AUSTRALIAN ENERGY MARKET OPERATOR

GAS POWERED GENERATION FORECAST MODELLING 2021 - FINAL REPORT

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Executive Summary

The Gas Services Information (GSI) Rules[1] require AEMO to produce a Gas Statement of Opportunities (GSOO) report for Western Australia (WA) on an annual basis. The WA GSOO must include a forecast of gas demand over a 10-calendar year horizon. One of the key drivers of gas demand in WA is the amount of gas-powered generation (GPG) which is expected to be dispatched over this horizon.

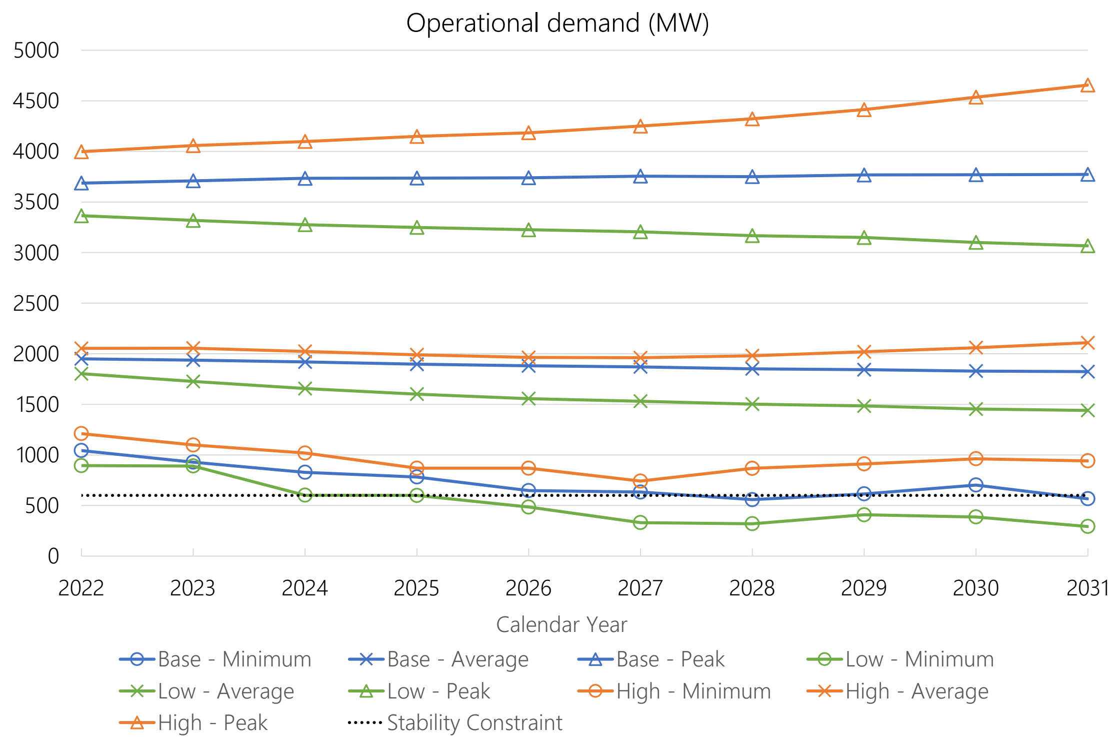
AEMO has engaged Robinson Bowmaker Paul (RBP) to forecast gas demand from GPG in the South West interconnected system (SWIS) across three scenarios reflecting high, expected (base), and low gas demand, over a 10-calendar year horizon (2022 - 2031).

Results

Operational Demand

Figure 1 shows the hourly average, peak and minimum demand for each Calendar Year in the modelling horizon.

Figure 1: Minimum, average, and peak operational demand



[1] See https://www.wa.gov.au/organisation/energy-policy-wa/gas-services-information.

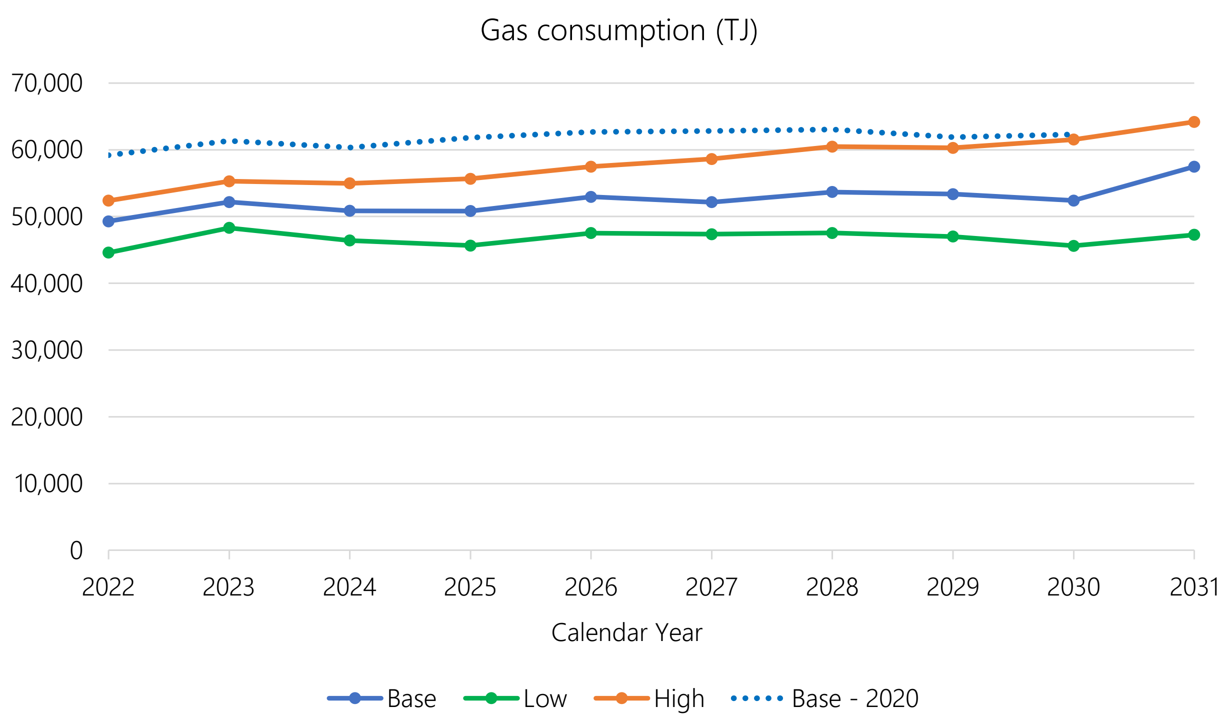
Relative to the 2020 GPG modelling demand assumptions, the following differences are significant:

- Average base scenario demand is lower,
- Average high scenario demand dips downward slightly in 2024-2026 to be close to base scenario demand,
- Peak high scenario demand is higher, and
- Minimum low scenario demand is lower.

Gas Consumption

Figure 2 shows the annual total gas consumption from GPG from the model results (on a calendar year basis). Base scenario gas consumption from the 2020 GPG forecasts is included for comparison.

Figure 2: Gas consumption



Compared to the 2020 GPG modelling results, in the base scenario gas demand is significantly lower until 2029. This is the result of a combination of factors including:

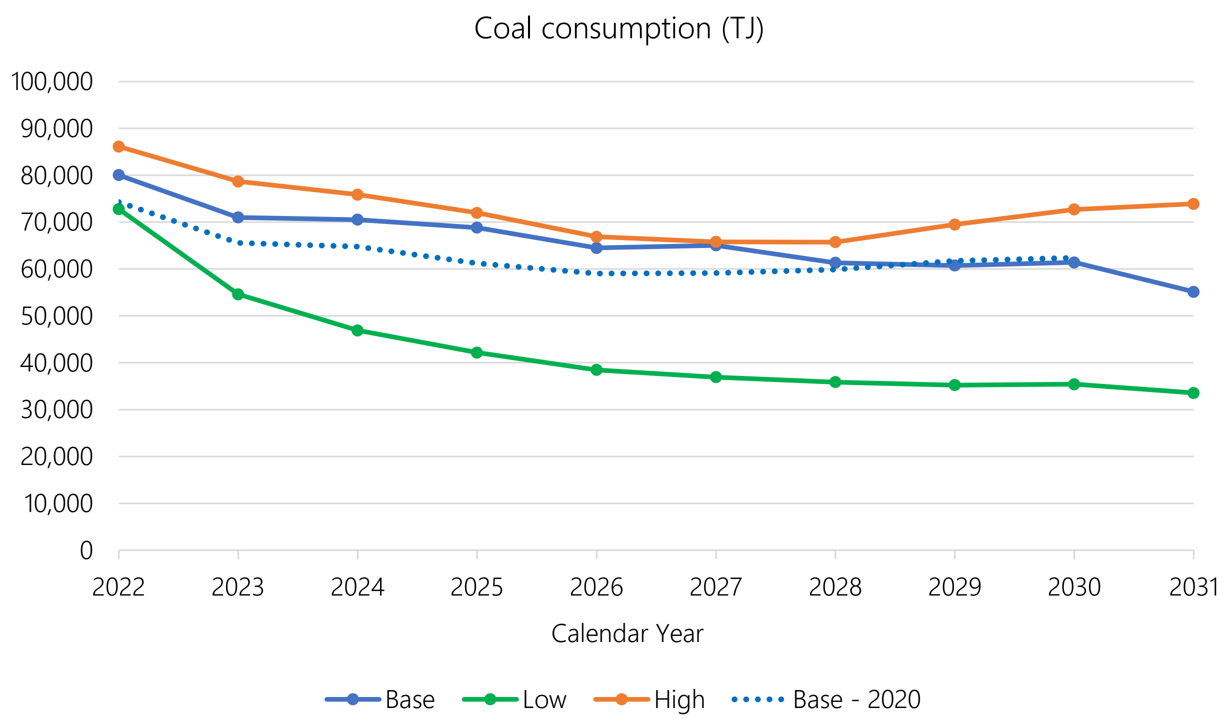
- Overall lower average electricity demand,
- A higher gas price, making coal more competitive relative to gas,

- Increased renewable generation capacity, and
- Increased BESS capacity, which has two consequences:
  - Batteries compete with gas peakers as providers of peak energy, and
  - Batteries provide flexibility to allow coal generators to continue to generate around their unit commitment constraints (e.g. start costs and minimum ramp up times).

Coal Consumption

Figure 3 shows the annual total coal consumption for electricity generation from the model results.

Figure 3: Coal consumption



Compared to the 2020 GPG modelling results, base scenario coal demand is initially higher. This is the result of a combination of factors:

- A higher gas price, making coal more competitive relative to gas, and
- Increased BESS capacity, enabling greater flexibility around coal unit commitment constraints (e.g. start costs and minimum ramp up times).

Over time, however, reduced average demand and increased renewable generation eliminate these advantages.

In the high scenario, the dip in average demand from 2024-2026 results in significantly lower coal demand.

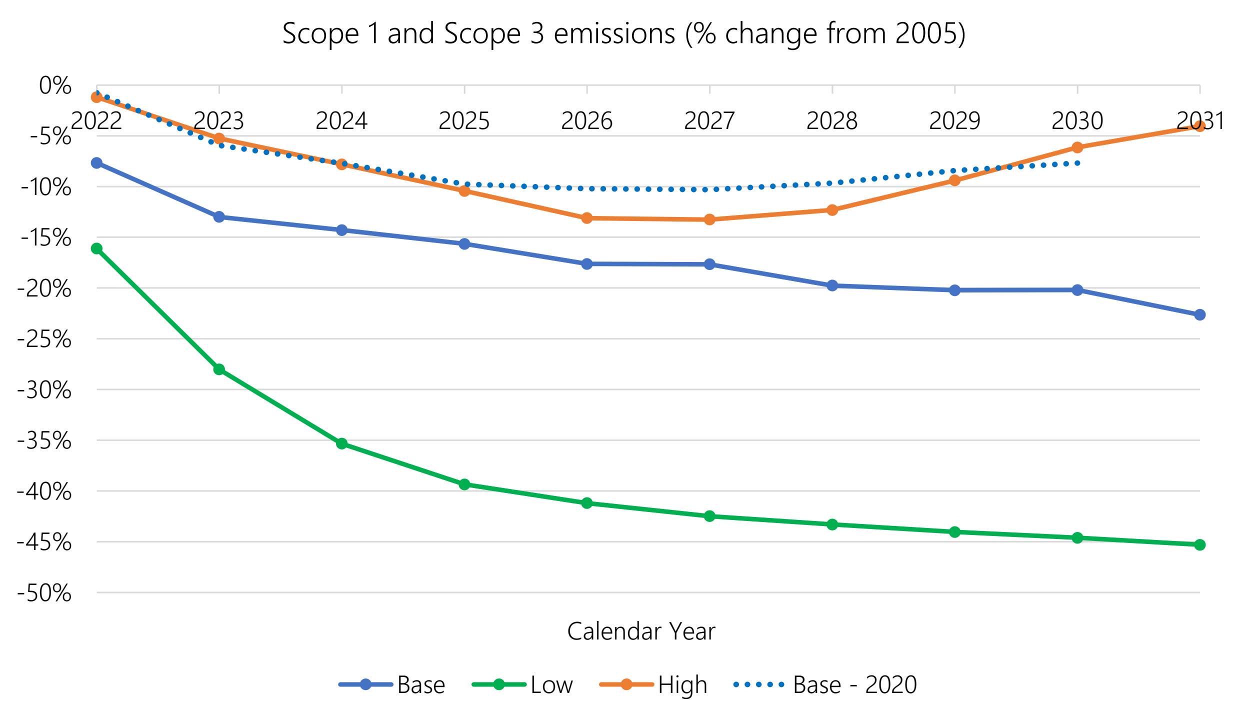
Coal demand in the low scenario is significantly lower than the base scenario. This is largely driven by the lower minimum demand levels in the low scenario, which makes it much more difficult for coal plants to meet their unit commitment constraints.

Emissions

Figure 4 shows total annual Scope 1 and Scope 3 emissions from the modelling results, in terms of the percentage change from 2005 levels (positive percentage values showing higher emissions than 2005 levels, negative values showing lower emissions).

The emissions presented here are the direct (Scope 1) and indirect (Scope 3) emissions from the combustion of fuels to generate electricity, so do not include emissions related to the use of electricity, nor the construction or decommissioning of generation plants.

Figure 4: Emissions



Relative to the 2020 GPG modelling results, base scenario emissions have reduced. Reduced gas generation and increased renewables generation have had a greater effect than the small increase in coal generation.

In the high scenario, the dip in average demand from 2024-2026 results in significantly lower emissions from lower coal generation.

Low scenario emissions are significantly lower, due to much lower coal generation levels. The low scenario is the only scenario that meets the Australian Government's emissions reduction target of 26-28% by 2030[2].

KEY INSIGHTS

The following key insights can be drawn from this analysis:

- Projected gas consumption is sensitive to electricity demand, gas price and new build of generating capacity assumptions. A modelled reduction in electricity demand and increase in gas prices have resulted in a lower gas use forecasts than the previous year's modelling.
- A projected dip in average energy in the high scenario has a significant impact on coal powered generation and emissions.
- The low scenario is the only scenario that meets the Australian Government's emissions reduction target of 26-28% by 2030. This is driven by lower minimum demand levels, which have a significant impact on coal powered generation.

[2] https://www.environment.gov.au/system/files/resources/f52d7587-8103-49a3-aeb6-651885fa6095/files/summary-australias-2030-emissions-reduction-target.pdf

Contents

1 Introduction

1.1 Project Background

The Gas Services Information (GSI) Rules[3] require AEMO to produce a Gas Statement of Opportunities (GSOO) report for Western Australia (WA) on an annual basis. The WA GSOO must include a forecast of gas demand over a 10-calendar year horizon. One of the key drivers of gas demand in WA is the amount of gas-powered generation (GPG) which is expected to be dispatched over this horizon.

AEMO has engaged RBP to forecast gas demand from GPG in the South West interconnected system (SWIS) across three scenarios reflecting high, expected (base), and low gas demand, over a 10-calendar year horizon (2022 - 2031).

1.2 Purpose of This Document

This document is the final deliverable of the GPG forecast project. This report includes:

- The finalised methodology and assumptions,
- A summary of the modelling results,
- Key insights and observations, and
- An assessment of limitation and gaps of the modelling methodology and results.

[3] https://www.wa.gov.au/organisation/energy-policy-wa/gas-services-information

2 Final Methodology and Assumptions

This section specifies the data that has been used for the modelling, the methodologies used to derive or obtain this data, the data sources that were used, and the simulation model used to obtain the results.

The input data assumptions for the modelling are a combination of:

- Data provided by AEMO specifically for this project,
- Data and methodologies used for the 2021 Reliability Assessment[4],
- Publicly available data from AEMO and other sources, and
- RBP's own knowledge and insights.

2.1 Simulation Model

We have used RBP's in-house dispatch optimisation tool WEMSIM to conduct the analysis to produce the forecast.

WEMSIM co-optimises energy dispatch and reserve provision using:

- Generation Facility data such as capacity, outage rates, ramp rates, heat rates and cost information (fuel prices, Variable Operation and Maintenance Costs (VO&M), Fixed Operation and Maintenance Costs (FO&M)),
- Transmission data, either via the specification of thermal limits or generic constraints (as used in the National Electricity Market (NEM) and for the Wholesale Electricity Market (WEM) Generator Interim Access (GIA)),
- Ancillary Service requirements (Spinning Reserve, Load Rejection Reserve and Load Following Ancillary Service Up/Down) and generator provision data.

2.2 Generators

In this section we set out our assumptions around:

- The technical parameters and operational costs of:

[4] See https://aemo.com.au/en/energy-systems/electricity/wholesale-electricity-market-wem/wem-forecasting-and-planning/wem-electricity-statement-of-opportunities-wem-esoo

  - Existing generation Facilities, and
  - New generation Facilities that will come online during the 10-year modelling horizon.
- The intermittent generation profiles of:
  - Utility-scale generation Facilities (wind/solar farms and biogas).

2.2.1 Existing Generators

Assumptions for the technical parameters and operational costs of existing generators[5] have been taken from the publicly available AEMO Costs and Technical Parameter Review, completed in 2018 by GHD[6], and refined during the 2019 and 2020 GPG modelling assignments.

2.2.2 Retirements

The following retirements are assumed to occur during the modelling horizon:

Unit	Retirement Date
MUJA_G5	1 October 2022
MUJA_G6	1 October 2024

2.2.3 New Build

There are some new generators coming online during the 10-year modelling horizon. Thermal Facilities are listed in Table 1 below. Section 2.8 specifies which of these new builds are included in each scenario. Other new facilities are included in the modelling scenarios but are not specified here due to confidentiality.

The charging/discharging and ancillary service provision profiles of the Battery Energy Storage Systems (BESS) are optimised by the WEMSIM model to minimise total system costs.

Table 1. Thermal New Build

Unit name	Commencement Date	Type
ERRRF_WTE_G1	1/10/2022	Biomass - electricity only
PHOENIX_KWINANA_WTE_G1	1/10/2021	Biomass - electricity only

[5] We have not modelled the dispatch of Network Control Service generators (Mungarra and West Kalgoorlie).

[6] Available from https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Planning-and-forecasting/Inputs-Assumptions-and-Methodologies.

Generic new build

If the modelling results indicate that new build is required in addition to the specific Facilities listed in Table 1, generic new build would be added according to the following methodology. In the final modelling result, generic new build was not required.

- Candidate new build Facilities will be chosen from the following options:
  - OCGT
  - CCGT
  - Biomass
  - Large scale Solar PV
  - Solar Thermal (8hrs Storage)
  - Battery storage (2hrs storage)
  - Battery Storage (4hrs storage)
  - Wind

Each suitable candidate will be modelled separately, and the economic viability of the new build will be assessed according to the capital costs and operating parameters used in the development of the 2019-2020 and 2020-2021 AEMO Integrated System plans (ISPs)[7], as summarised in Table 2 and Table 3.

The most profitable option will be chosen for the final scenario run.

[7] For the 2020-2021 ISP, some parameters were only provided by regions, not including WA, so these parameters remain the same as last year.

Table 2. Generic new build parameters

Technology Type	Connect - ion Cost ($/kW)	Lead Time (yrs)	Econ - omic Life (yrs)	Technical Life (yrs)	FOM ($/kW/ annum)	VOM ($/MWh sent out)	Heat Rate (GJ/MWh HHV s.o.)	Auxil - iary Load (%)
OCGT	78.54	4	25	30	4.49	11.26	11.75	1.53
CCGT	78.54	5	25	30	11.22	7.88	7.58	2.51
Biomass	95.08	5	25	50	140.65	8.99	13.39	6.10
Large scale Solar PV	96.30	1	25	30	16.26	0.00	0.00	2.00
Solar Thermal (8hrs Storage)	96.30	6	25	40	95.70	6.08	0.00	10.00
Battery storage (2hrs storage)	10.00	2	10	15	8.55	0.00	0.00	0.00
Battery Storage (4hrs storage)	10.00	2	10	15	8.55	0.00	0.00	0.00
Wind	96.30	2	25	30	40.55	3.00	0.00	2.00

Table 3. Generic new build capital costs (Real 2020 AUD/kW)

Technology Type	2021-22	2022-23	2023-24	2024-25	2025-26	2026-27	2027-28	2028-29	2029-30	2030-31
OCGT	1411	1411	1411	1411	1410	1410	1410	1410	1410	1410
CCGT	1690	1690	1689	1689	1689	1689	1689	1689	1688	1688
Biomass	12780	12773	12770	12770	12770	12770	12770	12770	12770	12769
Large scale Solar PV	1146	1056	1016	981	951	923	898	874	851	827
Solar Thermal (8hrs Storage)	6574	6574	6574	6574	6574	6574	6574	6574	6574	6574
Battery storage (2hrs storage)	1126	1114	1098	1022	892	777	695	644	614	540
Battery Storage (4hrs storage)	1751	1730	1701	1564	1329	1121	974	881	826	693
Wind	1723	1709	1696	1684	1671	1659	1646	1634	1621	1603

2.2.4 Utility-Scale Intermittent Profiles

Treatment of intermittent generation

We have reapplied the methodology used in the 2021 Reliability Assessment[8] to derive monthly intra-day hourly profiles for each intermittent utility-scale facility[9]. This has resulted in 12 intra-day profiles for each of the 29 intermittent Facilities. For facilities for which historical data was not available, the profile from the nearest facility of the same type was used.

2.2.5 Outages

Forced outages

We will use the forced outage assumptions developed for the 2021 Reliability Assessment. These were developed from analysing historical forced outage rates (FORs) over a 36-month period.

We have assumed a FOR of 0.1% for Facilities with a zero historic FOR (mainly intermittent Facilities). Assuming a FOR of 0% for these Facilities will be unrealistic as equipment is unlikely to have a zero-failure rate over the ten-year modelling horizon.

We have also included a Mean Time to Repair (MTR) value which denotes the amount of time a plant will be offline following a forced outage event. This value is derived by classifying plants into short (12 hours), medium (24 hours), and long (144 hours) duration outage plants, based on their historical downtimes. For new plants we have assumed forced outage rates and mean times to repair will be similar to current plants of a similar technology.

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[8] This was as follows:

- For each month (Jan, Feb, …, Nov, Dec), we assign an intra-day hourly profile to each intermittent generator.
- Each intermittent generator will have 12 intra-day hourly profiles (one for each month of the year).
- Hence, $\overline{Gen_{h,m}} = \sum_{Y\,(Years)=1}^{T} \left(\frac{\sum_{d\,(days) \in Month\,m} Gen_{Y,h,d} \big/ \#\,days\,in\,month\,m\,of\,Year\,Y}{T} \right)$

  For a given intermittent generator:
  - $\overline{Gen_{h,m}}$ denotes the average generation (MW) in hour h of month m (based on T years of historical or participant provided generation values)
  - $Gen_{Y,h,d}$ denotes the historical or estimated generation value in hour h or day d (in month m) of Year Y.

[9] Profiles of existing intermittent generation were derived using historical non-loss adjusted metered quantities. Profiles for new intermittent generation were derived using participant provided estimated generation (which AEMO provided to RBP to conduct the 2021 Reliability Assessment). The participant-provided estimated generation does not cover the last 6 months of the 2019-20 Capacity Year. AEMO has provided extended estimated generations for some of these generators based on correlations with other facilities, for the remaining facilities we have filled in the gap using the average intra-day profile over the reference years which do have data.

Planned outages

As part of the 2021 Reliability Assessment, AEMO provided RBP with participant provided planned outage schedules from 2022 to the end of 2031. We will reuse these for the GPG forecasting (zeroing out the relevant Facilities' capacity on dates where a participant has indicated an outage).Emissions Factors

The quantity of carbon emissions resulting from electricity generation will be calculated in WEMSIM, based on emission factors published by AEMO for existing and new generators in the SWIS[10].

2.2.6 Operational Stability Constraint

AEMO have advised that the minimum stable load that can be maintained is 600 MW. At or below this level of load, all generation must be synchronous thermal generation to maintain system stability.

To implement this requirement, we have added a constraint that a minimum of 600 MW of thermal generation must be maintained at all times. Should demand fall below 600 MW, a violation penalty price will be incurred, which will set the resulting market price. The presence of this penalty in the market price results will indicate an unstable level of system demand.

2.2.7 Other Operational Constraints and Offer Patterns

To replicate actual generation patterns, additional operational constraints are placed on some plant.

The WEMSIM model assumes by default that generators offer their capacity at their short-run marginal cost. An analysis of actual balancing market offers[11] (which are publicly available from the AEMO website) shows that many generators offer all or a portion of their capacity at negative prices to ensure that they are dispatched.

From this analysis, we replicate the listed Facilities' historical offer behaviour in the modelling. Fixed negative price tranches observed in the historical data are replicated in the modelling. Where there is remaining capacity offered at a positive price, we determine from the historical

[10] https://aemo.com.au/-/media/files/electricity/nem/planning_and_forecasting/ntndp/2016/data_sources/acil-allen---aemo-emissions-factors-20160511-pdf-document.pdf?la=en&hash=AB233ACCECC78768D7C236E307433C10

[11] This analysis was performed in 2019 using data from the 1st 6 months of 2019. The results of this analysis have been retained to avoid projecting covid-related changes in operations forward.

data whether the price is the Facilities' SRMC, another price that scales with the gas price, or a fixed price. Note some generators offer in a portion of the capacity at the minimum price cap (-$1000) but have auxiliary loads, resulting in an offer price close to, but not equal to, -$1000.

2.3 Transmission Network and Constraints

The WEM currently operates on an unconstrained basis, with GIA constraints used to manage the output of new GIA generators. Remaining generators are dispatched on an unconstrained basis using the Balancing Merit Order but can be constrained on or off in real-time to manage system security; when this occurs, participants are eligible to receive constraint payments.

It is expected that in 2023, Security Constrained Economic Dispatch (SCED) will be implemented on the basis of a single region hub and spoke model with a reference node located at Southern Terminal.

The GSOO horizon comprises 2022 to 2031. Hence, we have needed to form a view on what market design assumptions to adopt post market reform. We have adopted the following approach:

- Model the existing WEM with GIA constraints only up to 1 October 2022[12], excluding real-time interventions and subsequent constraint payments.
- From 1 Oct 2022 onward assume that NEM style SCED will apply (namely a single zone hub and spoke market with the reference node at Southern Terminal).

2.4 Demand

Our demand forecasting methodology has been taken from the 2021 Reliability Assessment.

This methodology was designed to capture ongoing and expected future changes in load shapes and the timing of peak periods (load chronology) in the SWIS, by modelling the impacts of behind-the-meter (BTM) generation and battery storage It involves creating underlying demand forecasts[13], and subtracting forecasted BTM PV and battery contributions to create preliminary hourly operational forecasts, which are then converted into a load profile. This load profile is then scaled to ensure alignment with AEMO's forecast operational summer peak and annual sent-out energy demand forecasts.

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[12] Subsequent to the completion of this modelling, it was announced that the implementation of SCED has been pushed back to October 2023, so the model implements SCED a year earlier than its new expected implementation date. This is not expected to have a significant impact on the results.

[13] Based on historical data and AEMO's underlying peak/energy demand forecasts.

This methodology produces a continuous series of hourly load values across the forecast horizon, so can be used for both Capacity Year and calendar year-based modelling.

This approach has five steps:

i. Create the underlying load profile: The underlying load shape is developed using historical sent out generation data (adding historical BTM PV generation to get underlying load) to derive an average load shape; this is applied to the load chronology implied by the most recently available Capacity Year to create the underlying load profile[14]
ii. Scale the underlying load profile to forecasted values: Hourly underlying load forecasts for each year in the modelling horizon are developed by scaling up the underlying reference load profile to match the underlying 50% POE peak and expected energy forecasts for the respective Capacity Year.
iii. Forecast hourly distributed energy resources (DER) contribution[15]: Using DER data provided by AEMO, we forecast hourly BTM PV generation (averaged across five 'outage sequences' reflecting stochastic weather and cloud cover), and battery charge/discharge, for each Capacity Year.
iv. Create the preliminary operational load profiles (chronology and load shapes): The hourly underlying load forecasts and hourly DER contribution forecasts are combined and adjusted for losses to create hourly operational load forecasts. These are processed into an operational load profile for each Capacity Year.
v. Scale the operational load to forecasted values: In order to ensure that our hourly operational load forecasts align with the operational peak and annual energy demand forecasts provided by AEMO, we scale the operational load profiles to forecasted values, producing the final hourly operational load forecasts to be used in the modelling.

Each of the bullets above are described in more detail in the sections below.

Figure 5 provides an overview of the load forecasting process. Boxes in green reference inputs, boxes in blue reference each step in the process (described in more detail in sections 2.4.1 - 2.4.5), while red boxes refer to outputs.

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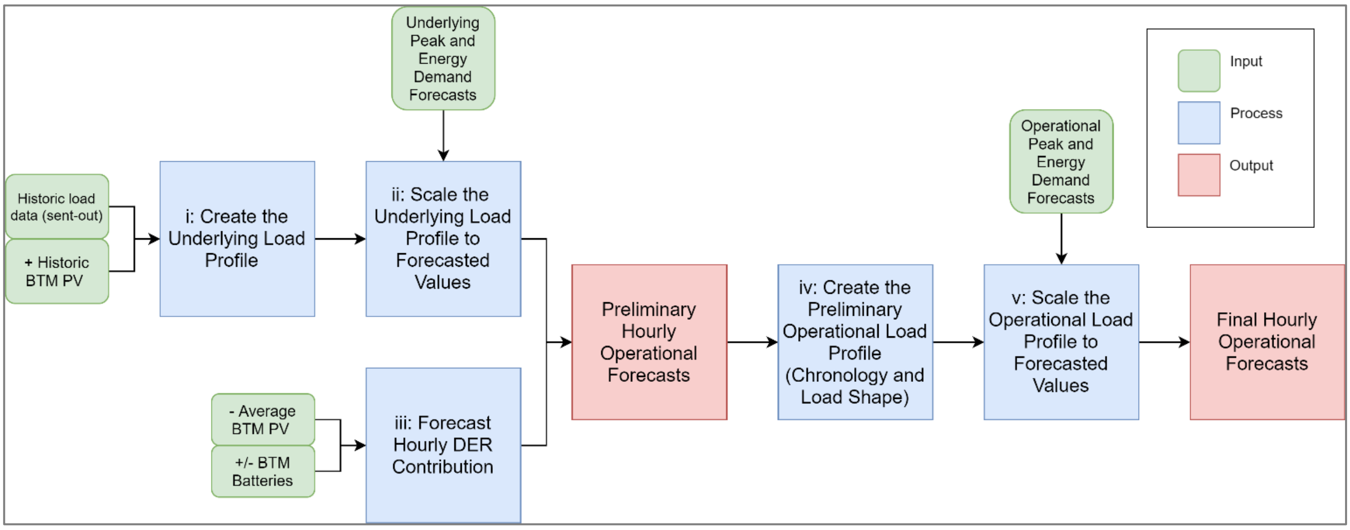
[14] Hence, we would use the load chronology from the 2019-20 Capacity Year to create the underlying reference profile, such that the hour with the largest underlying load in 2019-20 is the hour with the largest underlying load in our forecasts and likewise for the 2nd, 3rd - 8760th hour

[15] This includes contributions from BTM PV and battery storage uptake but does not include the impact of electric vehicle (EV) consumption.

Figure 5: Overview of forecasting process



Demand forecasts from the 2021 WEM ESOO have been provided by AEMO and are summarised for each of our GPG scenarios[16] in Tables 10 - 12. We have used the 10% - high demand growth/ 50% - expected demand growth/ 90% - low demand growth POE forecasts (referred to as 10/50/90% POE forecasts in the remainder of this report) for the High/Base/Low scenarios respectively, to reflect differences in forecast annual operational demand and to provide larger variation between scenarios.

Note that as the WEM ESOO horizon (Capacity Years 2021/22 to 2029/30) does not include the last three months of the GPG horizon (calendar years 2021 to 2030), we have extended the forecasts provided by AEMO by an additional year using an average growth rate.

[16] See Section 2.8 for further details about our scenario definitions.

Table 4: Demand forecasts - Base scenario

	Underlying Forecasts		Operational Sent-out Forecasts	
Capacity Year	50% POE peak forecast - Expected (MWh)	Annual Demand – Expected (MWh)	50% POE peak forecast - Expected (MW)	Annual Demand – Expected (MWh)
2021-22	4,059	18,431,930	3,686	17,127,210
2022-23	4,095	18,756,390	3,708	17,018,680
2023-24	4,135	18,966,020	3,733	16,841,560
2024-25	4,165	19,121,240	3,736	16,666,840
2025-26	4,196	19,276,520	3,739	16,521,750
2026-27	4,249	19,441,950	3,755	16,395,180
2027-28	4,218	19,608,660	3,750	16,263,580
2028-29	4,245	19,799,260	3,767	16,160,460
2029-30	4,271	19,963,840	3,769	16,050,720
2030-31	4,303	20,149,870	3,772	15,986,800
2031-32	4,331	20,350,375	3,782	15,864,871

Table 5: Demand forecasts - High scenario

	Underlying Forecasts		Operational Sent-out Forecasts	
Capacity Year	10% POE peak forecast - High (MW)	Annual Demand – High (MWh)	10% POE peak forecast - High (MW)	Annual Demand – High (MWh)
2021-22	4,362	19,309,573	3,996	17,963,460
2022-23	4,458	20,076,269	4,057	18,068,540
2023-24	4,519	20,566,865	4,098	17,824,930
2024-25	4,600	20,936,672	4,148	17,496,490
2025-26	4,669	21,293,801	4,185	17,218,570
2026-27	4,713	21,755,548	4,250	17,128,230
2027-28	4,816	22,387,704	4,323	17,308,610
2028-29	4,881	23,031,094	4,414	17,583,760
2029-30	4,984	23,680,152	4,537	17,947,950
2030-31	5,073	24,390,576	4,657	18,434,660
2031-32	5,159	25,031,923	4,737	18,487,773

Table 6: Demand forecasts - Low scenario

			Operational Sent-out Forecasts	
Capacity Year	**90% POE peak forecast - Low (MW)**	**Annual Demand – Low (MWh)**	**90% POE peak forecast - Low (MW)**	**Annual Demand – Low (MWh)**
2021-22	3,771	17,388,321	3,363	15,987,000
2022-23	3,748	17,227,122	3,318	15,265,870
2023-24	3,730	17,176,517	3,275	14,660,430
2024-25	3,712	17,115,037	3,248	14,118,030
2025-26	3,695	17,082,908	3,226	13,718,620
2026-27	3,679	17,094,857	3,205	13,468,620
2027-28	3,694	17,092,183	3,167	13,236,600
2028-29	3,665	17,084,863	3,149	13,023,410
2029-30	3,646	17,059,820	3,100	12,817,740
2030-31	3,701	17,052,488	3,067	12,645,180
2031-32	3,693	17,015,576	3,036	12,407,912

2.4.1 Creating the Underlying Load Profile

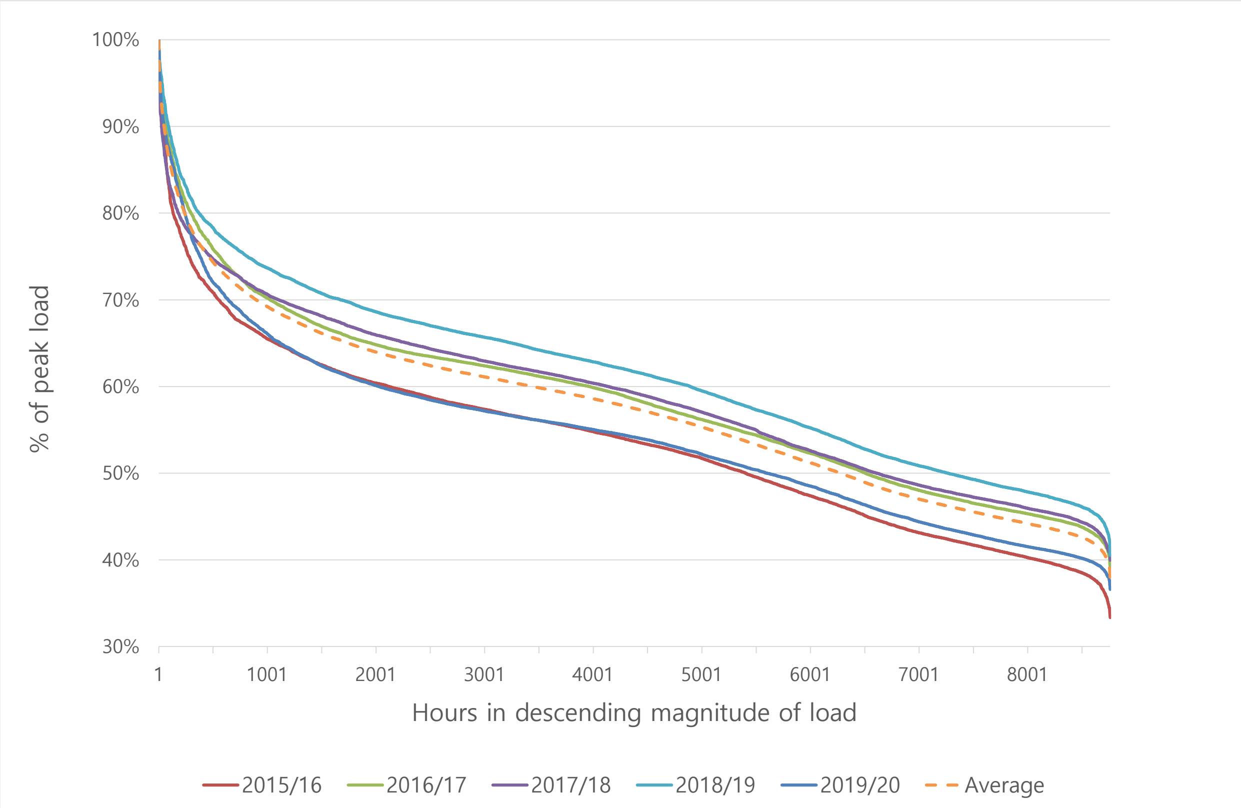
We first develop a 'reference' underlying load profile by constructing underlying historical load duration curves (LDCs)[17] for the last five full Capacity Years (2015-15 to 2019-20), averaging across these five LDCs to construct an average load shape, and applying this underlying average load shape to the most recent load chronology (2018/19). As the historical total sent-out generation from AEMO reflects operational demand and excludes the effects of BTM PV generation, we add historical BTM PV generation[18] (provided by AEMO) to the historical operational load data before conducting the above analysis.

[17] A load curve ordered in descending order

[18] PV DER generation causes total sent out generation to be lower than underlying demand.

We use the average load profile to ensure that the underlying demand profile reflects a representative underlying load shape, while ensuring that more recent trends are captured[19]. Figure 6 below shows the reference load shape:

Figure 6: Underlying reference load shape



2.4.2 Scaling the Underlying Load Profile to Forecasted Values

The next step in our load forecasting methodology is to scale the underlying profile to match the underlying 50% POE peak forecast and expected demand in any given year. This is done for each of the three scenarios to create three underlying load forecasts, each representing a different peak forecast.

Note that the underlying 10/50/90% POE forecasts provided by AEMO represent the underlying demand occurring at the time of the operational forecast peak, rather than the maximum underlying demand over the forecast year.

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[19] Note that our historical load chronology does not include the recent 2020-21 summer peak (which was particularly high) and would lead to relatively higher summer loads in the historical load profile. This peak was primarily driven by very hot temperature conditions leading to high underlying demand (with a maximum temperature of 43°C on the peak day, after two consecutive hot days of over 35°C.).

Historically, the peak underlying demand and the peak operational demand generally occur on the same day. However, the underlying peak demand occurs earlier in the day and will be higher than the underlying demand occurring at the time of operational peak. AEMO has provided the time of operational peak for each forecast year, and we have scaled up the underlying values provided by AEMO to represent the underlying 10/50/90% POE peak. This scaling is based on the average historical difference between the peak underlying demand and the forecast time[20] of operational peak, on the operational peak day.

Having scaled the underlying value to the underlying peak, for each year of the LT-PASA forecast horizon we produce a forecasted load profile with a shape such that:

- The peak of the load profile equals the 10/50/90% POE peak forecast
- The load allocated across all hours sums to the expected underlying annual demand consumption forecast and
- The shape of the profile should be "close" to the reference year profile developed above.

We have defined a function F(h) (h ∈ hours of the year), such that the shape underlying the profile for a given year t ($\widehat{PROF}(h)$) can be derived by multiplying the average load shape ($\overline{PROF}(h)$) by this function. That is:

- $\widehat{PROF}(h) = F(h) \times \overline{PROF}(h)$, such that:
  - $Max\left(\widehat{PROF}(h)\right) =$ underlying POE peak forecast in year t and
  - $\sum_{h=1}^{8760} \widehat{PROF}(h) =$ underlying expected demand forecast in year t.

The function is defined to ensure that the shape of the profile varies with differing peak/energy ratios in a way that is consistent with the historical load shapes of the last five years. Thus, we have defined F(h) as follows:

$$F(h) = \begin{cases} \dfrac{p - z}{m^2}(m - h)^2 + z \; if \; h \leq m \\ \dfrac{e - z}{(n - m)^2}(h - m)^2 + z \; if \; h > m. \end{cases}$$

Where:

- p denotes the ratio of the underlying peak forecast to the five-year average underlying peak demand
- e denotes the ratio of the underlying expected demand forecast to the five-year average underlying hourly demand
- m denotes the position in the profile in which the curve flattens (1,500 hours for this year’s modelling), as has been observed (on average) in historical years.
- n denotes the total number of hours in a year and

[20] We have assumed that the 90/10% POE peaks occur at the same time as the 50% POE peak.

- z represents a curvature constant that is adjusted to achieve the expected demand forecast in the profile's resulting load shape.

Repeating this process for each of 10/50/90% POE forecasts gives us hourly underlying demand across the modelling horizon, for each scenario.

2.4.3 Forecasting Hourly DER Contribution:

Our DER forecasts are the sum of the following data:

- BTM PV generation
- BTM battery charging demand and discharge

Each component has a separate methodology which is discussed below. These methodologies produce hourly forecasts which are aggregated together to produce hourly DER contribution for each Capacity Year over the modelling horizon. EVs are already included in the forecasts from AEMO, so we have not modelled these separately. Note that all scenarios use the same DER forecasts.

BTM PV Generation and Outages

The profile of BTM PV generation is complex, with seasonal and daily variability and random intermittency caused by cloud cover. For the purpose of modelling, this can be broken down into:

- Daily generation potential profiles for each month of the year, assuming zero cloud cover (we have assumed that the 99.5% percentile generation in a given month and hour represents a unit generating at its maximum capacity with zero cloud cover). These are deterministic (i.e., fixed and predictable) profiles and are expressed as capacity factors (i.e., fractions of installed capacity).
- BTM PV capacity forecasts (MW) over the modelling horizon.
- An outage probability distribution function (PDF), expressing the probability that a given unit of generation output will be eliminated by cloud cover. This PDF is dependent on the outage (i.e., cloud cover) in the previous hour, and this dependency needs to be factored in to avoid excessive changes in solar PV output from one period to the next. These factors have been developed from historical capacity factors, analysing actual generation compared to forecasted generation and 'adding features' to the PDF as necessary, validating it against historical generation. This dependency is also a function of the season of the year. Therefore, PDFs have been computed for a range of previous hour outage factors and each season (summer, winter, and shoulder).

AEMO has provided historical BTM PV capacity factor data for each trading period from 1 January 2010 to 23 February 2020. Using statistical analysis (comparing actual generation to zero cloud cover generation in a period, and processing this into percentiles) of the historical data, we process daily generation profiles for each month and outage PDF, as described above. AEMO has also provided installed capacity forecasts over the modelling horizon.

The following tables and figures provide the inputs into the PV modelling process

- Figure 7 shows the BTM PV potential generation factors
- Figures 12-14 show the BTM PV outage factor PDFs for each season (Summer, Shoulder, Winter)

Figure 7: BTM PV - potential capacity factors

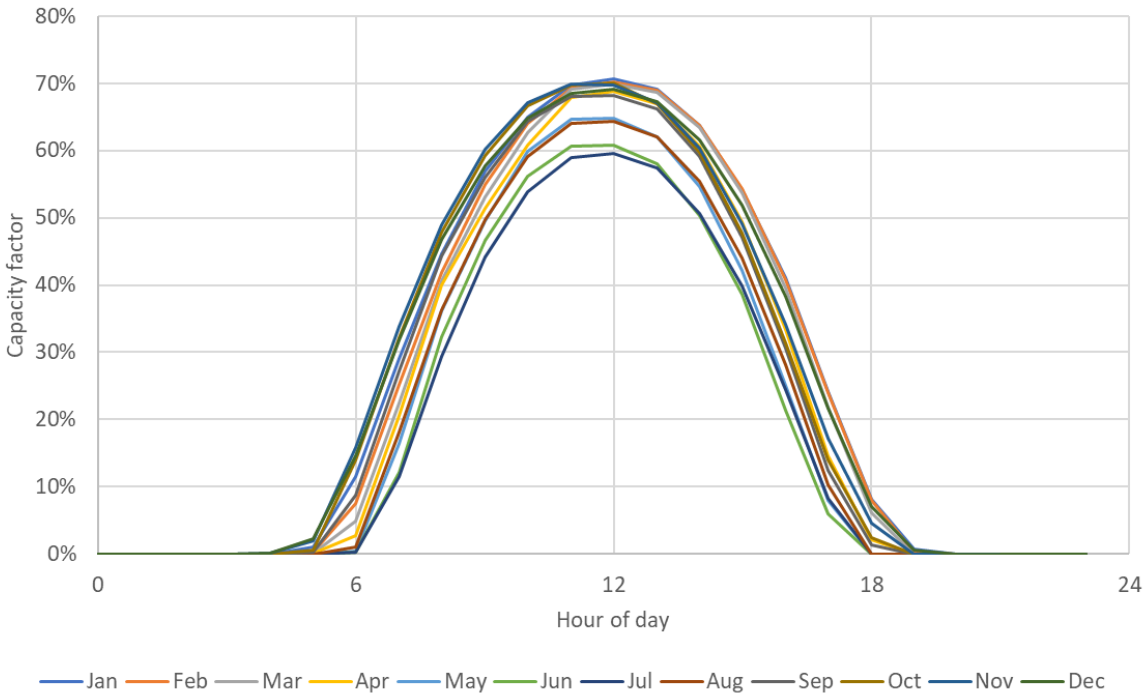


Figure 8: BTM PV - outage factor PDFs (Summer)

	Previous Outage Factor									
Outage Factor	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.05	0.2500	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.10	0.3333	0.0877	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.15	0.2500	0.1228	0.0598	0.0132	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.20	0.0833	0.3860	0.1538	0.0329	0.0043	0.0000	0.0000	0.0000	0.0000	0.0000
0.25	0.0833	0.2281	0.1880	0.0855	0.0043	0.0035	0.0000	0.0000	0.0000	0.0000
0.30	0.0000	0.1053	0.2735	0.1645	0.0216	0.0104	0.0000	0.0000	0.0000	0.0000
0.35	0.0000	0.0351	0.1453	0.1447	0.0647	0.0174	0.0018	0.0000	0.0000	0.0000
0.40	0.0000	0.0000	0.0598	0.1974	0.1595	0.0451	0.0126	0.0000	0.0000	0.0000
0.45	0.0000	0.0175	0.0598	0.1645	0.1724	0.0660	0.0072	0.0026	0.0000	0.0000
0.50	0.0000	0.0000	0.0513	0.0855	0.1897	0.1285	0.0450	0.0017	0.0000	0.0000
0.55	0.0000	0.0000	0.0085	0.0855	0.1422	0.1354	0.0649	0.0044	0.0003	0.0000
0.60	0.0000	0.0000	0.0000	0.0132	0.1250	0.1910	0.0919	0.0244	0.0006	0.0000
0.65	0.0000	0.0175	0.0000	0.0066	0.0733	0.1840	0.1766	0.0427	0.0019	0.0000
0.70	0.0000	0.0000	0.0000	0.0066	0.0302	0.1285	0.2270	0.0924	0.0075	0.0000
0.75	0.0000	0.0000	0.0000	0.0000	0.0086	0.0625	0.2342	0.1700	0.0180	0.0010
0.80	0.0000	0.0000	0.0000	0.0000	0.0043	0.0208	0.0901	0.2807	0.0652	0.0012
0.85	0.0000	0.0000	0.0000	0.0000	0.0000	0.0035	0.0288	0.2903	0.2336	0.0070
0.90	0.0000	0.0000	0.0000	0.0000	0.0000	0.0035	0.0180	0.0776	0.4908	0.0840
0.95	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0131	0.1780	0.5746
1.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0018	0.0000	0.0040	0.3323

Figure 9: BTM PV - outage factor PDFs (Shoulder)

	Previous Outage Factor									
Outage Factor	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.05	0.2500	0.0377	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.10	0.5000	0.0566	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.15	0.0000	0.2264	0.0721	0.0072	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.20	0.2500	0.3019	0.1712	0.0362	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.25	0.0000	0.2075	0.2793	0.0507	0.0217	0.0035	0.0000	0.0000	0.0000	0.0000
0.30	0.0000	0.1132	0.1622	0.1739	0.0326	0.0246	0.0000	0.0000	0.0000	0.0000
0.35	0.0000	0.0566	0.1892	0.1594	0.1033	0.0211	0.0043	0.0000	0.0000	0.0000
0.40	0.0000	0.0000	0.0721	0.2101	0.1304	0.0563	0.0043	0.0000	0.0000	0.0000
0.45	0.0000	0.0000	0.0270	0.1812	0.1576	0.0845	0.0108	0.0022	0.0000	0.0000
0.50	0.0000	0.0000	0.0090	0.0942	0.1957	0.1444	0.0409	0.0077	0.0005	0.0000
0.55	0.0000	0.0000	0.0090	0.0290	0.1413	0.1408	0.0989	0.0187	0.0000	0.0000
0.60	0.0000	0.0000	0.0000	0.0362	0.1522	0.1690	0.0989	0.0529	0.0009	0.0000
0.65	0.0000	0.0000	0.0090	0.0217	0.0326	0.1620	0.2065	0.0562	0.0087	0.0000
0.70	0.0000	0.0000	0.0000	0.0000	0.0217	0.1373	0.2301	0.1103	0.0160	0.0000
0.75	0.0000	0.0000	0.0000	0.0000	0.0109	0.0493	0.1892	0.1830	0.0375	0.0000
0.80	0.0000	0.0000	0.0000	0.0000	0.0000	0.0035	0.0968	0.3142	0.0970	0.0040
0.85	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0129	0.2073	0.2841	0.0198
0.90	0.0000	0.0000	0.0000	0.0000	0.0000	0.0035	0.0065	0.0441	0.4167	0.1323
0.95	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0033	0.1359	0.6005
1.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0027	0.2435

Figure 10: BTM PV - outage factor PDFs (Winter)

	Previous Outage Factor									
Outage Factor	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.05	0.1636	0.0061	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.10	0.3455	0.0547	0.0111	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.15	0.2909	0.2644	0.0348	0.0021	0.0014	0.0005	0.0000	0.0000	0.0000	0.0000
0.20	0.1273	0.2888	0.0981	0.0126	0.0048	0.0010	0.0000	0.0000	0.0000	0.0000
0.25	0.0545	0.1824	0.1883	0.0547	0.0109	0.0025	0.0000	0.0000	0.0000	0.0000
0.30	0.0182	0.0942	0.2215	0.1232	0.0280	0.0059	0.0030	0.0003	0.0000	0.0000
0.35	0.0000	0.0456	0.1804	0.1663	0.0478	0.0128	0.0034	0.0012	0.0000	0.0000
0.40	0.0000	0.0304	0.1203	0.1947	0.1031	0.0241	0.0086	0.0045	0.0002	0.0000
0.45	0.0000	0.0152	0.0823	0.1684	0.1612	0.0665	0.0132	0.0024	0.0007	0.0000
0.50	0.0000	0.0152	0.0301	0.1168	0.2083	0.1025	0.0365	0.0057	0.0004	0.0000
0.55	0.0000	0.0000	0.0206	0.0926	0.1803	0.1587	0.0609	0.0159	0.0015	0.0000
0.60	0.0000	0.0000	0.0063	0.0389	0.1352	0.2100	0.1177	0.0246	0.0022	0.0000
0.65	0.0000	0.0030	0.0032	0.0200	0.0615	0.1971	0.1880	0.0571	0.0064	0.0009
0.70	0.0000	0.0000	0.0032	0.0063	0.0294	0.1316	0.2237	0.1117	0.0148	0.0006
0.75	0.0000	0.0000	0.0000	0.0032	0.0178	0.0586	0.2038	0.1916	0.0427	0.0025
0.80	0.0000	0.0000	0.0000	0.0000	0.0096	0.0168	0.1045	0.2863	0.0925	0.0057
0.85	0.0000	0.0000	0.0000	0.0000	0.0000	0.0099	0.0248	0.2256	0.2663	0.0220
0.90	0.0000	0.0000	0.0000	0.0000	0.0007	0.0015	0.0105	0.0637	0.4286	0.1111
0.95	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0015	0.0090	0.1388	0.5765
1.00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0046	0.2807

These three factors are combined to simulate a realistic solar generation profile by:

1. For each modelled hour, selecting the generation potential value from Figure 7.
2. For each modelled hour, randomly generating an outage factor from the PDFs. This is done by generating a random number for each modelled hour. This random number looks up the cumulative PDF in Figure 8,9,10 for the relevant season, for the relevant previous outage factor, which gives the modelled hour's outage factor.
3. Multiplying these two factors by the forecast MW PV capacity for the period, to obtain a MWh generation value.

We use five outage seeds to provide a range of potential PV generation sequences. In order to vary BTM PV outages, we simply change the random outage seed and regenerate the random numbers, which then selects a different outage factor (and consequent generation) for each modelled hour. This gives us five varying PV generation sequences. We then take the hourly average of these sequences.

BTM Battery Storage

BTM batteries include installations at domestic and commercial properties, but do not include grid-connected storage Facilities.

From AEMO, we have received MW capacity and MWh duration forecasts by year and month for residential and two classes of commercial batteries (up to 100 kW and above 100 kW).

Normalised historical charge and discharge profiles for residential and commercial batteries, by period and month of year (expressed as a fraction of the installed kW battery capacity) have also been provided by AEMO. We take the charge and discharge profile for each period and month of year, over the last ten years (to align with the PV historical data) to create an average profile for the modelling.

The resulting net charge/discharge for a given period in a model year is calculated as:

$$\begin{aligned} BattNetCD_{y,p} = {} & 1000 \times \left(Charge^{Res}_{M(p),p} - Discharge^{Res}_{M(p),p}\right) \times BatMW^{Res}_{c,y,M(p)} \\ & + 1000 \times \left(Charge^{Com}_{M(p),p} - Discharge^{Com}_{M(p),p}\right) \times \left(BatMW^{ComSml}_{c,y,M(p)} + BatMW^{ComLge}_{c,y,M(p)}\right) \end{aligned}$$

Where:

$BattNetCD_{y,p}$	is the net battery charge/discharge for period *p* in year *y*
$Charge^{Res}_{m,p}$	is the residential charge profile for month *m*, period *p*
$Discharge^{Res}_{m,p}$	is the residential discharge profile for month *m*, period *p*
$Charge^{Com}_{m,p}$	is the commercial charge profile for month *m*, period *p*
$Discharge^{Com}_{m,p}$	is the commercial discharge profile for month *m*, period *p*
$M(p)$	is the number of the month that period *p* is in
$BatMW^{Res}_{c,y,m}$	is the forecast residential battery capacity in MW
$BatMW^{ComSml}_{c,y,m}$	is the forecast small commercial battery capacity in MW
$BatMW^{ComLge}_{c,y,m}$	is the forecast large commercial battery capacity in MW

This net charge/discharge is a negative value when discharge exceeds charge demand, so reduces the total demand.

2.4.4 Creating the Preliminary Operational Load Profile

In order to create the preliminary operational load profiles for each scenario, we first aggregate our hourly underlying load forecasts with our hourly DER contribution forecasts (which are the same in each scenario) to create hourly delivered (non-loss adjusted) load forecasts, such that:

$$DL_d = UL_d - DER_d$$

Where DL_d refers to the delivered load at datetime d, UL_d refers to the underlying load forecasts and DER_d refers to the hourly DER contributions. The delivered loads are then loss-adjusted by a weighted loss factor, calculated from a residential loss factor (1.0472) and a business loss factor

(1.0346) provided by AEMO[21], and the relative proportion of forecasted underlying residential to business annual demand, such that:

$$OL_d = DL_d \times \left(\left(LF_r \times \frac{L_r}{L_r + L_b} \right) + \left(LF_b \times \frac{L_b}{L_r + L_b} \right) \right)$$

Where OL_d refers to the operational load at datetime d, LF_r, LF_b refers to the residential and business loss factors (respectively), and L_r,L_b refers to total forecast underlying residential and business load/demand for a given Capacity Year.

Our derived loss factors are shown in Table 7:

Table 7: Loss factors applied

CY	Residential Annual Demand (MW) - Underlying	Business Annual Demand (MW) – Underlying	Loss Factor
2021-22	6,563	11,862	1.038
2022-23	6,649	12,100	1.038
2023-24	6,715	12,243	1.038
2024-25	6,770	12,342	1.038
2025-26	6,829	12,431	1.038
2026-27	6,889	12,512	1.038
2027-28	6,945	12,575	1.038
2028-29	6,995	12,643	1.038
2029-30	7,038	12,666	1.038
2030-31	7,085	12,680	1.038
2031-32	7,145	12,788	1.038

These preliminary operational load hourly forecasts are then aggregated into the operational load profile for each Capacity Year by:

- Converting the load values into a load shape by expressing each load value as a percentage of maximum demand, ranking these in descending order (largest to smallest).

[21] From https://aemo.com.au/-/media/files/electricity/wem/data/loss-factors/2019/2019-20-loss-factor-report.pdf?la=en. Residential: page 14, Distribution System Wide Average Loss Factor applied in 2018/19. Business: page 8, Transmission SWIN Average Loss Factor applied in 2018/19.

- Indexing the load shape by its associated date in the hourly forecasts to create a load chronology.

This gives us a preliminary operational load profile for each forecast Capacity Year and scenario.

2.4.5 Scaling the Operational Load Profile to Forecasted Values

In some cases, the derived operational peak and annual energy demands from our forecasts may not exactly match the forecasts provided by AEMO. This is for three reasons:

- The 10/50/90% peak demands provided by AEMO do not necessarily match the expected annual energy demands, as these may reflect different underlying demand conditions.
- The methodology used by AEMO to create the 10/50/90% POE forecasts relies on many iterations of BTM PV generation, the likelihood of one of our PV outage sequences exactly corresponding with AEMO's is low.
- The methodology used in forecasting battery charge/discharge by AEMO in producing their forecasts is not exactly reproducible by RBP, as it is a function of the PV simulations.

In order to ensure that the operational peaks from our forecast match AEMO's, we re-scale the operational load profiles created in Section 2.4.4, using the function described in Section 2.4.2. This gives us hourly load forecasts that capture year-on-year variation in load shape and chronology, while maintaining alignment with the forecasts provided by AEMO.

2.5 FUELS

Fuel prices will be specified in real 2020 AUD terms, so the market prices produced by the model will also be in Real 2020 AUD terms. Note that the fuel costs for fuels not listed in this section (landfill gas, waste, etc.) are assumed to be zero across all years.

2.5.1 Pipeline Natural Gas

The prices for pipeline natural gas have been provided by AEMO for the purpose of this analysis.

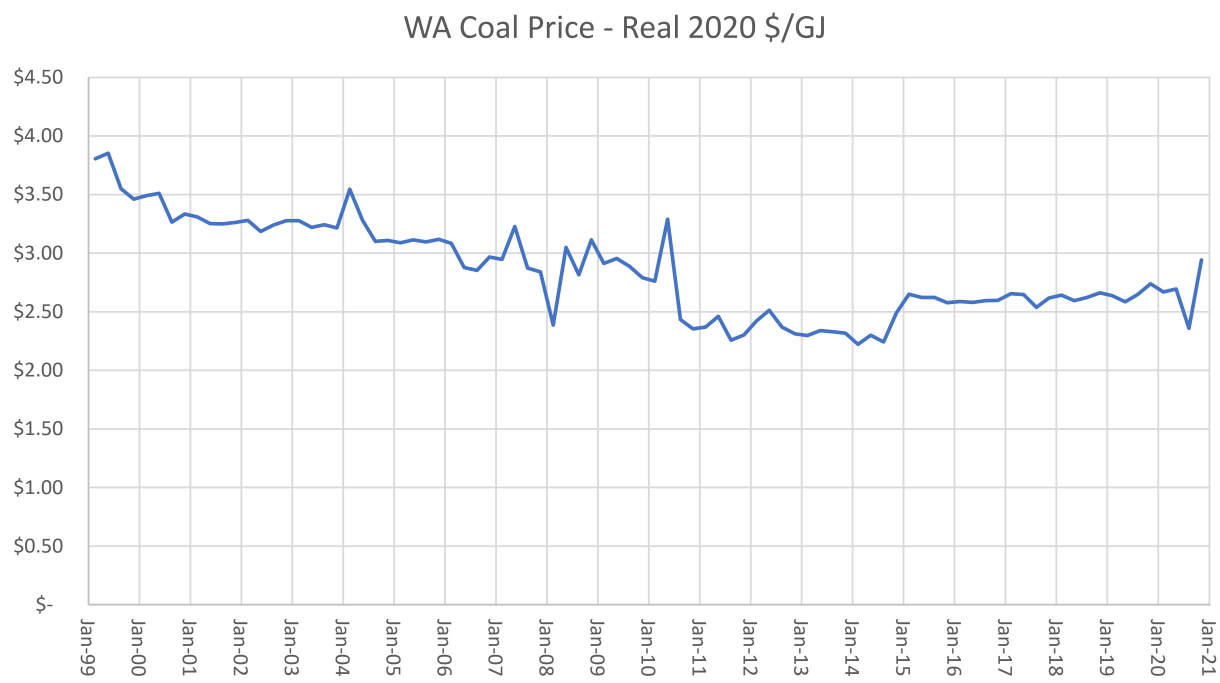
2.5.2 Coal

Coal-fired generators in WA receive coal directly from WA coal mines under a contract between the mining companies and the WA government. The terms of this contract are not public, so the cost of this coal needs to be estimated for modelling purposes.

WA coal is not exported beyond WA, so does not receive global market prices.

Data on the value of WA coal is provided in the *2020 Major Commodities Resources Data*, published by the Government of Western Australia Department of Mines, Industry Regulation and Safety[22]. This provides data on the quantity and value of coal produced in WA. Assuming a calorific value of 19.7 GJ/t[23], this yields the following historical prices (Figure 11):

Figure 11. Historical WA Coal Prices



This data shows a 5-year period of stable prices followed by a pandemic-related disruption. We propose to use a constant price (in real 2021 AUD terms) of the average price over the last 5 years. This results in a constant price of AUD 2.63/GJ.

2.5.3 Distillate

Historical "Perth Terminal Gate" prices for distillate (i.e., Diesel) are available from the Australian Institute of Petroleum[24]. Diesel prices are strongly correlated with global (e.g., Brent) crude oil prices, and a linear correlation can be obtained based on historical diesel and crude oil prices. By applying this correlation, the crude oil forecast that underlies the gas price forecasts (as referenced in section 2.5.1), a distillate price forecast can be obtained as provided in Table 8.

[22] https://www.dmp.wa.gov.au/About-Us-Careers/Latest-Statistics-Release-4081.aspx

[23] Guide to the Australian Energy Statistics 2017: https://www.energy.gov.au/sites/default/files/guide-to-australian-energy-statistics-2017_0.docx

[24] https://www.aip.com.au/pricing/terminal-gate-prices/perthDiesel

Table 8. Distillate price forecast

Year	Base (Real 2021 AUD/GJ)	Low (Real 2021 AUD/GJ)	High (Real 2021 AUD/GJ)
2022	15.64	14.21	17.43
2023	15.20	13.68	17.43
2024	15.20	13.32	17.43
2025	15.20	13.32	17.43
2026	15.20	13.50	17.43
2027	15.20	13.68	17.43
2028	15.20	13.68	17.43
2029	15.20	13.68	17.43
2030	15.20	13.68	17.43
2031	15.20	13.68	17.43

The following parameters are also assumed in this forecast:

- Excise tax (currently 0.423 c/l) and GST (10%) are rebated
- Calorific value is 38.6 MJ/l[25]
- Transport cost to Parkeston area is 1.1 c/l[26]

2.6 Ancillary Services

In all years we will model four Ancillary Services, as set out in Table 9 below:

[25] Page 318 of the National Greenhouse and Energy Reporting (Measurement) Determination 2008: https://www.legislation.gov.au/Details/F2019C00553/6a96c1f2-5a98-4edc-a2c0-769253a56017

[26] AEMO 2020-21 Energy Price Limits Review: https://aemo.com.au/en/consultations/current-and-closed-consultations/2020-energy-price-limits

Table 9: Modelled Ancillary Services and Requirements

Ancillary Service	Requirement[27]
Spinning Reserve (SR)	70% of the largest generating unit
Load Rejection Reserve (LRR)	90 MW
Load Following Ancillary Service Up (LFAS Up)	105 MW (5:30 AM – 7:30 PM) 80 MW (7:30 PM – 5: 30 AM)
Load Following Ancillary Service Down (LFAS Down)	105 MW (5:30 AM – 7:30 PM) 80 MW (7:30 PM – 5: 30 AM)

We note that there is currently reform work under way defining new Ancillary Services that may be required in the future. As it is still unclear what those services may look like and how they may be procured, we will assume that the above quantities will remain in force. However, it is reasonable to assume that the market for SR will be opened up post-reform, so that a larger number of Facilities will be able to provide this service. We will not assume the same for LFAS, as there are entry barriers to providing LFAS.

[27] Source: https://www.erawa.com.au/electricity/wholesale-electricity-market/ancillary-services-parameters/aemos-ancillary-services-requirements

2.7 Energy Storage

2.7.1 Distributed Energy Storage

Distributed energy storage is modelled as a fixed charge and discharge profile, as specified in section2.4.3.

2.7.2 Grid-Connected Storage

New build of grid-connected storage is specified in section 2.2.3.

2.8 Scenario Definitions

In consultation with AEMO, we have developed a range of scenarios to be modelled for the GPG forecast study, as specified in Table 10:

Table 10. Scenario definitions

Scenario	High	Base	Low
Operational consumption	High	Expected	Low
Peak demand	High case - 10% probability of exceedance (POE)	Expected case - 50% POE	Low case - 90% POE
Gas price	Low	Expected	High
Distillate price	Low	Expected	High
Behind the meter PV and battery storage	Expected	Expected	Expected
Generation retirements	Staged retirement of Muja C: • MUJA_G5 retires 1 October 2022. • MUJA_G6 retires 1 October 2024.		
Generation new builds[28]	PHOENIX_KWINANA_WTE_G1 ERRRF_WTE_G1		

[28] Other new facilities are included in the modelling scenarios but are not specified here due to confidentiality.

3 Summary of Modelling Results

In this section we provide a summary of the key modelling results. Full modelling results, down to an hourly time resolution, have been provided to AEMO in spreadsheet form.

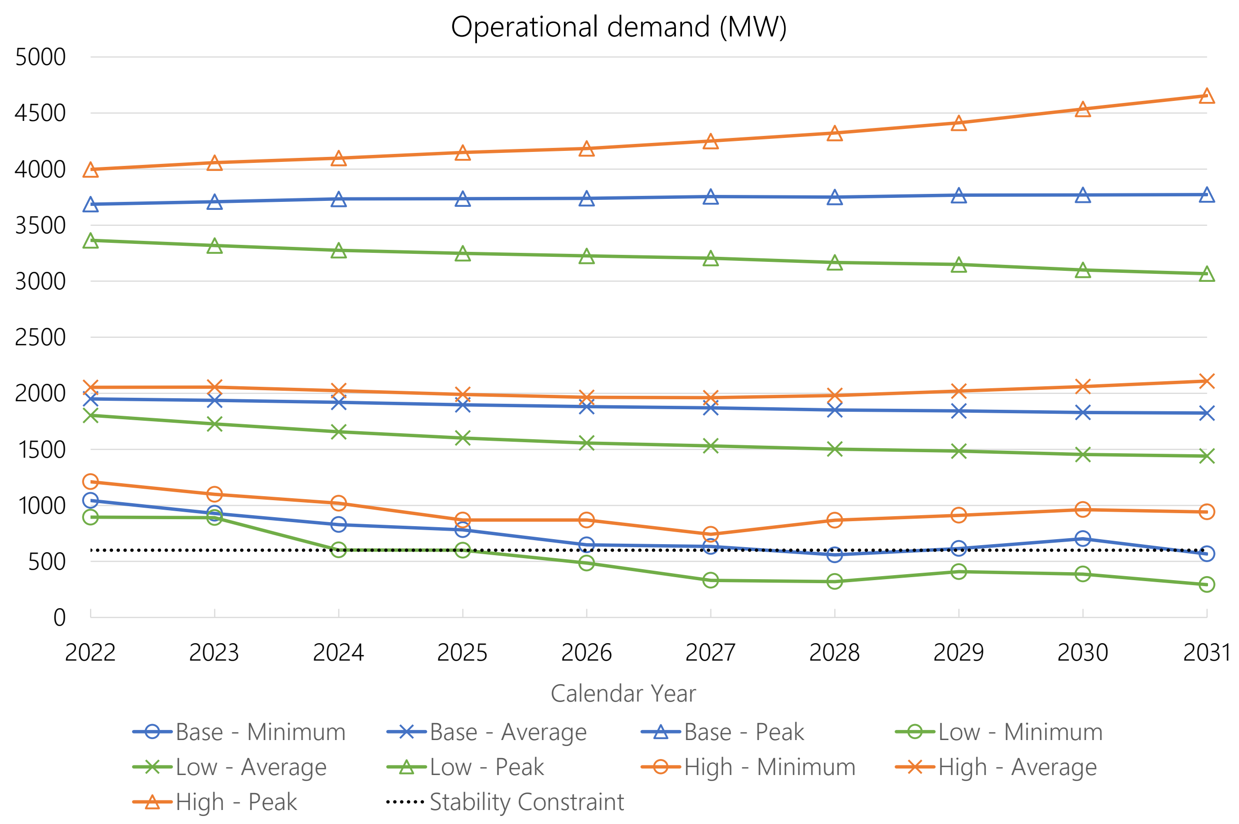
In the following sections, we provide summaries of the following results on an annual basis:

- Operational demand
- Gas consumption
- Coal consumption
- Carbon emissions

3.1 Operational Demand

Figure 12 shows the hourly average, peak and minimum demand for each Capacity year in the modelling horizon.

Figure 12: Minimum, average, and peak operational demand



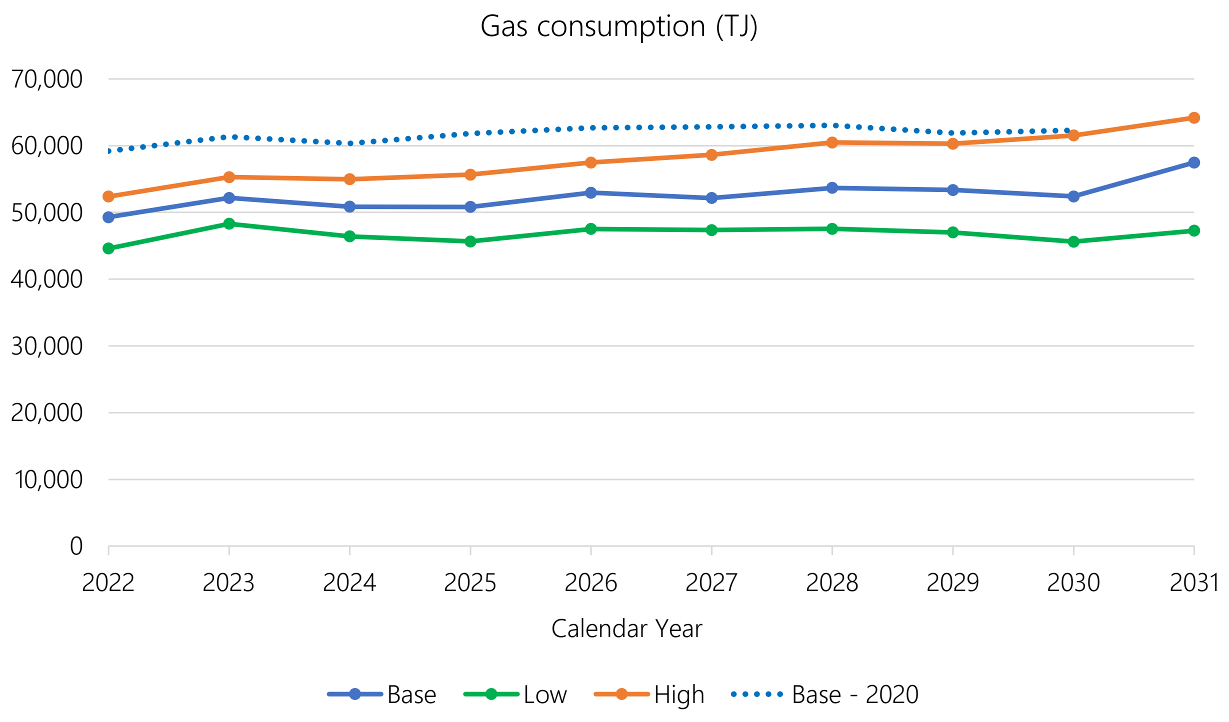
Relative to the 2020 GPG modelling demand assumptions, the following differences are significant:

- Average Base scenario demand is lower
- Average High scenario demand dips downward in 2024-2026 to be close to Base scenario demand.
- Peak High scenario demand is higher
- Minimum Low scenario demand is lower

3.2 Gas Consumption

Figure 13 shows the annual total gas consumption from GPG from the model results (on a calendar year basis). Base gas consumption from the 2020 GPG forecasts is included for comparison.

Figure 13: Gas consumption



Compared to the 2020 GPG modelling results, Base scenario gas demand is significantly lower for the entire outlook horizon. This is the result of a combination of factors:

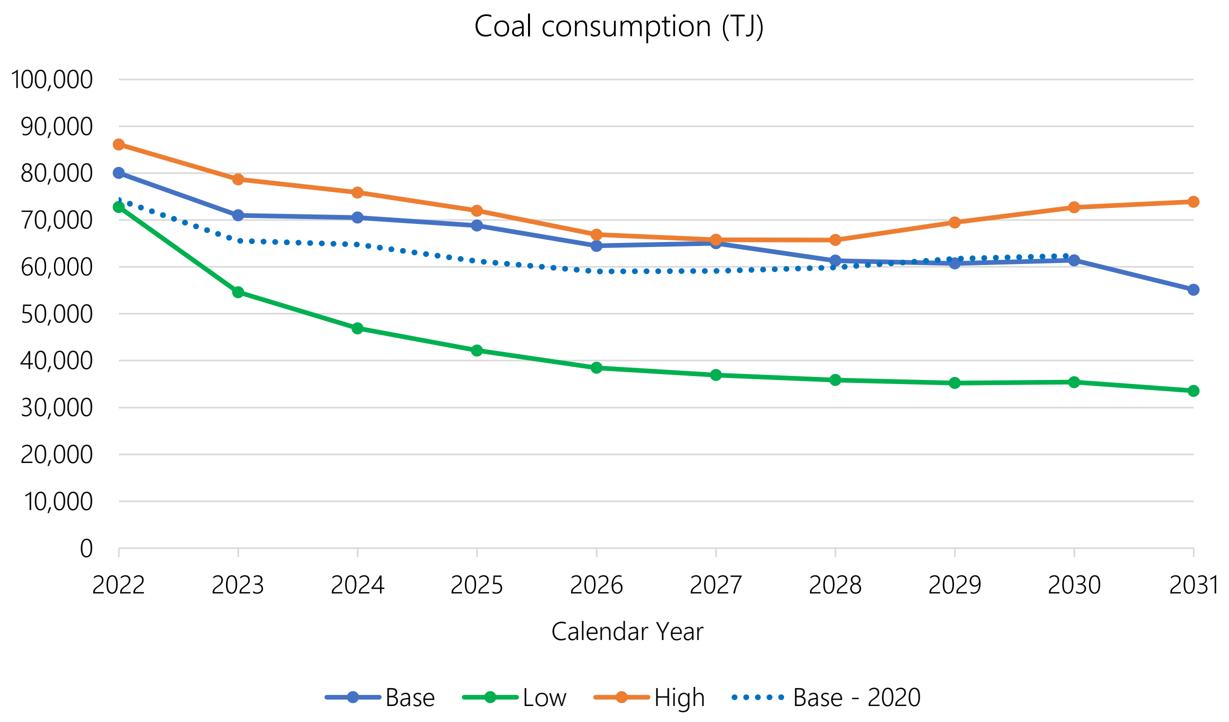
- Overall lower average electricity consumption and operational demand
- A higher gas price, making coal more competitive relative to gas

- Increased renewable generation capacity
- Introduction of BESS capacity, which has two consequences:
  - Batteries compete with gas peakers as providers of peak energy
  - Batteries provide flexibility to allow coal generators to continue to generate around their unit commitment constraints (e.g. start costs and minimum up times)

3.3 Coal Consumption

Figure 14 shows the annual total coal consumption for electricity generation from the model results.

Figure 14: Coal consumption



Compared to the 2020 GPG modelling results, Base scenario coal demand is initially higher. This is the result of a combination of factors:

- A higher gas price, making coal more competitive relative to gas
- Increased BESS capacity, enabling greater flexibility around coal unit commitment constraints (e.g. start costs and minimum up times)

Over time, however, reduced average electricity demand and increased renewable generation eliminate these advantages.

In the High scenario, the dip in average electricity demand from 2024-2026 results in significantly lower coal demand.

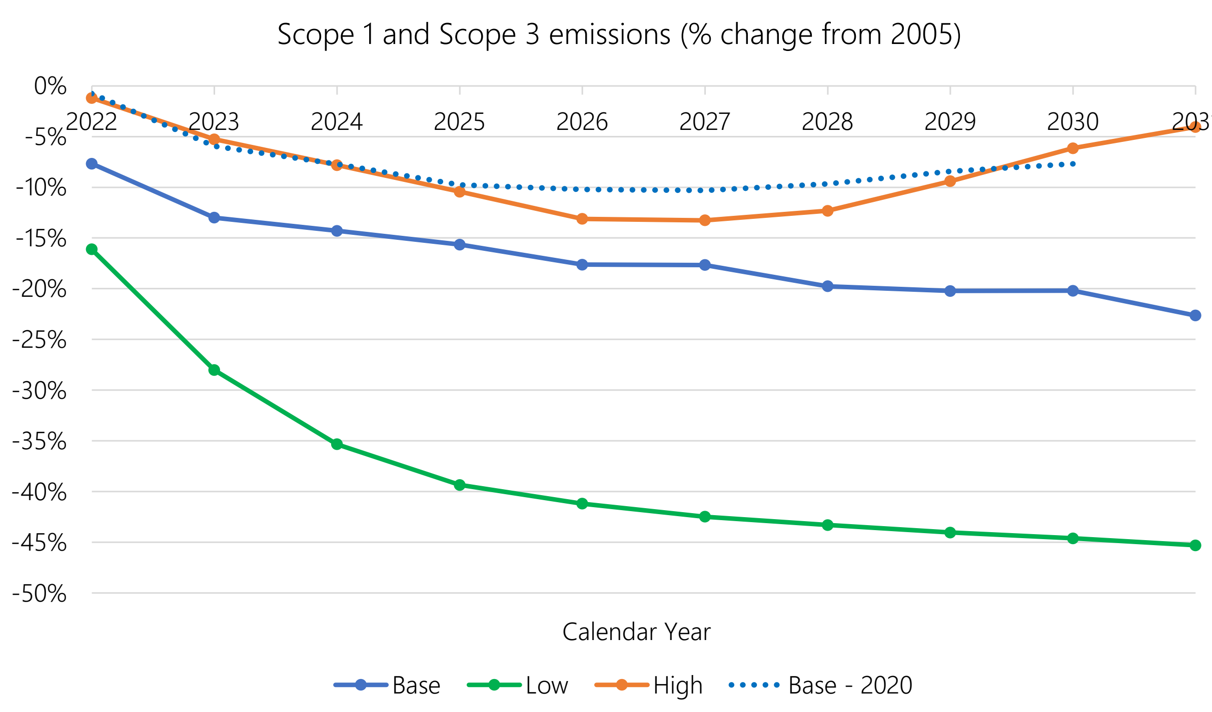
Coal demand in the Low scenario is significantly lower. This is largely driven by the lower minimum demand levels in the Low scenario, which makes it much more difficult for coal plants to meet their unit commitment constraints.

3.4 Emissions

Figure 15 shows total annual Scope 1 and Scope 3 emissions from the modelling results, in terms of the percentage change from 2005 levels (positive percentage values showing higher emissions than 2005 levels, negative values showing lower emissions).

The emissions presented here are the direct (Scope 1) and indirect (Scope 3) emissions from the combustion of fuels to generate electricity, so do not include emissions related to the use of electricity, nor the construction or decommissioning of generation plants.

Figure 15: Emissions



Relative to the 2020 GPG modelling results, Base scenario emissions have reduced. Reduced gas generation and increased renewables generation have had a greater effect than the small increase in coal generation.

In the High scenario, the dip in average demand from 2024-2026 results in significantly lower emissions from lower coal generation.

Low scenario emissions are significantly lower, due to much lower coal generation levels. The low scenario is the only scenario that meets the Australian Government's emissions reduction target of 26-28% by 2030.

4 Conclusions

4.1 Key Insights

The following key insights can be drawn from this analysis:

- Projected gas consumption is sensitive to electricity demand and gas price assumptions. Higher gas price assumptions and overall lower demand forecasts have resulted in a lower gas use forecasts than the previous year's modelling.
- A projected dip in average energy in the High scenario has a significant impact on coal generation and emissions.
- The Low scenario is the only scenario that meets the Australian Government's emissions reduction target of 26-28% by 2030. This is driven by lower minimum demand levels, which have a significant impact on coal generation.
- The increased level of renewable generation in this year's assumptions has further contributed to lower gas demand forecasts and lower emissions.
- The BESS capacity introduced in this year's assumptions competes with gas peakers and enables coal generators to overcome their unit commitment constraints to generate more. This results in a shift of some generation from gas to coal.

4.2 Limitations and Gaps

It is acknowledged that the following limitations in the modelling techniques are present. These are necessary to provide valid results within a reasonable time and budget:

- The model used is a 'perfect competition' model - market power modelling has not been applied. We would expect that the main impact of market power would be that market prices may be higher in general, especially in periods of high demand and prices. In periods of low demand, there is very little market power, so we would not expect the insights to be affected. We would not expect physical results (e.g. fuel demand and emissions) to be significantly affected.
- Integer unit commitment decisions are only applied to select generators to ensure reasonable run-times (all coal units, ALINTA_PNJ_U1/2, COCKBURN_CCG1,

NEWGEN_KWINANA_CCG1 and PPP_KCP_EG1[29]). The impact of this is that some generators may cycle (i.e. start up and shut down) more often than in reality, and some may occasionally be dispatched below their minimum stable operating level. The expected impact of this will be the allocation of dispatch between individual units on an hour-by-hour basis, but we do not expect significant impacts on a system-wide level, so this will not affect the insights and results presented above.

- The model is an hourly dispatch model, rather than half-hourly. Analysis by RBP confirms that this is not significant for this purpose.
- Minimum demand forecasts produced by AEMO for the 2021 WEM ESOO have not been reflected in our load forecasting methodology. The impact of this is lessened due to the modelling of the operational stability constraint.

Furthermore, the validity of modelling results is dependent on the accuracy of modelling input assumptions. This model is dependent on data supplied by AEMO and third parties as specified in Section 2 of this document.

[29] These units were chosen from a comparison of historical and modelled dispatch as the units that most required integer unit commitment to achieve accurate unit dispatch modelling.

GLOSSARY

Table 11 presents a glossary of the terms used in this report:

Table 11: Glossary

Term	Definition
Behind-the-meter	PV and battery systems that produce energy and are connected at a customer's premises. Behind-the-meter PV capacity includes both residential and commercial PV that is less than 100 kilowatts (kW) and commercial PV systems ranging between 100 kW and 10MW
BESS	Battery Energy Storage System
Capacity Credit	A notional unit of Reserve Capacity provided by a Facility during a Capacity Year, where each Capacity Credit is equal to 1 MW of capacity
Capacity Year	A period of 12 months commencing on 1 October and ending on 1 October of the following calendar year
Intermittent generator	A generator that cannot be scheduled because its output level is dependent on factors beyond the control of its operator (e.g. wind speed).
Long Term Projected Assessment of System Adequacy (LT-PASA)	A study conducted in accordance with clause 4.5 of the WEM Rules to determine the Reserve Capacity Target for each year in the Long Term PASA Study Horizon and prepare the WEM ESOO.
Long Term PASA Study Horizon	The 10-year period commencing on 1 October of Year 1 of a Reserve Capacity Cycle.

Term	Definition
Load chronology	The chronology of a year (periods), ranked by magnitude of load (i.e. 1 is the peak period), sorted into chronological order.
Load shape	Hourly load data for a year (expressed in percentage of peak demand), in descending order of magnitude.
Operational demand	Operational demand refers to network demand, met by utility-scale generation, and excludes demand met by behind-the-meter PV generation
Probability of exceedance (POE)	The likelihood of a forecast being exceeded. For example, a 10% POE forecast is expected to be exceeded once in every 10 years.
Reserve Capacity Cycle	A four-year period covering the cycle of events described in clause 4.1 of the WEM Rules.
Underlying demand	Operational demand plus an estimation of behind-the-meter PV generation and the impacts of battery storage. Due to the small uptake of battery storage to date, for historical values the impact of behind-the-meter battery is assumed to be negligible.