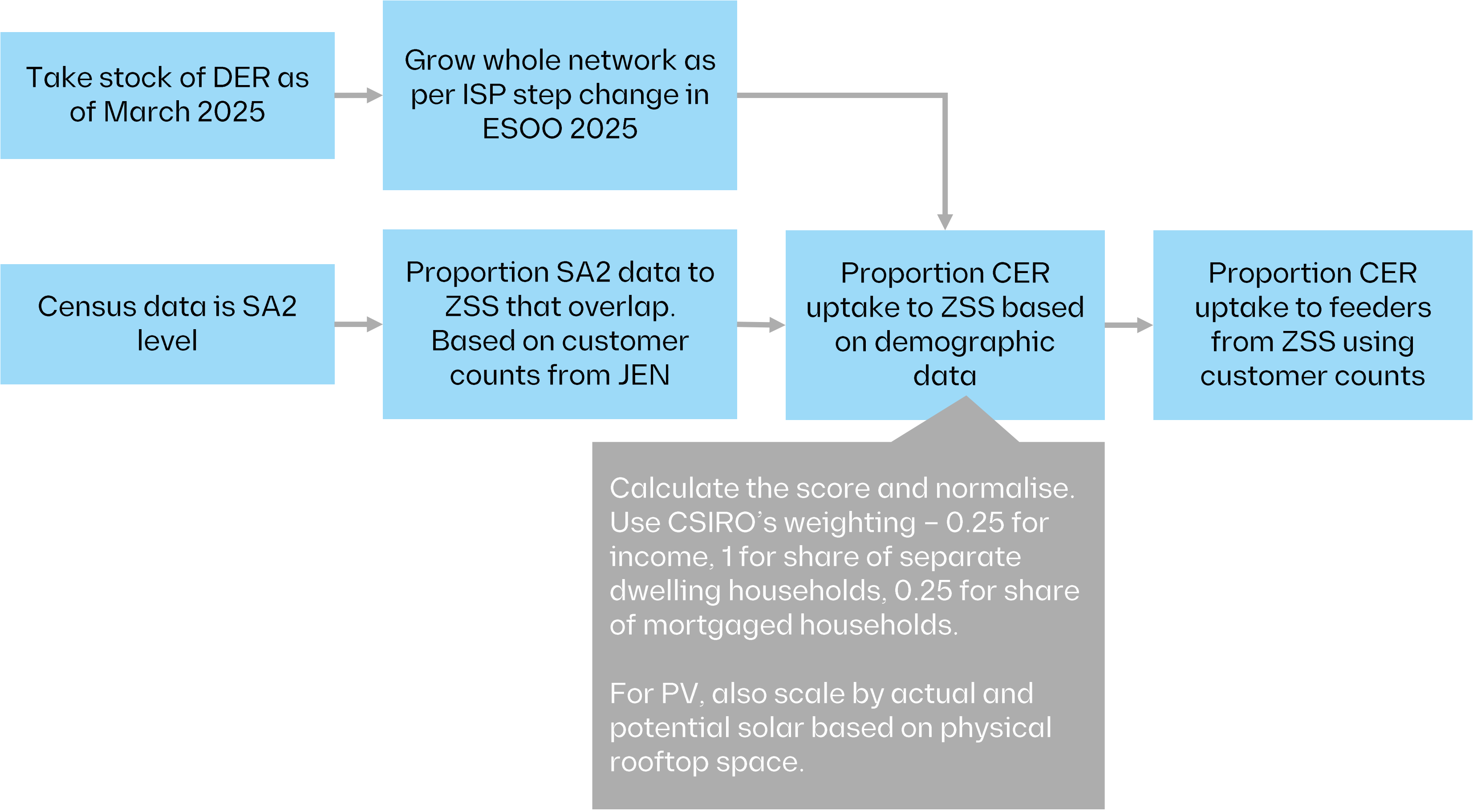
We spatially allocated CER to each zone substation using income, household and financial information on an SA2 basis from the ABS's census data.

We followed the CSIRO's approach, who produce small-scale solar PV and battery projections for AEMO's scenarios. They weight demographic factors and calculate a score using the table below[1].

Factor	Weight
Average income	0.25
Share of separate dwelling households	1
Share of owned or mortgaged households	0.25

Note that we used median income rather than average income.

We also scaled our score based on physical roof space, assuming that each standalone or semi-detached house can support a solar system of 4.7kW, which was Jemena's average in March 2025.



1: https://www.aemo.com.au/-/media/files/major-publications/isp/2025/CSIRO-2024-Solar-PV-and-Battery-Projections-Report

System time-series projections

The components referenced earlier come together to produce time-series projections.

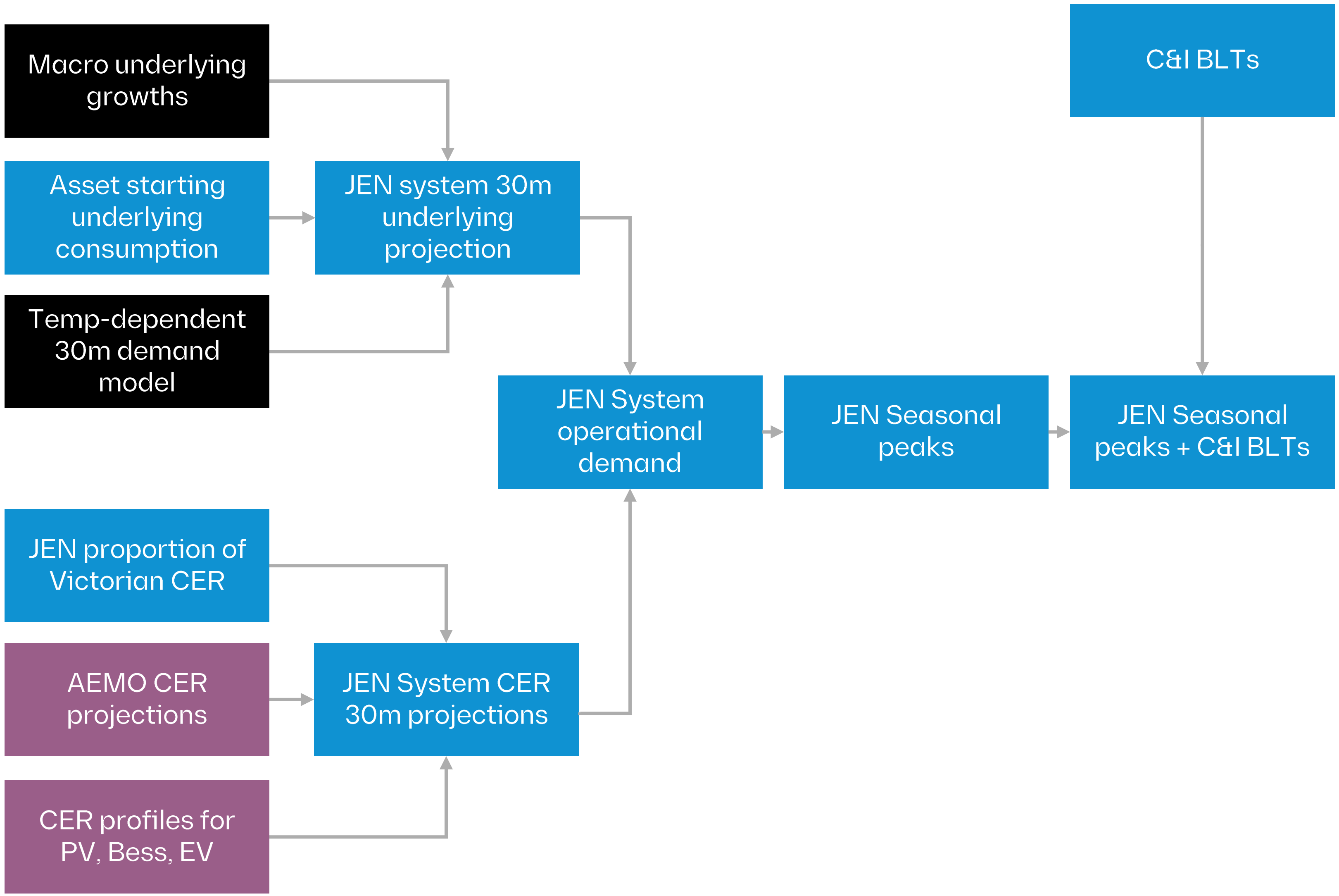
To produce the system forecast, we start with weather-normalised current underlying consumption and grow it by our macro trends.

We then combine this with projected CER uptake to get operational demand forecasts. CER uptake is based on AEMO's step change scenario, proportioned to Jemena's network using historical underlying demand.

Household rooftop PV profiles are based on solar irradiance data using the same weather reference year as the underlying demand temperature model. EV and battery profiles are also sourced from AEMO.

This results in a consumption forecast for Jemena's total network on a 30-minute basis for each future year. We take seasonal peak demand and apply C&I block loads.

Note that we do not include residential block loads, as these should be accommodated in population-driven underlying growth. Residential loads are included in the asset-level forecasts, but demands are reconciled to ensure there is no additionality.

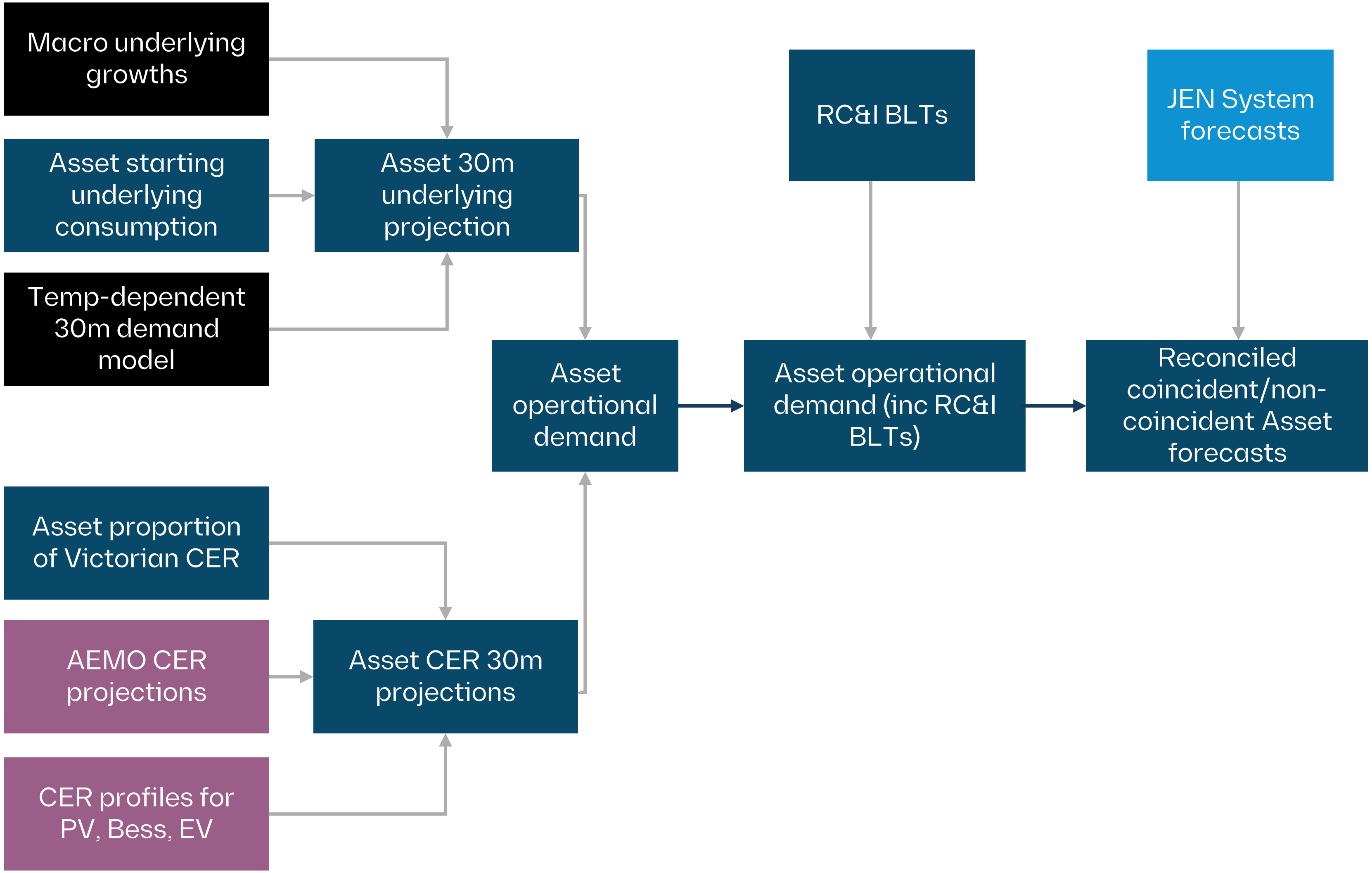


Asset time-series projections

A similar methodology is employed at each asset level (both Zone substation and HV feeder); however, we proportion CER uptake across zone substations based on demographic information.

In this process, an additional reconciliation step is performed to include residential block loads (as well as commercial and industrial). We reconcile the asset consumption growth to the system, ensuring there is no double-counting residential loads.

The reconciliation process involves calculated the total non-reconciled system peak forecasts (sum of all asset forecasts) and then calculating a scaling factor to ensure sum of reconciled asset forecasts is equal to the system peak forecasts. The same factor is also used to identify non-coincident asset-level forecasts.



03
Results

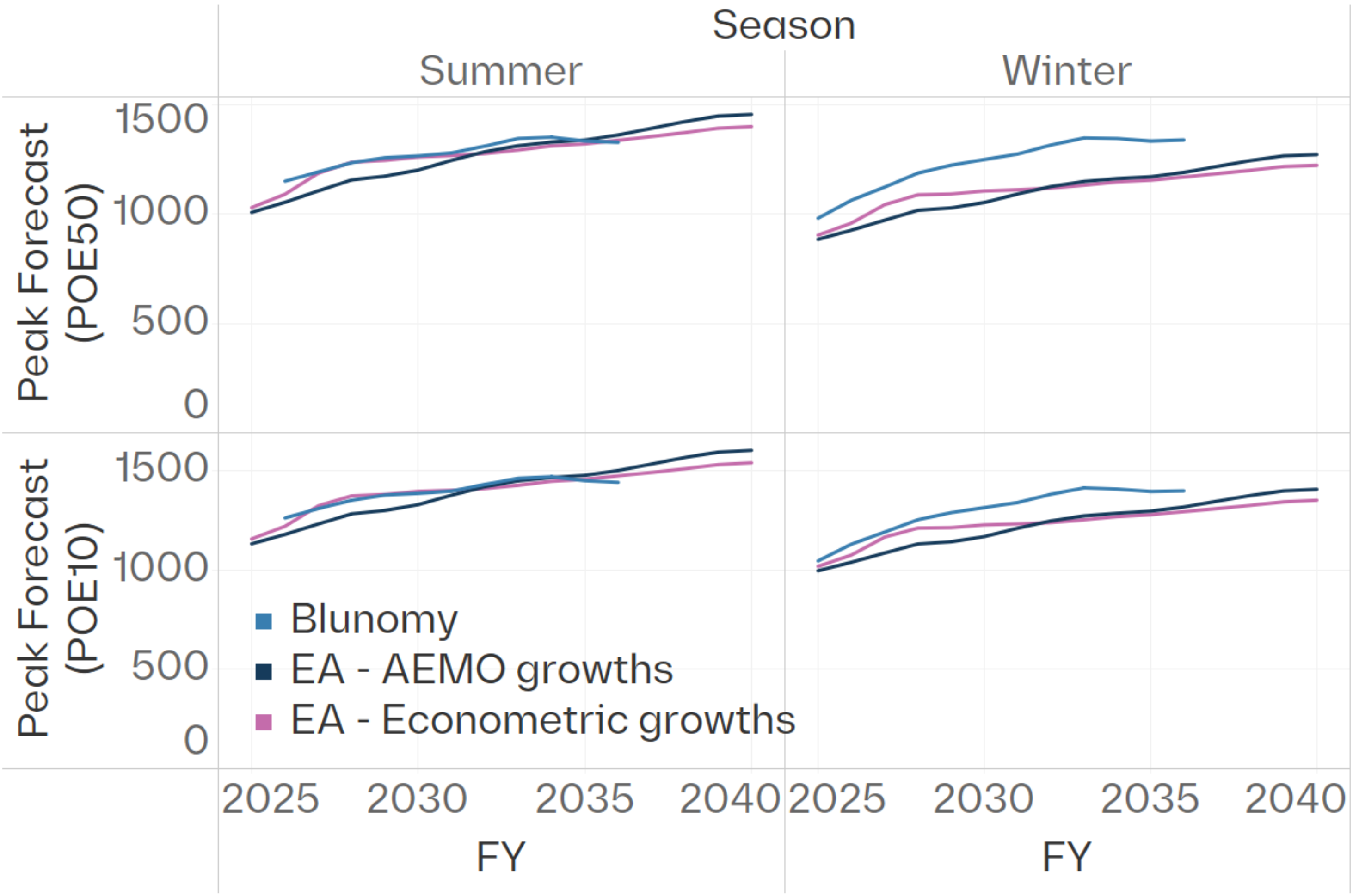
JEN System forecasts are consistent with recent Blunomy forecasts

Summer forecasts are broadly consistent across both Endgame's growth model and AEMO's growth assumptions. This indicates a shared view of the main drivers of summer demand, including population growth, economic activity, and baseline electrification trends. Both modelling frameworks appear to capture similar dynamics in cooling load and general consumption patterns during warmer months.

In contrast, winter forecasts are noticeably higher in Blunomy's results. This difference likely stems from Blunomy's treatment of electrification, where custom profiles for electric hot water and cooking are used. These end uses are more prominent in colder months and therefore result in a stronger winter uplift.

Note: 2024 weather years are used in final forecasts

Peak demand foreasts by source, season and POE



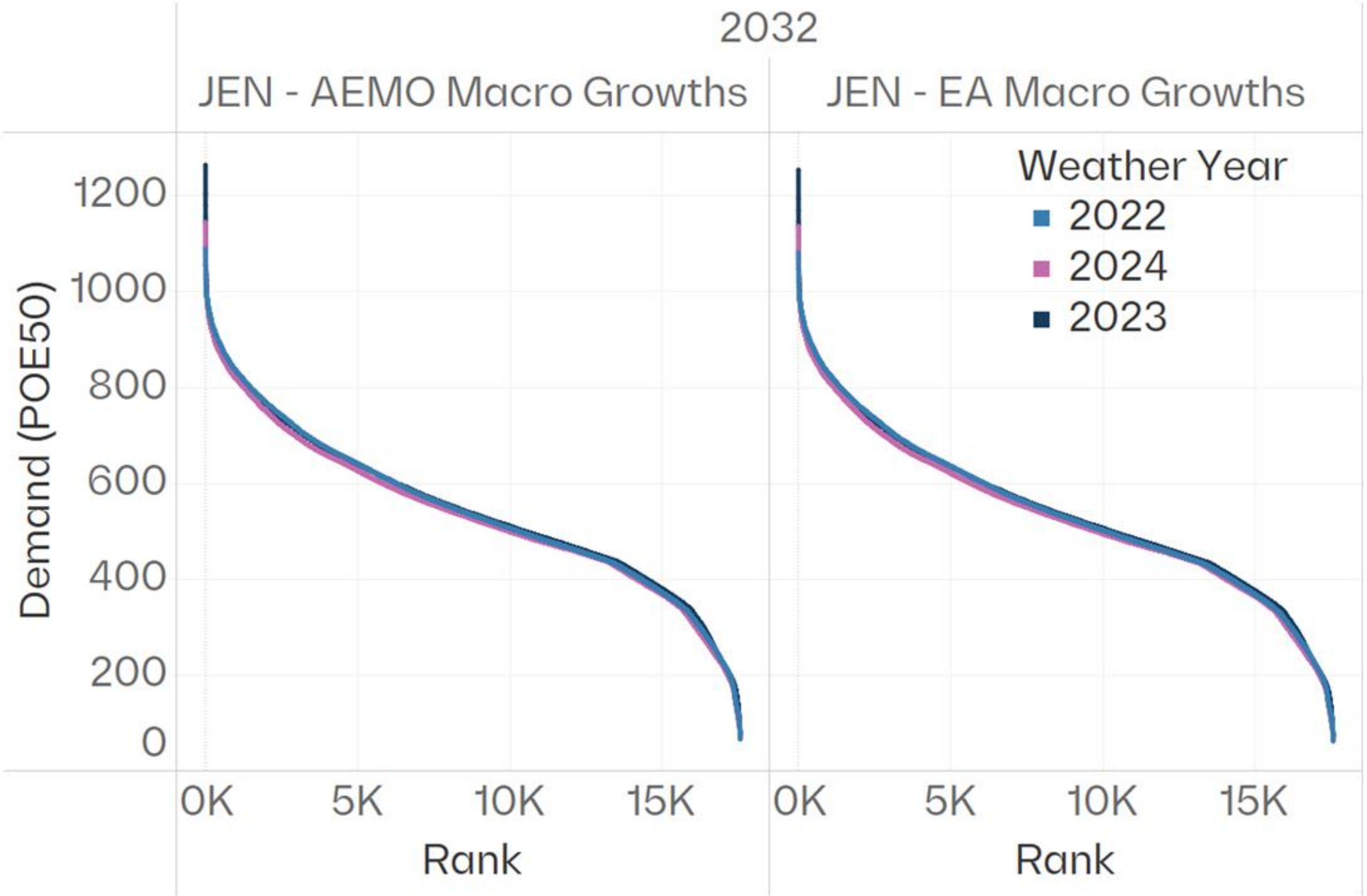
Different weather years shows that 2024-year estimates are conservative

The 2024 weather year is used as the reference case, consistent with the accepted approach shown previously. It provides a balanced representation of temperature and demand conditions for forecasting.

If the 2023 weather year were used instead, the model would produce higher peak demands. This reflects the confluence of temperature and timing effects captured in the OLS-GEV model, where extreme heat days align with high-demand periods.

This is reflected in the duration curves for FY2032 demand for 3 different weather years (2022, 2023 and 2024).

Duration curve of Demand by weather year and underlying growth assumption



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Thank You