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AUSTRALIAN ENERGY MARKET OPERATOR

Final Report: 2019 Assessment of System Reliability (Expected Unserved Energy), Development of Availability Curve and DSM Dispatch Quantity Forecasts for the South West Interconnected System

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EXECUTIVE SUMMARY

Australian Energy Market Operator (AEMO) has engaged Robinson Bowmaker Paul (RBP) to:

- Undertake the Reliability Assessment and Development of the Availability Curve and Availability Classes for the Southwest interconnected system (SWIS)
- Forecast the Expected DSM Dispatch Quantity (EDDQ) in accordance with Market Rule (MR) 4.5.14A and the Market Procedure: Determination of the Expected DSM Dispatch Quantity and the DSM Activation Price.

This report contains the details and results of our analysis.

CONTEXT

AEMO is responsible for operating a Reserve Capacity Mechanism to ensure that adequate supply is available over the long term. To assess the amount of Reserve Capacity that will be required, AEMO undertakes a Long Term Projected Assessment of System Adequacy (Long Term PASA). The results of the Long Term PASA analysis feed into the AEMO's WEM Electricity Statement of Opportunities (ESOO) report which forecasts:

- The Reserve Capacity Target (RCT) (MR 4.5.10(b)) for each year in the Long Term PASA study and the reserve capacity requirement (MR 4.6.1). The RCT is set so as to meet the Planning Criterion which is defined in MR 4.5.9. The Planning Criterion comprises two components:
  - A forecast peak component to ensure that adequate supply is available to meet a one in ten-year peak (MR 4.5.9(a)) and
  - A reliability component to ensure expected energy shortfalls are limited to 0.002% of annual energy consumption (MR 4.5.9(b)).
- Generation capacity and Demand Side Management (DSM) requirements in the form of the Availability Classes, which is defined by MR 4.5.12.
- The Availability Curve to determine the minimum capacity requirement for each Trading Interval in the Capacity Year, which is defined by MR 4.5.10(e).

Additionally, MR 4.5.14A and 4.5.13(h) require AEMO to calculate and publish the Expected DSM Dispatch Quantity (EDDQ) for each Capacity Year in the Long Term PASA study.

The purpose of this modelling exercise is to:

- Undertake a simulation of unserved energy and Reliability Assessment to ensure the RCT is compliant with MR 4.5.9(b) and
- Develop the Availability Curve defined by MR 4.5.10(e).
- Determine the minimum capacity required to be provided by the two Availability Classes defined by MR 4.5.12.
- Forecast the EDDQ defined by MR 4.5.14A.

Scope of modelling

Our modelling covers:

- The Reliability Assessment for the 2019 Reserve Capacity Cycle covering Capacity Years 2019/20 to 2028/29
- The Availability Curve and Classes for the second and third Capacity Year of the relevant Reserve Capacity Cycle, namely 2020/2021 and 2021/22.
- The EDDQ covering Capacity Years 2019/20 to 2028/29.

Methodology

There are four components to the analysis undertaken in this report:

- Forecasting the load duration curves (LDCs)
- Simulating unserved energy and performing the Reliability Assessment
- Developing the Availability Curve and Availability Classes
- Determining the EDDQ

Each phase is described in further detail in the sections below.

Development of load duration curves

Load duration curves (or LDCs) are forecast by:

- Developing five base year load profiles matching the LDCs for the last five full Capacity Years (2013/14 to 2017/18).
- Scaling up the base load profiles to match the 50% POE peak and expected energy forecast for each Capacity Year.

For more details on our LDC development methodology refer to Section 2.3.

Simulation of unserved energy and Reliability Assessment

This year, we have changed the methodology used to implement the Reliability Assessment and simulation of unserved energy.

We have developed a bespoke Capacity Simulation Model (CAPSIM) which simulates the capacity gap (a simple arithmetic calculation subtracting load from available generation capacity) for every hour of every year, sequentially, given a specific generation mix, load profile, planned outage schedule and random forced outages. Generator Interim Access (GIA) constraints have been modelled to ensure available GIA generation is constrained down when a constraint is binding.

This updated approach allows us to model intermittent generation at a detailed and granular level while maintaining a high degree of statistical power. For more details on the new approach to simulating unserved energy refer to Section 2.4.

Development of the Availability Curve and Availability Classes

The Availability Curve is developed in accordance with MR 4.5.10(e) by developing a two-dimensional duration curve of the forecast minimum capacity requirements. This is undertaken by scaling the base year LDC up to the relevant forecast peak demand quantity (consistent with MR 4.5.10(e)(i)), and then adding the Reserve Margin, Intermittent Load (IL) allowance and Load Following Ancillary Service requirement (as required by MR 4.5.10(e)(ii)).

The Availability Classes are developed in accordance with MR 4.5.12(b) and MR 4.5.12(c) by forecasting the minimum capacity (Availability Class 1) required such that if all available DSM (Availability Class 2) were activated and System Management's outage evaluation criteria (as defined in MR 3.18.11) were to apply, then the Planning Criterion would still be met (MR 4.5.12(b)). This is undertaken by repeating the modelling exercise described above with four differences:

- Firstly, DSM is modelled in greater detail to take into account the constraints around the availability of DSM facilities. We have allocated DSM throughout the year using an optimisation model that dispatches DSM so as to minimise the peak load subject to scheduling and availability constraints. See Section 2.5.1 for further details on our approach to modelling DSM.
- Secondly, we have specified a Reserve Requirement of 518 MW[1] in the model to represent the Ready Reserve Standard and Ancillary Services Requirements required under MR 3.18.11. This will ensure that there is always a capacity margin of 518 MW in any given hour.

[1] Source: AEMO. See APPENDIX A.4.

- Thirdly, forced outages are taken out of the model, and the only stochastic component of the simulation is random load. The reason for the removal of forced outages is that the specification of a 518 MW reserve requirement on top of forced outages effectively over-estimates the capacity margin. The purpose of the 518 MW margin is to cover unforeseen events such as forced outages. As such, if there were a forced outage in a given period, the operating reserve would be used to prevent unserved energy. Hence, including forced outages and maintaining the 518 MW capacity margin (for reserve only) could lead to expected unserved energy (EUE) spuriously exceeding 0.002% of annual energy consumption.
- Finally, for each Capacity Year of the relevant Reserve Capacity Cycle, we iterate the model so as to reallocate the amount of DSM and generating capacity (keeping the total capacity capped at the RCT level) until the EUE requirement in MR 4.5.9(b) is violated.

The level of generation capacity at which the EUE equals 0.002% of expected energy consumption sets the minimum capacity prescribed in MR 4.5.12(b).

For more details on the development of the Availability Curve and Availability Classes, refer to Section 2.5

EDDQ

We have forecast the EDDQ using the following approach:

1. Forecast EUE when DSM is dispatched for zero hours ($EUE_{t,0}$). This involves repeating the Reliability Assessment as described in Section 2.3 but setting the available capacity of all DSM facilities to zero. Hence, only generation capacity is available to meet demand as described in MR 4.5.14C(a).
2. Forecast EUE when DSM is dispatched for 200 hours ($EUE_{t,200}$). This involves repeating Step 1 above but with the forecast LDC adjusted to take into account the dispatch of all current DSM in the market (66MW)[2], for exactly 200 hours. The optimised DSM dispatch is deducted off the forecast LDC, and it is this adjusted LDC that becomes an input into the market model. Hence, generation capacity plus exactly 200 hours of DSM dispatch is available to meet demand as described in MR 4.5.14C(b).
3. Calculate EDDQ in year t as follows:

$$EDDQ_t = \frac{EUE_{t,0} - EUE_{t,200}}{Expected\ DSM\ Capacity\ Credits_t}.$$

[2] Currently, there are two DSM facilities in the WEM providing a total of 66MW of capacity.

Results

Reliability Assessment

The Reliability Assessment indicated that for all Capacity Years of the Long Term PASA Study Horizon (2019/20 to 2028/29), the RCT will be set by the forecast peak quantity determined by MR 4.5.9(a).

The EUE as a percentage of annual energy consumption when total capacity is capped at the forecast peak component given by MR 4.5.9(a) (first column) is summarised in Table 1. Here we see that the peak forecast component is sufficient to limit expected energy shortfalls to 0.002% of annual energy consumption in all Capacity Years.

Table 1. Results of Reliability Assessment

Capacity Year	10% POE + Reserve Margin + LFAS requirement + IL allowance (MW)	50% POE Peak Load (MW)	Expected annual energy consumption (MWh)	0.002% of Expected annual energy consumption (MWh)	EUE (MWh)	EUE as % of load
2019/20	4414	3,758	18,241,450	364.83	0.1832	0.0000010%
2020/21	4470	3,813	18,267,580	365.35	0.1608	0.0000009%
2021/22	4482	3,819	18,124,527	362.49	0.0248	0.0000001%
2022/23	4481	3,822	17,977,902	359.56	0.636	0.0000035%
2023/24	4485	3,826	17,845,426	356.91	0.4304	0.0000024%
2024/25	4486	3,832	17,760,672	355.21	0.1416	0.0000008%
2025/26	4499	3,847	17,683,313	353.67	0.2248	0.0000013%
2026/27	4524	3,860	17,622,475	352.45	0.0208	0.0000001%
2027/28	4535	3,876	17,566,216	351.32	0.7976	0.0000045%
2028/29	4559	3,897	17,542,936	350.86	0.1968	0.0000011%

The 2027/28 Capacity Year has the highest EUE when averaged across all historic LDC shapes (0.7976 MWh); this is caused by a lower capacity margin (relative to other years) due to higher than usual planned outages for that year. Note that even though the Planning Margin requirement is satisfied for planned outages occurring in 2027/28, the capacity margin (available generation less load) is smaller compared with other years; this means that 2027/28 is more likely to have unserved energy as a result of multiple forced outages.

Availability Curve and Forecast Capacity Requirements

The Availability Classes for the Capacity Years 2020/21 and 2021/22 are summarised in Table 2 below. The Availability Curves determined in accordance with MR 4.5.10(e) are illustrated in Figure 1 and Figure 2.

Table 2: Availability Classes, 2020/21 - 2021/22.

	2020/21	2021/22
MR 4.5.12(b): Minimum capacity required to be provided by Availability Class 1		
Minimum capacity	4,110	3657
MR 4.5.12(c): Capacity associated with Availability Class 2		
DSM	360	825

Figure 1: Forecast capacity required, 2020/21

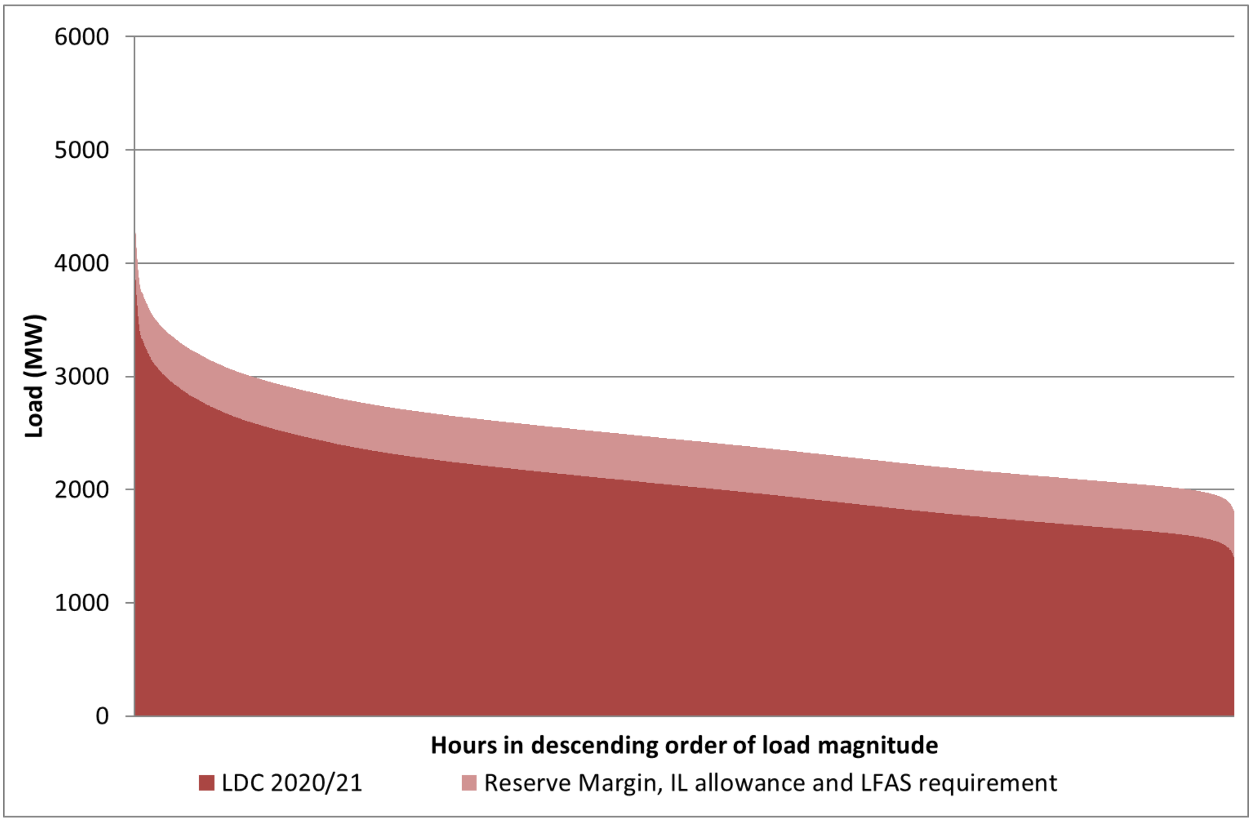


Figure 2: Forecast capacity required, 2021/22

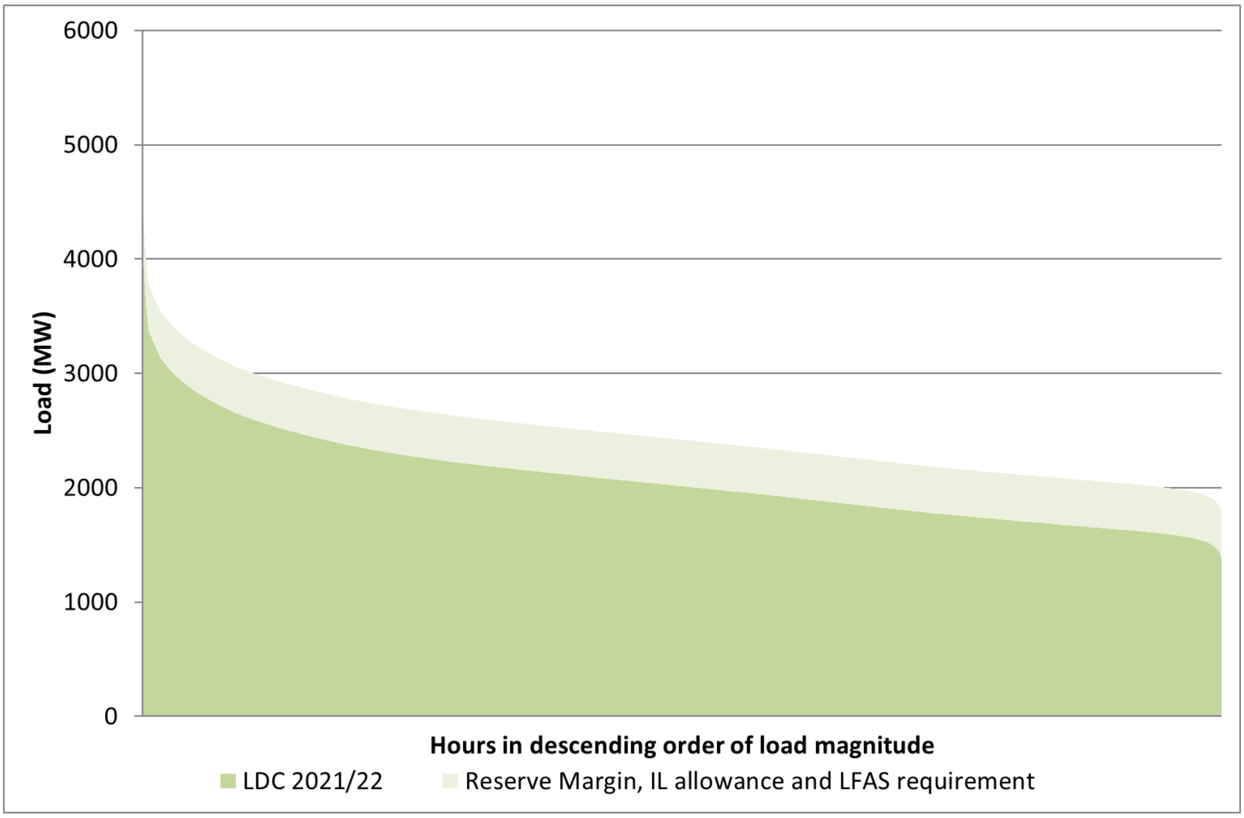


Table 3 compares the Availability Classes derived for the 2018 Long Term PASA to the current (Long Term PASA 2019) results. The 2018 Long Term PASA values are provided in parentheses.

Table 3: Comparing Long Term PASA 2019 Availability Curve to Long Term PASA 2018 Availability Curve (2018 results in parentheses)

2020/21	
MR 4.5.12(b): Minimum capacity required to be provided by Availability Class 1	
Minimum capacity	4,110 (3,946)
Reserve Capacity Target	
Reserve Capacity Target	4,470 (4,581)
MR 4.5.12(c): Capacity associated with Availability Class 2	
DSM	360 (635)

The capacity associated with Availability Class 2 has decreased by 275 MW from the previous year (which was also a decrease from the year previous to that). This is a continuation of the same issue highlighted in last year's reliability report:

- 900MW of thermal plants on planned outage in the first two weeks of November 2020[3].
- The DSM optimisation model allocating hourly DSM to minimise the peak[4] subject to availability constraints. This means that most of the DSM is dispatched in the peakiest part of the LDC which occurs in the summer months (with some intervals in winter due to changing load shape). The model dispatches lower levels of DSM in November which is not enough to meet the net load with 900MW of scheduled generation on planned outage.
- The increased amount of solar in the capacity stack which means that in the evening (non-daylight) hours in November the amount of available generation decreases further.

Note that the level of Availability Class 2 capacity (DSM) is 465MW higher in 2021/22 due to fewer planned outages during the same November period.

[3] Based on information provided by market participants under MR 4.5.3.

[4] In accordance with MR 4.5.12(b), the DSM optimisation model dispatches DSM facilities to minimise peak demand throughout the year (as opposed to maximising the operating reserve margin).

EDDQ

The EDDQ results are summarised in Table 4. This also provides the resulting DSM Reserve Capacity Price (RCP), assuming a DSM Activation Price of $33,460/MWh[5] which remains unchanged over the Long Term PASA Study Horizon.

Table 4. EDDQ results

Capacity Year	EUE(t,0)	EUE(t,200)	CC(t)	EDDQ(t)	DSM RCP based on $33,460 DSM Activation Price (MR 4.5.14F)
2019/20	0.6968	0.1832	0.5136	0.0078	$16,990.38
2020/21	0.3584	0.1792	0.1792	0.0027	$16,820.85
2021/22	0.2528	0.0312	0.2216	0.0034	$16,842.34
2022/23	1.1048	0.6864	0.4184	0.0063	$16,942.12
2023/24	0.9112	0.4488	0.4624	0.0070	$16,964.42
2024/25	0.3824	0.1528	0.2296	0.0035	$16,846.40
2025/26	0.6440	0.248	0.3960	0.0060	$16,930.76
2026/27	0.0744	0.0248	0.0496	0.0008	$16,755.15
2027/28	2.0448	0.796	1.2488	0.0189	$17,363.10
2028/29	0.4048	0.2232	0.1816	0.0028	$16,822.07

The EDDQ this year is relatively low and constant. This is a result of averaging across the five LDC shapes and chronologies, which smooths out the year on year volatility.

Figure 3 and Figure 4 compare the 2018 Long Term PASA EDDQ and DSM RCP to the 2019 Long Term PASA results.

[5] As specified in MR 4.5.14F; the DSM Activation Price represents the Value of Lost Load (VoLL).

Figure 3: Comparing 2018 and 2019 Long Term PASA EDDQ values

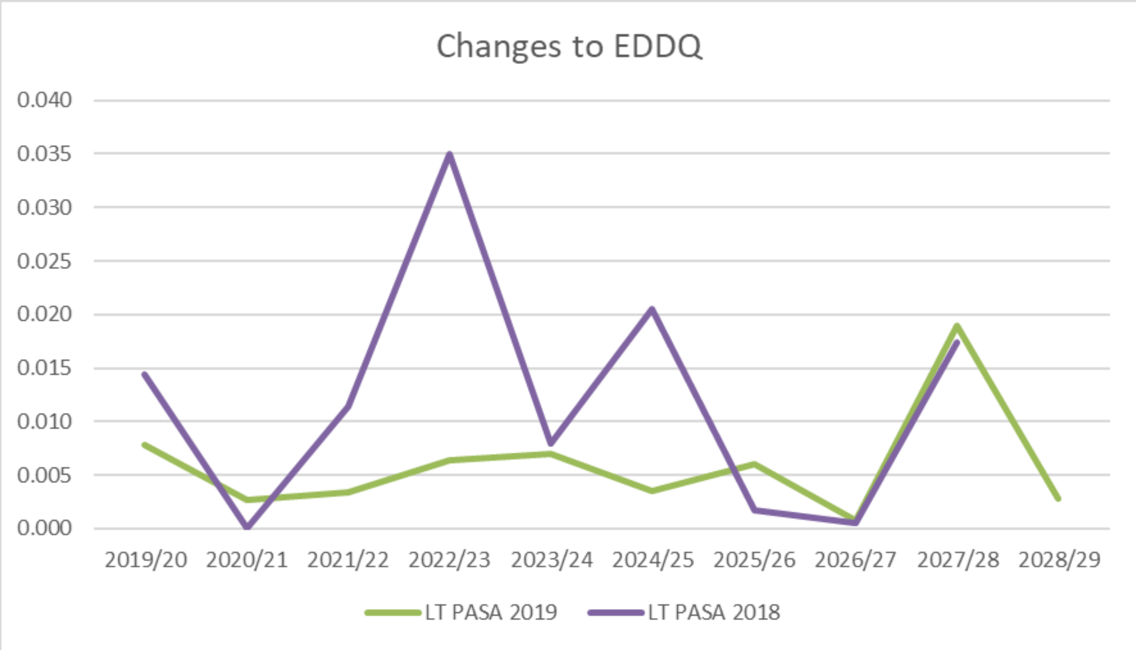
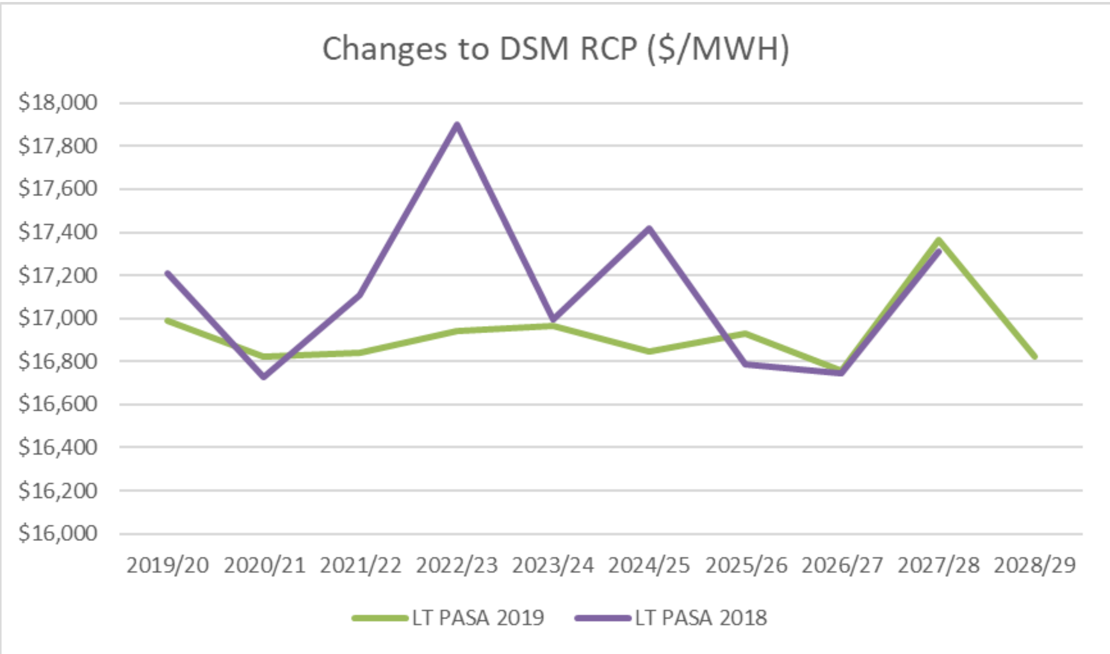


Figure 4: Comparing 2018 and 2019 Long Term PASA DSM RCP values



The highest EDDQ occurs in 2027/28 due to a lower capacity margin (relative to other years) as a result of higher than usual planned outages for that year.

EDDQ is otherwise low with limited variation across the years. This is a reflection of the fact that unserved energy is very low under the reliability scenario to begin with. This combined with the fact that there are only two Demand Side Programme (DSP) facilities (with a combined CC assignment of 66 MW over the Long Term PASA horizon), means that not running these DSPs has a minimal impact on the level of unserved energy.

CONTENTS

1 Introduction

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- Forecast the Expected DSM Dispatch Quantity (EDDQ) in accordance with Market Rule (MR) 4.5.14A and the Market Procedure: Determination of the Expected DSM Dispatch Quantity and the DSM Activation Price.

This report contains our modelling methodology, results and assumptions.

1.1 Context

AEMO is responsible for operating a Reserve Capacity Mechanism to ensure that adequate supply is available over the long term. To assess the amount of reserve capacity that will be required the AEMO undertakes a Long Term Projected Assessment of System Adequacy (Long Term PASA). The results of the Long Term PASA analysis feed into the AEMO's WEM Electricity Statement of Opportunities (ESOO) report which forecasts:

- The Reserve Capacity Target (RCT) (MR 4.5.10(b)) for each year in the Long Term PASA study and the reserve capacity requirement (MR 4.6.1). The RCT is set so as to meet the Planning Criterion which is defined in MR 4.5.9. The Planning Criterion comprises two components:
  - A forecast peak component to ensure that adequate supply is available to meet a one in ten-year peak (MR 4.5.9(a)) and
  - A reliability component to ensure expected energy shortfalls are limited to 0.002% of annual energy consumption (MR 4.5.9(b)).
- Generation capacity and Demand Side Management (DSM) requirements in the form of the Availability Classes, which are defined by MR 4.5.12.
- The Availability Curve to determine the minimum capacity requirement for each Trading Interval in the Capacity Year, which is defined by MR 4.5.10(e).

Additionally, MR 4.5.14A and MR 4.5.13(h) require AEMO to calculate and publish the Expected DSM Dispatch Quantity (EDDQ) for each Capacity Year in the Long Term PASA study.

The purpose of this modelling exercise is to:

- Undertake a simulation of unserved energy and Reliability Assessment to ensure the RCT is compliant with MR 4.5.9(b) and
- Develop the Availability Curve defined by MR 4.5.10(e).
- Determine the minimum capacity required to be provided by the two Availability Classes defined by MR 4.5.12.
- Forecast the EDDQ defined by MR 4.5.14A.

1.2 SCOPE OF MODELLING

Our modelling covers:

- The Reliability Assessment for the 2019 Reserve Capacity Cycle covering the Capacity Years 2019/20 to 2028/29
- The Availability Curve and Classes for the second and third year of the relevant Reserve Capacity Cycle, namely 2020/2021 and 2021/22.
- The EDDQ covering the Capacity Years 2019/20 to 2028/29.

1.3 STRUCTURE OF THIS REPORT

The remainder of our report is structured as follows:

- Our modelling methodology is described in Chapter 2
- Modelling results are summarised in Chapter 3
- Key assumptions underpinning our modelling are summarised in APPENDIX A.

2 METHODOLOGY

2.1 INTRODUCTION AND BACKGROUND

RBP has undertaken the Reliability Assessment and development of the Availability Classes for the SWIS since 2012. Our methodology involved the modelling of Expected Unserved Energy (EUE)[6] using a non-sequential Monte Carlo sampling methodology[7] applied to our in-house electricity market dispatch optimisation tool (WEMSIM).

Our historical approach was used to ensure a large number of iterations were conducted in determining expected unserved energy (EUE) while using an existing dispatch model (as opposed to building a bespoke model from scratch). The non-sequential approach meant that the modelling database was set up in a manner that prevented very granular modelling of intermittent generation. Historically, this did not impact on results due to the very low proportion of renewable generation. However, in recent years, the entry of wind and solar generation has been increasing steadily and is projected to continue to do so. Hence, it has now become necessary to model the daily and hourly profiles of intermittent generation in greater detail (noting particularly that the solar induced "duck curve" may mean that unserved energy will start to move into times where it was previously uncommon (e.g. evenings or winters)).

Additionally, Generator Interim Access (GIA) constraints have recently been introduced into the WEM as an interim measure to enable the connection of new generation under the existing unconstrained access regime until the security constrained market goes live in the future. The GIA constraints are linear constraints which constrain the generation of GIA generators under certain conditions (e.g. load, season, time of day, etc.). These constraints are described in greater detail in Section 2.4.5.

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[6] MR 4.5.9(b) uses the term "expected energy shortfalls" in relation to the Planning Criterion. Our interpretation (previously cleared with the Independent Market Operator (IMO) and subsequently AEMO) of this phrase has been that it refers to the Expected Value (MWh) of Unserved Energy. That is, if we consider the probability distribution of unserved energy (with randomness arising as a result of random load and forced outages), then the expected value of that distribution should give us the expected energy shortfalls in MWh as contemplated by MR 4.5.9(b).

[7] Rather than simulating load and available generation sequentially (day by day, hour by hour) we sampled specific hours (based on load characteristics) during the year and simulated unserved energy for those sampled hours.

Therefore, an amended approach to simulate unserved energy is now required. This year we have used a bespoke Capacity Simulation model (CAPSIM) which simulates the capacity gap (a simple arithmetic calculation subtracting load from available generation capacity) for every hour of every Capacity Year sequentially given a specific generation mix, load profile, planned outage schedule and random forced outages. GIA constraints have been modelled to ensure available GIA generation is constrained down when a constraint is binding (see Section 2.4.5 for further details).

The remainder of this chapter is structured as follows:

- In Section 2.2, we provide an overview of the modelling stages required to undertake the Reliability Assessment, determine the Availability Classes, develop the Availability Curve and derive the Expected DSM Dispatch Quantity (EDDQ). Note that the only component of our modelling framework which we have changed materially is the simulation of unserved energy, which was used to undertake the Reliability Assessment, derive the minimum generation capacity component of the Availability Classes (MR 4.5.12(b)) and derive the EDDQ.
- In Section 2.3 to 2.6 we describe each modelling stage in further detail. The simulation of unserved energy is covered in Section 2.4

2.2 OVERVIEW OF MODELLING APPROACH

Our modelling has four phases:

- *Phase 1: Forecast load profiles over the Long Term PASA Study Horizon*. Forecasting the Load Duration Curve (LDC) over the Long Term PASA Study Horizon, taking into account the 50% Probability of Exceedance (POE) peak forecast and the expected annual energy consumption forecasts (see Section 2.3). The forecast LDCs are a key input for Phases 2, 3 and 4.
- *Phase 2: Simulate Unserved Energy and Undertake Reliability Assessment*. Simulating unserved energy over the Long Term PASA Study Horizon, in order to apply the second component of the Planning Criterion (MR 4.5.9(b)) and determine the amount of Reserve Capacity required to limit expected energy shortfalls to 0.002% of forecast annual energy consumption. This enables AEMO to determine the RCT for each year in the Long Term PASA Study Horizon.
- *Phase 3: Determine Availability Classes and Curve. Forecasting the Availability Classes and Curve* for the second and third years of the Long Term PASA Study Horizon. This phase involves:

   - Determining the quantities contemplated by MR 4.5.12(b)[8] and 4.5.12(c)[9] and
   - Developing the two-dimensional duration curve required under MR 4.5.10(e)
- Phase 4: *Determine EDDQ*. Determining the EDDQ for each Capacity Year of the Long Term PASA Study Horizon.

Each phase is described in further detail in the sections below.

2.3 Phase 1: Forecast load profile over the Long Term PASA Study Horizon

One of the key inputs to the Reliability Assessment and Availability Classes is the forecast load profile and load chronology over the Long Term PASA study horizon. Our approach to forecasting the load profile included two components:

- Developing the base year load profiles: Five base load shapes have been used, matching the shapes of the load duration curve (LDC) for the last five Capacity Years (2013/14 to 2017/18).
- Scaling the base year load profiles to forecast values: Forecast load duration curves for each year in the Long Term PASA Study Horizon have been developed by scaling the base load profiles up or down to match the 50% POE peak and expected energy forecast for each year[10].

Each of the above bullet points is described in more detail in the sections below.

2.3.1 Developing the base load profiles

In previous years we have used an average load shape, where we averaged the LDCs from the past five Capacity Years.

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[8] The capacity associated with Availability Class 1 or the minimum generation capacity required if all DSM were activated to meet the reliability component of the Planning Criterion (MR 4.5.9(b)) and ensure the outage scheduling requirements set by MR 3.18.11(a) are met.

[9] The capacity associated with Availability Class 2.

[10] As we are using historic load shapes, the hourly pattern will not reflect the impacts of increased behind the meter solar PV uptake on demand over the next ten years. For example, under this approach the hourly load in "minimum demand" intervals are likely to be higher than what AEMO expects given trends in PV uptake. However, discrepancies in load during low demand intervals has no impact on unserved energy.

This year we have individually modelled five different LDC shapes (corresponding to the past five Capacity Years and adjusted for the 50% POE peak and expected energy forecast for the given year modelled). Under this approach, for a given year and a given analysis[11], our model has been run five times using the different load shapes and we have averaged the EUE results across these five shapes. This approach provides a greater level of variation in load chronology than in previous years.

We have used an average base year load shape (with chronology from the most recent full capacity year) for the following:

- Deriving the forecast capacity requirement for the Availability Curve under MR 4.5.10(e), (as the rules require a single Availability Curve with its peak at the RCT).
- Modelling the Minimum Generation Capacity (MR 4.5.12(b)). This was to ensure the iteration required to arrive at generation capacity value where EUE exactly equals 0.002% was computationally feasible. See also Section 2.5.1.

2.3.2 **Scaling the base year load profiles to forecast values**

Having developed the five base year profiles, the next step is to scale the base year profiles to match the 50% POE peak forecast and expected demand in any given year.

In other words, for each year of the Long Term PASA Study Horizon we require a forecast LDC such that:

- The peak of the LDC equals the 50% POE profile
- The load allocated across all hours sums to the expected annual energy demand forecast and
- The shape of the LDC should be "close" to the base year profiles developed above.

Before describing the LDC forecasting methodology it is important to note the following:

- First, the peak and annual energy consumption forecasts are developed separately by AEMO's Forecasting Consultant[12]. As such, there is no explicit relationship between the peak and annual energy consumption forecasts

[11] Reliability Assessment, Availability Curve and EDDQ forecasts.

[12] ACIL Allen, 2019. Peak demand and energy forecasts for the South West interconnected system. Available at: https://www.aemo.com.au/Electricity/Wholesale-Electricity-Market-WEM/Planning-and-forecasting/WEM-Electricity-Statement-of-Opportunities.

- Second, the historical ratio of peak to average energy and forecast peak to average energy ratio can be different.
- Hence, the "peakiness" envisaged by the forecasts may not necessarily be consistent with recent history. This means that based on these forecasts it is not possible to derive a forecast LDC that exactly matches the base profile.

Given the above, we have defined a function F(h) (h ∈ hours of the year), such that the forecast LDC for a given year t ($L\widehat{D}C(h)$) can be derived by multiplying the base year LDC ($\overline{LDC}(h)$) by this function. That is:

- $L\widehat{D}C(h) = F(h) \times \overline{LDC}(h)$, such that:
- $Max\left(L\widehat{D}C(h)\right)$ = 50% POE peak forecast in year t and
- $\sum_{h=1}^{8760} L\widehat{D}C(h)$ = Expected demand forecast in year t.

The function is defined to ensure that the shape of the LDC varies with differing peak/energy ratios in a way that is consistent with the historical LDCs of the last five Capacity 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 50% POE peak forecast to the base year peak demand
- e denotes the ratio of the expected annual energy consumption forecast to the base year hourly demand
- m denotes the position in the LDC in which the curve flattens, as has been observed in the historical years. See Table 5 for the value that m is set to for the different LDC base years.
- n denotes the total number of hours in a year and
- z represents a curvature constant that is adjusted to achieve the expected demand forecast in the resulting LDC.

Table 5: "m" values by LDC base year

LDC Base year	"m" value
2013/14	2250
2014/15	2600
2015/16	2500

2016/17	2100
2017/18	2650
Average LDC shape	2650

As noted previously, the scaled load profiles are key inputs into both Phases 2 and 3. Specifically:

- They are used to project the hourly load in a forecast year to be used for market modelling component of the Reliability Assessment.
- They are also used to derive the two-dimensional duration curve defined in MR 4.5.10(e), which is developed by adjusting further the scaled profiles in Section 2.3 to incorporate the requirements of MR 4.5.10(e). This is addressed in further detail in Section 2.5 (Determine MR 4.5.10(e)).

2.4 Phase 2: Simulation of unserved energy and Reliability Assessment

The purpose of this phase is to assess the amount of Reserve Capacity required to limit energy shortfalls to the Planning Criterion set by MR 4.5.9(b) (0.002% of annual energy), in doing this we follow the subsequent steps:

1. For each year of the Long Term PASA Study Horizon, we assume Reserve Capacity (generating capacity and DSM) equals the forecast peak quantity plus the reserve margin, Intermittent Load (IL) allowance and Load Following Ancillary Services (LFAS) quantity determined by MR 4.5.9(a).
2. For each of the five forecast load profiles (see Section 1.1.1), based on assumptions of the availability of intermittent generation (see Section 2.4.3) and randomised forced outages (see Section 2.4.4), we simulate the capacity gap (the difference between available capacity and load) in CAPSIM. Each iteration yields an estimate of unserved energy.
3. We then use the N iterations above to estimate EUE as follows:

$$\mathrm{EUE}_{\mathrm{loadshape}_{s,t}} = \frac{1}{N}\sum_{i=1}^{N} Unserved\ Energy_{i,s,t}$$

$\mathrm{EUE}_{\mathrm{loadshape}_{s,t}}$ denotes the estimate of EUE simulated by CAPSIM using load forecasts that are based on the shape of the LDC s, using the 50% POE peak and expected annual energy consumption forecasts for year t.

4. We then calculate the EUE for a given year by averaging the EUE obtained using the five different load shapes.

$$\mathrm{EUE_t} = \frac{1}{5}\sum_{s=1}^{5} \mathrm{EUE}_{\mathrm{loadshape}_{s,t}}$$

5. We then calculate this average EUE as a percentage of annual energy consumption.
6. If the percentage in Step 5 is less than or equal to 0.002% then we stop; the RCT will be set by the first component of the Planning Criterion (MR 4.5.9(a)).
7. If the percentage is greater than 0.002%, then:
   - We incrementally increase the Reserve Capacity (over and above the forecast peak quantity determined by MR 4.5.9(a)) and
   - Repeat steps 1 to 6 until the percentage in Step 5 is less than or equal to 0.002%.

The above steps are a high-level summary of our modelling methodology for the Reliability Assessment. In the remainder of this section we provide a more detailed description of the modelling. Specifically, the following sections outline how Steps 2 and 3 will be implemented in practice as follows:

- We first provide an overview of the CAPSIM tool used to implement our new approach
- We then provide further detail on why optimised dispatch (as modelled previous years) is unnecessary with respect to modelling unserved energy (i.e. a simple arithmetic calculation comparing total available capacity to load is sufficient for the purposes of conducting the Long Term PASA Reliability Assessment).
- We then describe our approach to modelling GIA constraints
- Finally, we describe how intermittent generation and outages are modelled in CAPSIM.

2.4.1 Overview of CAPSIM

We have developed a bespoke model (CAPSIM) in Python to complete the Reliability Assessment this year. This model compares the total available capacity in each trading period (hourly) across the Long Term PASA modelling horizon and compares it to the corresponding load. Total available capacity takes into account planned outages, intermittent generation, the GIA constraints and randomly sampled forced outages. Unserved energy occurs whenever load is greater than total available generation in a period.

CAPSIM does not optimise dispatch or create a merit order, because it is not necessary in the context of unserved energy[13]. CAPSIM has been run over multiple iterations with varying random number seeds for forced outages, to generate a probability distribution of unserved energy and to estimate EUE.

CAPSIM is significantly faster than dispatch optimisation models. This is because we do not simulate optimal dispatch; the latter is a computationally intensive process which is not necessary for the modelling of unserved energy. This significantly speeds up the computations required and enables us to run a sequential model with more granular data and a high degree of statistical power.

2.4.2 Rationale for removing optimised dispatch

The derivation of EUE (a key input into the Reliability Assessment, Availability Classes and EDDQ calculations) requires us to model unserved energy accurately and robustly. Unserved energy can be defined for a given hour t, as:

$$\boldsymbol{UE_t} = \boldsymbol{Load_t} - \boldsymbol{Generation_t} \tag{1}$$

An optimised dispatch model is superfluous in the context of modelling unserved energy. This is a logical consequence of the reserve capacity obligations placed on a participant under MR 4.12.1. In particular, MR 4.12.1(c) requires a participant to make their capacity up to their Reserve Capacity Obligation Quantity (RCOQ) available for System Management to dispatch. This implies that the total dispatched generation at any given time meets the following condition:

$$\boldsymbol{Generation_t} = \mathbf{min}[\boldsymbol{Load_t}, \boldsymbol{Capacity_t}] \tag{2}$$

Where $Generation_t$ refers to the total generation in the SWIS in trading interval t, $Load_t$ refers to the total load of the system and $Capacity_t$ refers to the total available capacity in the SWIS (i.e. total capacity taking into account current intermittent generation and subtracting planned and forced outages).

If we substitute Equation (1) into Equation (2) we get the following relationship:

$$\boldsymbol{UE_t} = \boldsymbol{Load_t} - \mathbf{min}[\boldsymbol{Load_t}, \boldsymbol{Capacity_t}] \tag{3}$$

Equation (3) implies:

[13] See Section 2.4.2 below.

- Unserved energy is zero whenever load is less than total available capacity ($Load_t \leq Capacity_t$)
- Unserved energy can only be non-zero when $Load_t > Capacity_t$; that is when the demand is greater than all available capacity. In other words, you **cannot get unserved energy** when there is available generation that is not running (as MR 4.12.1(c) requires facilities to offer in all available generation (up to their RCOQ)).

This means that optimising dispatch is unnecessary and simply comparing load to total available capacity in each and every hour is sufficient to calculate unserved energy in a given Capacity Year.

- Note, furthermore, that our approach to modelling the GIA constraints (described below) is based on the logical consequence of the must-offer rule. Particularly, our approach is premised on the fact that when unserved energy is likely and a GIA constraint is binding, available non-GIA generators would be dispatched to their maximum capacity.

2.4.3 Treatment of intermittent generation

We have used historical generation for existing facilities[14] and participant provided estimated generation for new facilities to develop intra-day hourly generation profiles for a given month as follows:

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

  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.

This approach captures both intra-day and seasonal variation, while ensuring the average hourly generation values are based on a sample size large enough to yield robust generation estimates.

Note that the $\overline{Gen_{h,m}}$ value for a given intermittent generator will be scaled in accordance with Section A.1 to reflect the ratio of the RCT to total Capacity Credits.

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[14] Based on their non-loss adjusted metered quantities

2.4.4 **Treatment of outages**

Planned outages

There are two types of planned outages that can occur in the SWIS:

- Scheduled outages
- Opportunistic maintenance

When performing the Reliability Assessment in 2018, RBP noted there were instances of multiple large facilities concurrently going on outage in a manner which would violate MR 3.18.11

This year, we have used participant provided scheduled outage dates as a starting point but have then systematically evaluated these outages to ensure that the Planning Margin contemplated under MR 3.18.11 is met. This approach is not designed to replicate the process System Management uses to approve planned outages under MR 3.18.11; instead it is intended to remove concurrent planned outages which would not be allowed under real operating conditions.

We first describe, at a high level, how System Management approves outages.

System Management long duration outage approval process

For a given week in the Medium Term PASA 3-year horizon[15]:

- System Management computes the Planning Margin which reflects the requirements of the Ready Reserve Standard defined in MR 3.18.11A and the Spinning Reserve requirement specified in MR 3.10.2[16]. The Planning Margin reflects the MW capacity of the largest current generator and 70% of the capacity of the second-largest generator, minus any Interruptible Loads. See Section A.4 for our assumptions on the Planning Margin.
- System Management calculates the second deviation weekly peak load forecast. The second deviation weekly peak forecast is analogous to an annual 10% POE forecast.
- For a given outage, System Management subtracts the 2nd deviation weekly peak load forecast from the total available generation (taking into account known outages).

[15] System Management also uses Short Term PASA (10 day forecasts) to schedule opportunistic maintenance and to re-assess long duration outages in the short-term.

[16] System Management uses as-generated values at 15 degrees C when undertaking their outage approval. We have used sent-out values at 41 degrees C.

- If the difference is greater than the Planning Margin, System Management approves the outage request
- If the difference is less than the Planning Margin, then System Management denies the outage request[17].

RBP Planned Outage scheduling methodology

We have followed System Management's high level process described above as follows:

- Compute weekly peak load for each week of each year of the Long Term PASA horizon, for each base year LDC. We cannot use the second deviation load forecast from MT PASA as the forecast horizon for the MT PASA is only three years. We have compared weekly peak load forecasts derived using the 2019 WEM ESOO 50% POE peak load and expected annual energy consumption forecasts to the MT PASA second deviation weekly peak load forecasts for the years 2019/20 to 2020/21. Our analysis shows that the MT PASA forecasts are generally higher than our forecasts based on the 50% POE and that this difference varies with season and by year - see Table 6. We have therefore scaled up our weekly peak load forecasts as follows:
  - From 2019/20 to 2021/22, we scale up the 50% POE expected energy forecasts using the seasonal and annual scaling factors summarised in Table 6.
  - From 2022/23 onward, we use the seasonal scaling factors derived for the year 2021/22.

  The purpose of this scaling is to ensure that we use a weekly peak load forecast for planned outage scheduling that is sufficiently conservative (as opposed to trying to replicate the Medium Term PASA load forecasts which are derived using a completely different methodology to the Long Term PASA load forecasts).

Table 6: Average percentage difference between MT PASA and 2019 WEM ESOO weekly peak load forecasts

	2019	2020	2021
Jan-Mar	N/A	16.15%	13.99%
Apr-Jun	N/A	6.79%	6.83%

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[17] System Management conducts additional Ancillary Services checks to ensure that there are units online to provide black start, load rejection, spinning reserve and load following reserve. However, as we are not modelling dispatch of reserves, we will not carry out this additional check. System Management also checks if there are any transmission outages that could result in a potential clash.

	2019	2020	2021
Jul-Sep	N/A	-4.26%	-5.37%
Oct-Dec	17.9%	15.83%	17.29%

- Subtract the weekly peak load (as derived above) from available generation[18] to calculate the capacity margin.
- If the capacity margin is greater than the Planning Margin, then we use the participant provided planned outage inputs (and zero out the relevant facility capacity on those dates).
- If the capacity margin is less than the Planning Margin, we move the participant provided planned outage inputs so as to meet the outage evaluation criteria, while ensuring that the timing of the outage request is similar to what the participant has requested. As above, we zero out the relevant capacity on the amended dates

This analysis has been repeated for each of the five forecast load profiles. Note that due to lower peak energy forecasts, the planning margin was satisfied in all periods using the original participant provided outage schedule. We have therefore made no modifications to the outage schedule and have used participant provided outages 'as-is'.

Following previous years, we have not modelled opportunistic maintenance. This is because opportunistic maintenances are subject to System Management's evaluation process, whereby an outage will not be approved if it violates the requirements in Section 3.18 of the Market Rules. Furthermore, no planned outage would proceed in a period with a tight margin and a non-trivial risk of unserved energy.

Forced outages

Forced outages are randomised by:

- Determining a forced outage probability (FO_g) for each plant.
- Determining a mean time to repair for each plant.
- Inputting these probabilities into CAPSIM (which will then randomly assign plant forced outages in a sampled hour based on the specified probability for each Monte Carlo iteration).

[18] Total Generation less capacity on planned outages (as provided by participants). Intermittent generation would be de-rated based on seasonal profiles to reflect available generation.

Forced outage rates and mean time to repair were set based on an analysis of facility specific forced outages available from AEMO's public website. Forced outages for new facilities were set based on existing plants with similar characteristics.

Where forced outage data is missing (e.g. for new plants) or inadequate (e.g. due to a small sample size of outages), our assumptions are based on available forced outage data of plants of a similar size, technology and age.

2.4.5 Application of GIA constraints

RBP has implemented the full set of constraints in every period, substituting available capacity[19] into the constraint coefficients. The methodology is as follows:

- **Step 1:** The full set of constraints are inputted into the CAPSIM model (noting that all constraints are of a <= nature, with all GIA generation on the LHS and load and non-GIA generation on the RHS).
- **Step 2:** CAPSIM calculates a scaling factor, for each constraint, for each period, in each iteration:

$$Scaling_{cpi} = \begin{cases} 1 - \dfrac{(LHS_{cpi} - RHS_{cpi})}{GIA_{cpi}} & if\ LHS_{cpi} > RHS_{cpi} \bigcap LHS_{cpi} - RHS_{cpi} < GIA_{cpi} \\ 0 & if\ LHS_{cpi} > RHS_{cpi} \bigcap LHS_{cpi} - RHS_{cpi} \geq GIA_{cpi} \\ 1 & if\ LHS_{cpi} \leq RHS_{cpi} \end{cases}$$ [20]

  - Where LHS_{cpi} refers to the constraint coefficients on the LHS applied to the relevant GIA generators' capacities
    - $LHS_{cpi} = \sum_{g \in GIA\ generators\ appearing\ in\ Constraint\ c} GIAcoefficient_{g,c} \times GIACapacity_g$
  - RHS_{cpi} refers to the constraint coefficients on the RHS multiplied through the applicable non-GIA generator's capacity, a load multiplier (multiplied by a period's load) and the constraint constant, summed together

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[19] The use of capacity is valid due to the implications of the must-offer rule described in Section 2.1.3 In other words, unserved energy can only occur when total load is more than total available capacity. If a GIA constraint binds when generators are not generating at their full capacity, then this is irrelevant for our analysis as unserved energy would not occur under these conditions. The only condition relevant for our analysis is where backing-off a GIA generator due to a binding GIA constraint causes unserved energy. Under such circumstances, all available non-GIA generators would have to be generating at full capacity due to the must-offer rule.

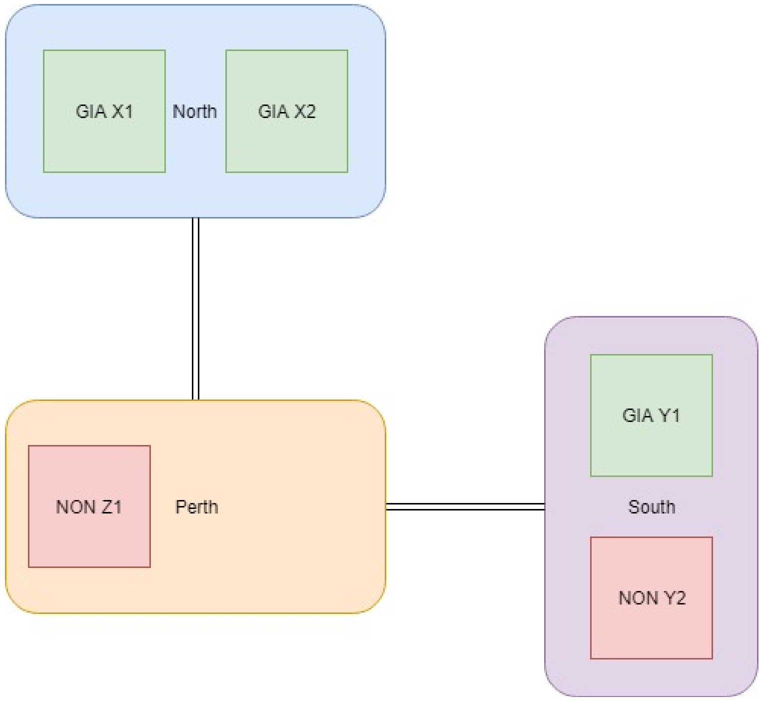
[20] This condition is applied to ensure that in the event $(LHS_{cpi} - RHS_{cpi}) > GIA_{cpi}$, we do not apply a negative scaling factor. In this circumstance, all GIA generation would need to be scaled down to 0 as the amount of generation required to meet the constraint exceeds the amount of available generation capacity.

  - $RHS_{cpi} = \sum_{ng \in nonGIA\ generators\ appearing\ in\ Constraint\ c} nonGIAcoefficient_{g,c} \times nonGIACapacity_g + Load_p \times LoadCoefficient_c + Constant_c$
- GIA_{cpi} refers to the sum of the capacity of all GIA generators appearing in constraint c.
- $0 \leq Scaling_{cpi} \leq 1$ refers to the scaling factor for constraint *c* in period *p* in iteration *i*. In other words:
  - If the LHS<=RHS, the constraint is not binding (or just binding) and we will get a scaling factor of 1 (i.e. GIA generation does not need to be constrained down, as the constraint has not been violated).
  - If the LHS>RHS, the constraint has been violated and $0 \leq Scaling_{cpi} < 1$; this means GIA generation needs to be constrained down.
- Step 3: Finally, we determine which scaling factor should be applied to each GIA generator (in each period and iteration) by selecting the minimum scaling factor calculated for that GIA generator across all constraints it appears in. GIA generators are then de-rated by the minimum Scaling Factor observed across the constraints.

Worked example of GIA constraints methodology.

This reflects the application of the tightest binding constraint; meeting the tightest constraint implies that all other constraints are also met. Consider the following example:

Figure 5: GIA constraint application example



In Figure 5, we have three regions, North, Perth and South. There are two GIA generators in the North (X1 and X2); one non-GIA generator Z1 in Perth; one GIA generator (Y1), and one non-GIA generator (Y2) in South.

Step 1:

Consider the following set of two constraints in Table 7. This is the generic format of all constraint equations. For example, Constraint 2 can be read as:

$$Gen_{X1} + Gen_{X2} + Gen_{Y1} \leq 100 + 0.1 \times Load + 0.5 \times Gen_{Y2} + Gen_{Z1}$$

Table 7: Set of Example GIA Constraints:

	LHS			RHS			
Number	X1 - GIA	X2 - GIA	Y1 - GIA	Constant	Load Multiplier	Y2 - Non-GIA	Z1 - Non-GIA
1	2	2	0	100	0.1	0	1
2	1	1	1	100	0.1	0.5	1

Step 2:

We next derive scaling factors to apply to GIA generation to ensure the constraints above are just binding. To find the scaling factor needed, we follow the equation from Step 2 above, first finding the LHS and RHS of each constraint

To find the LHS and RHS of a constraint we multiply the coefficients from that coefficient through the GIA available generation for the LHS, and the non-GIA available generation[21] plus a constant and load multiplier for the RHS. Take the following dummy data for a given period:

Table 8: Dummy generation and load data

Generation	Value
Load	1000
GIA - X1	200
GIA - X2	200
GIA - Y1	200
Non-GIA - Y2	100
Non-GIA - Z1	100

Given these values, our constraint values for Constraint 1 are:

Table 9: Constraint values - Constraint 1

Side	LHS			RHS			
Generator	X1	X2	Y1	Y2	Z1	Constant	Load Multiplier
Coefficient	2	2	0	0	1	100	0.1
Coefficient * Generation or Load	2*200 =400	2*200 =400	0	0*100 = 0	1*100 = 100	100	0.1*1000 = 100

Applying the same process for Constraint 2:

[21] The available generation for GIA and non-GIA generators takes into account forced and planned outages and seasonal de-rating factors for intermittent generation.

Table 10: Constraint values - Constraint 2

Side	LHS			RHS			
Generator	X1	X2	Y1	Y2	Z1	Constant	Load Multiplier
Coefficient	1	1	1	0.5	1	100	0.1
Coefficient * Generation or Load	1*200=200	1*200=200	1*200=200	0.5*100=50	1*100 = 100	100	0.1*1000=100

We now have the values from the LHS and the RHS. We take the sum of these for each constraint and calculate the relevant scaling factors for each constraint.

Table 11: Scaling factors calculations

	Constraint 1	Constraint 2
LHS	(400+400) =800	(200+200+200) =600
RHS	(100+100+100) =300	(50+100+100+100) =350
GIA	400	600
Scaling factor	"Raw" scaling factor: -0.25 (=1 - 500/400) Scaling factor to use: 0	1-(250/600) = 0.583

Both constraints have been violated, as the LHS exceeds the RHS.

For Constraint 1, the LHS exceeds the RHS by 500, but we only have 400 MWs of GIA generation. This gives us a scaling factor of 1-(500/400) = -0.25. As $LHS_{cpi} - RHS_{cpi} \geq GIA_{cpi}$ we must curtail the relevant (X1, X2) GIA generation entirely[22]. Hence the scaling factor to be applied is zero.

For Constraint 2, the LHS exceeds the RHS by 250. We must reduce the GIA generation by this amount. In order to achieve this, a scaling factor of 1-(250/600) =0.583 must be applied. This constraint is applied only where it is the minimum scaling factor, i.e. for Y1.

[22] We cannot reduce GIA generation beyond zero, this implies a lower bound of zero for all scaling factors.

Step 3

Finally, we determine which scaling factors to apply to GIA generators and constrain their generation accordingly[23].

In the table below, we note:

- GIA X1 and GIA X2 appear in constraints 1 and 2. For both these generators we must select the lowest applicable scaling factor (i.e. Min(0, 0.583)) so that the tightest constraint (Constraint 1) is met. Hence, both GIA X1 and X2 must be scaled down to zero.
- GIA Y1 only appears in constraint 2 and therefore gets a scaling factor of 0.583 and is constrained down to 200*0.583 = 116.6MW of generation.

Table 12: Summary of constrained GIA generation to be used in CAPSIM

Generator	Generation	Constraints	Scaling Factor	Constrained Generation
X1	200	Constraints 1 & 2	Min(0, 0.583) = 0	200*0 = 0
X2	200	Constraints 1 & 2	Min(0, 0.583) = 0	200*0 = 0
Y1	200	Constraint 2	0.583	200*0.58 3= 116.6

2.5 Development of the Availability Classes and Availability Curve

Having determined the Reserve Capacity Targets for each year, the next step assesses how much capacity is required for the two Availability Classes defined in the Market Rules to satisfy the targets for the second and third Capacity Years of the Long Term PASA Study Horizon as set out in MR 4.5.12.

Additionally, MR 4.5.10(e) requires AEMO to develop a two-dimensional duration curve of the forecast minimum capacity requirements over the Capacity Year (“Availability Curve”) for each of the second and third Capacity Years of the Long Term PASA Study Horizon.

[23] For avoidance of doubt, scaling factors are calculated for every hour of every Capacity Year for every Monte Carlo iteration.

In this section, we outline our approach in determining the Availability Classes set forth in MR 4.5.12(b) and MR 4.5.12(c) and the Availability Curve set out in MR 4.5.10(e).

2.5.1 Determine MR 4.5.12(b)

MR 4.5.12(b) requires the determination of the minimum generation capacity requirement:

For the second and third Capacity Years of the Long Term PASA Study Horizon, AEMO must determine the following information:

b) the minimum capacity required to be provided by Availability Class 1 capacity if Power System Security and Power System Reliability is to be maintained. This minimum capacity is to be set at a level such that if:

- *i. all Availability Class 2 capacity (excluding Interruptible Load used to provide Spinning Reserve to the extent that it is anticipated to provide Certified Reserve Capacity), were activated during the Capacity Year so as to minimise the peak demand during that Capacity Year; and*
- *ii. the Planning Criterion and the criteria for evaluating Outage Plans set out in clause 3.18.11 were to be applied to the load scenario defined by clause 4.5.12(b)(i), then*

it would be possible to satisfy the Planning Criterion and the criteria for evaluating Outage Plans set out in clause 3.18.11, as applied in clause 4.5.12(b)(ii), using, to the extent that the capacity is anticipated to provide Certified Reserve Capacity, the anticipated installed Availability Class 1 capacity, the anticipated Interruptible Load capacity available as Spinning Reserve and, to the extent that further Availability Class 1 capacity would be required, an appropriate mix of Availability Class 1 capacity to make up that shortfall;

RBP has calculated the minimum generation requirement by repeating the modelling exercise (for the second and third years of the Long Term PASA Study Horizon) described in Section 2.4 with the following differences:

- DSM has been modelled in greater detail to take into account the constraints around the availability of DSM providers. In short, we allocate DSM throughout the year using an optimisation model that dispatches DSM to minimise the peak and subject to scheduling and availability constraints. See below for further details on our approach to modelling DSM.
- We incorporate a Planning Margin into CAPSIM that represents the outage planning criteria set out in MR 3.18.11. In other words, unserved energy will occur when

$\boldsymbol{Generation_t} - \boldsymbol{Load_t} < Planning\ Margin$. For the Reliability Assessment, we consider unserved energy to occur when $\boldsymbol{Generation_t} - \boldsymbol{Load_t} < 0$.

- Forced outages are taken out of the model, and the only stochastic component of the simulation will be load. The reason for the removal of forced outages is that the specification of a reserve requirement on top of forced outages effectively over-estimates the capacity margin. The purpose of the Ancillary Services Requirement is to cover unforeseen events such as forced outages. As such, if there were a forced outage in a given period, the operating reserve would be used to generate to prevent unserved energy. Hence, including forced outages and maintaining the Ancillary Services Requirement could lead to expected unserved energy exceeding 0.002% of annual demand.
- We revert to using a base year load shape that is based on the average shape of the LDCs from the past five Capacity Years with the 2017/18 load chronology (as modelling individual LDC shapes and iterating (see below) to ensure the Planning Criterion is met across all five years is very computationally intensive).
- Finally, for each year of the relevant Reserve Capacity Cycle, we iterate the model to reallocate the amount of DSM and generating capacity (keeping the total capacity capped at the RCT level) until the EUE requirement in MR 4.5.9(b) is violated.

The level of generation capacity at which the EUE equals 0.002% of expected demand sets the minimum generation capacity.

DSM Modelling Methodology

DSM in the WEM is subject to availability constraints. RBP has forecast hourly DSM dispatch by allocating available DSM throughout the year based on an optimisation model that takes into account the constraints above. Our approach is detailed further below:

1. Forecast sequential hourly load for the year using the methodology described in Section 2.3.
2. Use a spreadsheet-based optimisation model which, given the forecast hourly load, dispatches DSM facilities (excluding Interruptible Load, as that is excluded under MR 4.5.12(b)) for each year to minimise the demand in the intervals with the highest forecast demand (i.e. peak demand intervals) subject to the DSM's availability and dispatch constraints. This is in accordance with MR 4.5.12(b) which requires DSM to be dispatched so as to minimise peak demand. The model performs the dispatch using a heuristic allocation method.

- The model allocates DSM dispatch to intervals in descending order of peak demand until all available DSM has been exhausted[24].
- We reiterate that by optimal we mean annual DSM dispatch which will minimise peak demand; this is a requirement specified in MR 4.5.12(b). Hence, we assume perfect foresight with respect to knowing when peak intervals will occur, and the model dispatches DSM facilities during those intervals subject to their availability restrictions. It is also important to note that a DSM dispatch plan which minimises peak demand would be different to a DSM dispatch plan which minimises unserved energy. Particularly, the intervals in which unserved energy is most likely is not necessarily the same as peak demand intervals due to increasing intermittent generation with lower availability in off-peak demand intervals combined with more planned outages also occurring in these off-peak demand intervals. This is highlighted in our findings with respect to deriving the maximum Availability Class 2 capacity (MR 4.5.12(c)), and its counterpart, the Minimum Generation Capacity (MR4.5.12(b)). For further details refer to Section 3.2.

3. Adjust the LDC used in the market modelling by subtracting the forecast DSM dispatch in the relevant hours (from Step 1 above). This adjusted LDC represents the "effective demand" and has been used in the derivation of the minimum generation capacity contemplated by MR 4.5.12(b).

The participant data indicates that only two DSM facilities have applied for Capacity Credits. Both facilities are interruptible load facilities and have been excluded from the analysis above. For the purposes of the iteration, however, we will use hypothetical DSM facilities with the same availability profile of the two interruptible load facilities. In each iteration, we will add additional facilities of a similar size and availability to the two interruptible load facilities.

2.5.2 Determine MR 4.5.12(c)

MR 4.5.12(c) requires determining the capacity associated with Availability Class 2:

For the second and third Capacity Years of the Long Term PASA Study Horizon, AEMO must determine the following information:

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[24] It should be noted that the nature of the problem of optimally allocating DSM is such that it would be computationally infeasible to guarantee that the result is the absolute optimum dispatch of DSM. The heuristic used will produce a dispatch that is close to optimal. We consider this to be acceptable, as the real-world dispatch of DSM is unlikely to be optimal either.

c) the capacity associated with Availability Class 2, where this is equal to the Reserve Capacity Target for the Capacity Year less the minimum capacity required to be provided by Availability Class 1 capacity under clause 4.5.12(b).

This is a straightforward calculation that has been computed by:

- Subtracting the minimum generation capacity, calculated above (see Section 2.5, Determine MR 4.5.12) from
- The RCT for the relevant Reserve Capacity Cycle (determined in Section 2.4).

2.5.3 Determine MR 4.5.10(e)

MR 4.5.10(e) requires AEMO to:

develop a two-dimensional duration curve of the forecast minimum capacity requirements over the Capacity Year ("Availability Curve") for each of the second and third Capacity Years of the Long Term PASA Study Horizon. The forecast minimum capacity requirement for each Trading Interval in the Capacity Year must be determined as the sum of:

- *i) all Availability Class 2 capacity (excluding Interruptible Load used to provide Spinning Reserve to the extent that it is anticipated to provide Certified Reserve Capacity), were activated during the Capacity Year so as to minimise the peak demand during that Capacity Year; and*
- *ii) the Planning Criterion and the criteria for evaluating Outage Plans set out in clause 3.18.11 were to be applied to the load scenario defined by clause 4.5.12(b)(i), then*

Our interpretation of MR 4.5.10(e)(i) and the load scenario contemplated in MR 4.5.10(a)(iv) in deriving the LDC above was undertaken in consultation with the IMO and AEMO in previous years. Particularly, the approach above is predicated on the assumption that the difference between a 10% POE peak year and a 50% POE peak year (assuming expected demand growth) would only manifest itself in the first 24 hours (i.e. the peakiest part of the LDC). Hence, we model the forecast capacity requirement as a combination of the 10% POE peak LDC and 50% POE peak LDC (where these LDCs are derived in the manner described in Section 2.3.2).

Our approach to determining this quantity is summarised below.

1. Forecast the LDC for a given year as specified in MR 4.5.10(e)(i). To do this:
    a. We estimate the forecast load in the first 24 hours assuming a 10% POE peak forecast and expected demand growth (i.e. the load scenario contemplated in MR 4.5.10(a)(iv)). This estimation has been undertaken using the scaling methodology

described in Section 2.3; as noted previously, we use an average load shape from the past five Capacity Years, using the 2017/18 load chronology.

b. We then estimate the forecast load for the remaining hours (hours 25-8,760) assuming a 50% POE peak forecast and expected demand growth.

c. We then use a smoothing function[25] to smooth out the LDC in the first 72 hours.

2. Add the Reserve Margin, Intermittent Load allowance and LFAS component of the MR 4.5.9(a) calculation (as provided by the AEMO) on top of the above LDC as required by MR 4.5.10(e)(ii).

2.6 CALCULATION OF EDDQ

We have forecast the EDDQ using the following approach:

1. Forecast EUE when DSM is dispatched for zero hours ($EUE_{t,0}$). This involves repeating the Reliability Assessment as described in Section 2.3 but setting the available capacity of all DSM facilities to zero. Hence, only generation capacity is available to meet demand as described in MR 4.5.14C(a).
2. Forecast Expected Unserved Energy when DSM is dispatched for 200 hours ($EUE_{t,200}$). This involves repeating Step 1 above but with the forecast LDC adjusted to take into account DSM dispatch for exactly 200 hours. The optimised DSM dispatch is deducted off the forecast LDC, and it is this adjusted LDC that becomes an input into the market model. Hence, generation capacity plus exactly 200 hours of DSM dispatch is available to meet demand as described in MR 4.5.14C(b).
3. Calculate EDDQ in year t as follows:

$$EDDQ_t = \frac{EUE_{t,0} - EUE_{t,200}}{Expected\ DSM\ Capacity\ Credits_t}.$$

[25] We used a quadratic approximation to smooth the LDC.

3 Results

3.1 Reliability Assessment

The Reliability Assessment indicated that for all Capacity Years of the Long Term PASA Study Horizon (2019/20 to 2028/29) the RCT will be set by the forecast peak quantity determined by MR 4.5.9(a).

The EUE as a percentage of annual energy consumption when total capacity is capped at the forecast peak component given by MR 4.5.9(a) (first column) is summarised in Table 13. The fourth column summarises the amount of unserved energy at which the reliability criterion in MR 4.5.9(b) binds. Here we see that the peak forecast component is sufficient to limit EUE to 0.002% of annual energy consumption in all years. Furthermore, the absolute value of EUE is well short of the reliability threshold specified in MR 4.5.9(a).

Table 13. Results of Reliability Assessment

Capacity Year	Reserve Capacity Target[26]	50% POE Peak Load (MW)	Expected annual energy consumption (MWh)	0.002% of annual energy consumption (MWh)	EUE (MWh)	EUE as % of load
2019/20	4414	3,758	18,241,450	364.83	0.1832	0.0000010%
2020/21	4470	3,813	18,267,580	365.35	0.1608	0.0000009%
2021/22	4482	3,819	18,124,527	362.49	0.0248	0.0000001%
2022/23	4481	3,822	17,977,902	359.56	0.636	0.0000035%
2023/24	4485	3,826	17,845,426	356.91	0.4304	0.0000024%
2024/25	4486	3,832	17,760,672	355.21	0.1416	0.0000008%
2025/26	4499	3,847	17,683,313	353.67	0.2248	0.0000013%
2026/27	4524	3,860	17,622,475	352.45	0.0208	0.0000001%
2027/28	4535	3,876	17,566,216	351.32	0.7976	0.0000045%

[26] Set by MR 4.5.9(a) 10% POE peak+ Reserve Margin + LFAS requirement + IL Allowance

Capacity Year	Reserve Capacity Target[26]	50% POE Peak Load (MW)	Expected annual energy consumption (MWh)	0.002% of annual energy consumption (MWh)	EUE (MWh)	EUE as % of load
2028/29	4559	3,897	17,542,936	350.86	0.1968	0.0000011%

In Table 14, we summarise:

- The EUE observed for each of the five historic LDC shapes and chronologies (2013/14 - 2017/18)
- The EUE averaged across the five historic LDC shapes (which is equal to the LDC reported in Table 13)
- The EUE from the 2018 Long Term PASA which was modelled using a load shape averaged across Capacity Years 2012/13-2016/17 using the chronology of the 2016/17 Capacity Year.

Table 14. Results of Reliability Assessment by LDC, EUE in MWh

	LDC Year starting 1 October						
Capacity Year starting 1 Oct	2013	2014	2015	2016	2017	Average	Long Term PASA 2018
2019/20	0.136	0.000	0.000	0.780	0.000	0.183	0.000
2020/21	0.000	0.000	0.000	0.804	0.000	0.161	0.000
2021/22	0.000	0.000	0.000	0.000	0.124	0.025	0.063
2022/23	0.000	0.000	0.000	3.180	0.000	0.636	2.537
2023/24	0.000	0.000	0.164	0.000	1.988	0.430	0.062
2024/25	0.148	0.000	0.000	0.560	0.000	0.142	0.947
2025/26	0.000	1.016	0.000	0.108	0.000	0.225	0.000
2026/27	0.000	0.000	0.104	0.000	0.000	0.021	0.000
2027/28	0.000	0.000	0.000	2.640	1.348	0.798	0.013
2028/29	0.984	0.000	0.000	0.000	0.000	0.197	
Average	0.127	0.102	0.027	0.807	0.346	0.282	

The unserved energy is more evenly distributed in this year's modelling than the previous year due to the averaging across the five LDCs. There is heterogeneity in the distribution of unserved energy across the LDCs, which is driven by differing load chronologies.

The LDC with the highest average EUE is 2016/17 (0.807 MWh averaged across the Long Term PASA horizon); this is driven by an unusual load chronology with more of the highest load periods occurring during winter evenings (compared with the other historic LDCs). For the 2016/17 LDC load shape, we note the highest EUE occurring in the year 2022/23 (3.180MWh) and 2027/28 (2.640MWh); the majority of unserved energy occurs in July where available intermittent generation is at its lowest (due to seasonal factors).

Note that 2027/28 has the highest EUE when averaged across all historic LDC shapes (0.798 MWh); this is caused by a lower capacity margin (relative to other years) due to higher than usual planned outages for that year. Note, even though the Planning Margin requirement is satisfied for planned outages occurring in 2027/28, the capacity margin (available generation less load) is smaller compared with other years; this means that 2027/28 is more likely to have unserved energy as a result of multiple forced outages.

In terms of the relationship between increasing levels of intermittent generation and unserved energy, we note that there are multiple ways in which unserved energy occurs as a result of increasing intermittent facilities in the generation mix:

- The first relates to the seasonal and time of day availability of intermittent generation (as noted above, where unserved energy occurring during winter months drives up the EUE in 2027/28). Specifically, lower availability of intermittent generation during winter months can lead to a lower capacity margin and increased likelihood of unserved energy.
- The second is through GIA constraints backing off generation during summer peak intervals[27]. For LDC chronologies where there is a higher than usual proportion of high load periods in winter, we do not observe binding GIA constraints due to lower levels of intermittent generation in winter months (e.g. the 2016/17 LDC chronology). However, for LDC chronologies with more peak intervals during summer months (e.g. 2013/14 which has a 4:00pm January peak), we observe binding constraints driven by high levels of intermittent generation. Here, GIA constraints do reduce GIA generation to around 75% capacity, causing unserved energy. As the load chronology continues to shift to later months in the Hot Season (e.g. March), the GIA

[27] The GIA constraints are generally non-binding or entail a small inconsequential reduction in generation for one or two generators. The constraints tend to bind in January/February when intermittent generation is at its highest (due to seasonal factors). In these cases, the reduction can be quite large, reducing GIA generation to up to 75% of its capacity.

constraints have less impact on unserved energy (as the constraints are unlikely to bind due to lower levels of intermittent generation in the later Hot Season months).

In Table 15 and Table 16 we break down the total amount of EUE across the Long Term PASA Horizon, by hour[28] or month for each load curve (I.e. the value for (13:00, 2013) refers to the sum of all EUE over the Long Term PASA Horizon that occurs at 1 PM for the 2013/14 load curve). We note a shift from 2013/14 to 2017/18 whereby unserved energy occurs later in the day and occurs more often in winter/autumn months:

Table 15: Total Unserved Energy by Hour (MWh)

Hour/LDC Year	2013	2014	2015	2016	2017
13:00	0.07	0.00	0.00	0.00	0.00
14:00	0.34	0.08	0.00	0.00	0.00
15:00	0.26	0.16	0.17	0.00	0.00
16:00	0.46	0.29	0.11	0.11	0.00
17:00	0.08	0.33	0.00	1.10	0.87
18:00	0.06	0.16	0.00	6.07	2.28
19:00	0.00	0.00	0.00	0.84	0.34

Table 16: Total Unserved Energy by Month (MWh)

Month/LDC Year	2013	2014	2015	2016	2017
January	1.12	1.02	0.00	0.00	0.00
February	0.00	0.00	0.11	0.00	0.00
March	0.00	0.00	0.17	1.12	1.99
April	0.00	0.00	0.00	0.00	0.00
May	0.00	0.00	0.00	0.00	0.00
June	0.00	0.00	0.00	0.00	0.00
July	0.00	0.00	0.00	5.76	0.00

[28] Note that unserved energy only occurs between 13:00 and 19:00 in any capacity year, for all LDCS.

Month/LDC Year	2013	2014	2015	2016	2017
August	0.00	0.00	0.00	1.24	1.49
September	0.00	0.00	0.00	0.00	0.00
October	0.00	0.00	0.00	0.00	0.00
November	0.00	0.00	0.00	0.00	0.00
December	0.15	0.00	0.00	0.00	0.00

3.2 Availability Classes and Availability Curves

The Availability Classes for Capacity Years 2020/21 and 2021/22 are summarised in Table 17 below. The Availability Curves developed under MR 4.5.10(e) are illustrated in Figure 6 and Figure 7.

Table 17: Availability Curve, 2020/21 - 2021/22.

	2020/21	2021/22
MR 4.5.12(b): Minimum capacity required to be provided by Availability Class 1		
Minimum capacity	4,110	3657
MR 4.5.12(c): Capacity associated with Availability Class 2		
DSM	360	825
RCT	4,470	4,482

Figure 6: Forecast capacity required, 2020/21

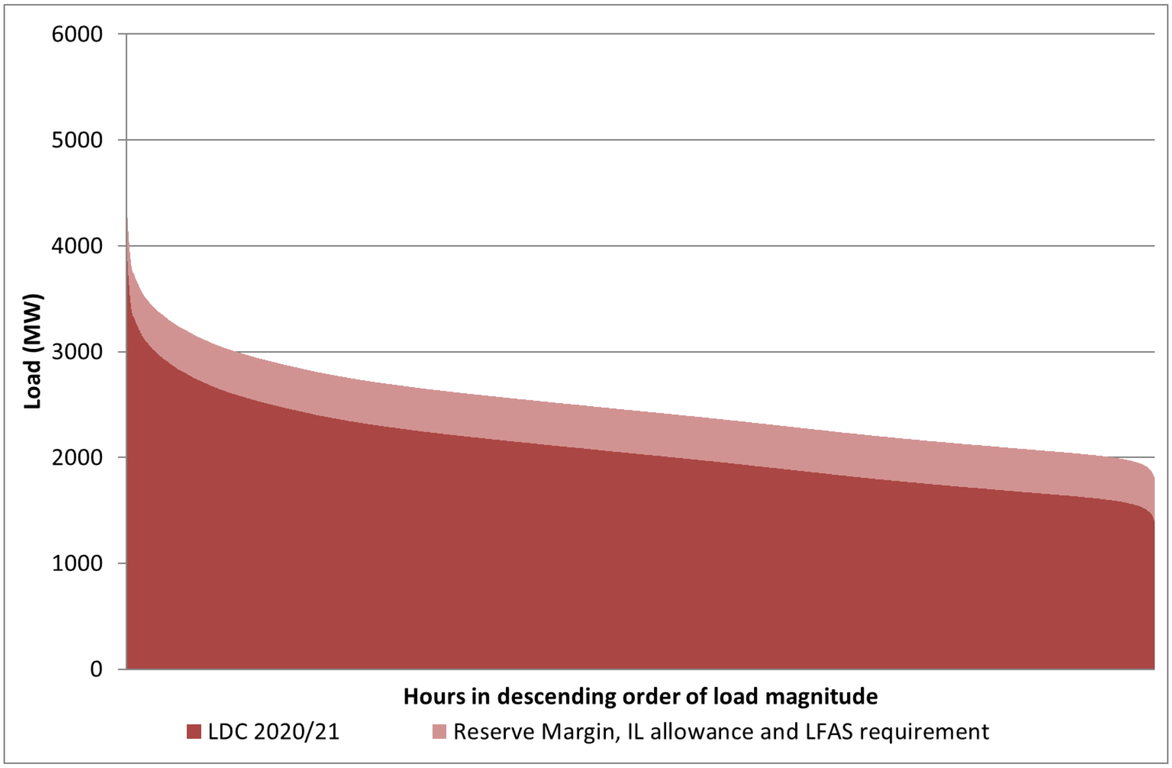


Figure 7: Forecast capacity required, 2021/22

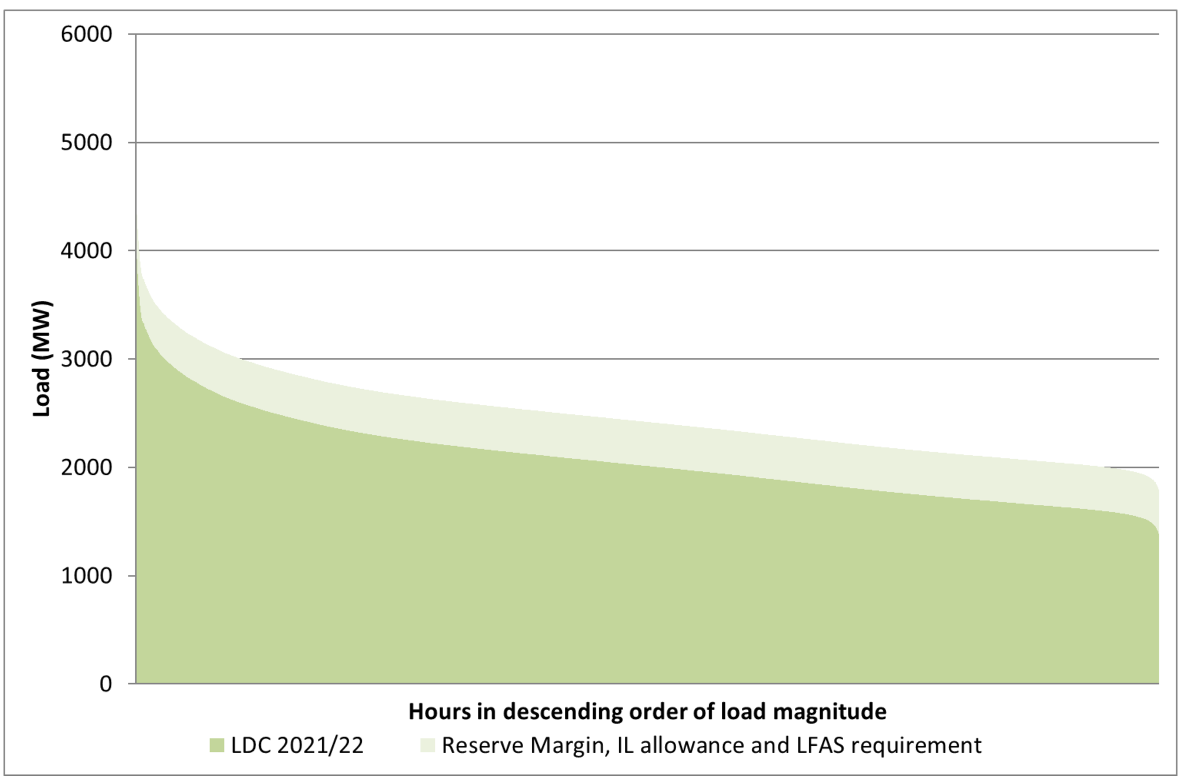


Table 18 compares the Availability Classes derived for the 2018 Long Term PASA to the current (2019 Long Term PASA) results. The 2018 Long Term PASA values are provided in parentheses.

Table 18: Comparing Long Term PASA 2019 Availability Curve to Long Term PASA 2018 Availability Curve (2018 results in parentheses)

2020/21	
MR 4.5.12(b): Minimum capacity required to be provided by Availability Class 1	
Minimum capacity	4,110 (3,946)
Reserve Capacity Target	
Reserve Capacity Target	4,470 (4,581)
MR 4.5.12(c): Capacity associated with Availability Class 2	
DSM	360 (635)

The capacity associated with Availability Class 2 has decreased by 274 MW from the previous year (which was also a decrease from the year previous to that). This is a continuation of the same issue highlighted in last year's reliability report:

- 900MW of thermal plants on planned outage in the first two weeks of November 2020[29].
- The DSM optimisation model allocates hourly DSM to minimise the peak[30] subject to availability constraints. As noted in Section 2.5.1, the DSM optimisation model dispatches DSM during peak demand intervals in descending magnitude of load until all available DSM is exhausted. We also noted in Section 2.5.1, that dispatching DSM to minimise unserved energy (versus peak demand) would result in a different DSM dispatch plan. As a result, the model dispatches lower levels of DSM during the off-peak/shoulder intervals in November which is not enough to meet the net load with 900MW of scheduled generation on outage.

[29] Based on information provided by market participants under MR 4.5.3.

[30] In accordance with MR 4.5.12(b), the DSM optimisation model dispatches DSM facilities to minimise peak demand throughout the year (as opposed to maximising the operating reserve margin).

- The increased amount of solar in the capacity stack which means that in the evening (non-daylight) hours in November the amount of available generation decreases further.

As a result, EUE reaches the 0.002% threshold due to the unserved energy occurring in the first two weeks of November. Note that the amount of unserved energy is not alleviated by the planned outage scheduling that we have conducted. In periods with relatively low load, the unscaled capacity used in the planned outage scheduling (See Section 2.4.4) is enough to meet the Planning Margin even with planned outages[31]. However, the planned outage scheduling is conducted assuming availability of DSM throughout the year (as opposed to 200 hours), whereas MR 4.5.12(b) requires DSM to be deployed to minimise the peak. Hence, the ex-ante outage scheduling assumes available DSM; however, the ex-post DSM deployment means that DSM is, in reality, not available during the November 2020 periods when unserved energy is occurring; as noted above peak demand intervals in which DSM is deployed (in accordance with MR 4.5.12(b)) will not be the same as deploying DSM in intervals to minimise unserved energy is minimised.

Note that the level of Class 2 capacity (DSM) is 465MW higher in 2021/22 due to fewer planned outages during the same November period.

It follows from the above, that if DSM were available for more than 200 hours per year, then the allowable level of DSM may increase as they may not be exhausted during the shoulder months with higher planned outages.

3.3 EDDQ

The EDDQ results are summarised in Table 19. This also provides the resulting DSM Reserve Capacity Price (RCP) assuming an interim DSM Activation Price of $33,460[32].

[31] Market Participants provided planned outages were used 'as-is', as no outages violated the scheduling criterion developed in consultation with AEMO. This is due to the much lower peak demand in the draft forecasts when compared to previous years.

[32] As specified in Market Rule 4.5.14F; the DSM Activation Price represents the Value of Lost Load (VoLL).

Table 19. EDDQ results

Capacity Year	EUE(t,0)	EUE(t,200)	CC(t)	EDDQ(t)	DSM RCP based on $33,460 DSM Activation Price (MR 4.5.14F)
2019/20	0.6968	0.1832	0.5136	0.0078	$16,990.38
2020/21	0.3584	0.1792	0.1792	0.0027	$16,820.85
2021/22	0.2528	0.0312	0.2216	0.0034	$16,842.34
2022/23	1.1048	0.6864	0.4184	0.0063	$16,942.12
2023/24	0.9112	0.4488	0.4624	0.0070	$16,964.42
2024/25	0.3824	0.1528	0.2296	0.0035	$16,846.40
2025/26	0.6440	0.248	0.3960	0.0060	$16,930.76
2026/27	0.0744	0.0248	0.0496	0.0008	$16,755.15
2027/28	2.0448	0.796	1.2488	0.0189	$17,363.10
2028/29	0.4048	0.2232	0.1816	0.0028	$16,822.07

The EDDQ this year is relatively low and constant. As noted in Section 3.1, this is a result of averaging across the five historic LDC shapes and chronologies which smooths out the year on year volatility. Table 20 summarises the EDDQ observed for each historic LDC shape, the average across the five shapes and the 2018 Long Term PASA 2018 results.

Table 20. EDDQ results by LDC

Capacity Year	LDC Year						
	2013	2014	2015	2016	2017	Average	Long Term PASA 2018
2019/20	0.0095	0.0000	0.0000	0.0294	0.0000	0.0078	0.0144
2020/21	0.0009	0.0000	0.0000	0.0127	0.0000	0.0027	0.0000
2021/22	0.0000	0.0000	0.0053	0.0000	0.0115	0.0034	0.0114
2022/23	0.0000	0.0000	0.0000	0.0317	0.0000	0.0063	0.0350
2023/24	0.0000	0.0000	0.0047	0.0011	0.0292	0.0070	0.0079
2024/25	0.0066	0.0000	0.0000	0.0108	0.0000	0.0035	0.0205
2025/26	0.0000	0.0246	0.0000	0.0054	0.0000	0.0060	0.0017
2026/27	0.0000	0.0000	0.0036	0.0000	0.0002	0.0008	0.0005

Capacity Year	LDC Year						
	2013	2014	2015	2016	2017	Average	Long Term PASA 2018
2027/28	0.0101	0.0000	0.0029	0.0573	0.0243	0.0189	0.0174
2028/29	0.0138	0.0000	0.0000	0.0000	0.0000	0.0028	
Average	0.0041	0.0025	0.0017	0.0148	0.0065	0.0059	

As in Section 3.1, the highest EDDQs appear in the 2016 LDC, in 2022/23 and 2027/28. Overall, the EDDQ is relatively low due to the low level of unserved energy in the model and the low amount of DSM (2 facilities with a combined capacity of 66 MW).

Figure 8 and Figure 9 compare the 2018 Long Term PASA EDDQ and DSM RCP to the 2019 Long Term PASA results.

Figure 8: Comparing 2018 and 2019 Long Term PASA EDDQ values

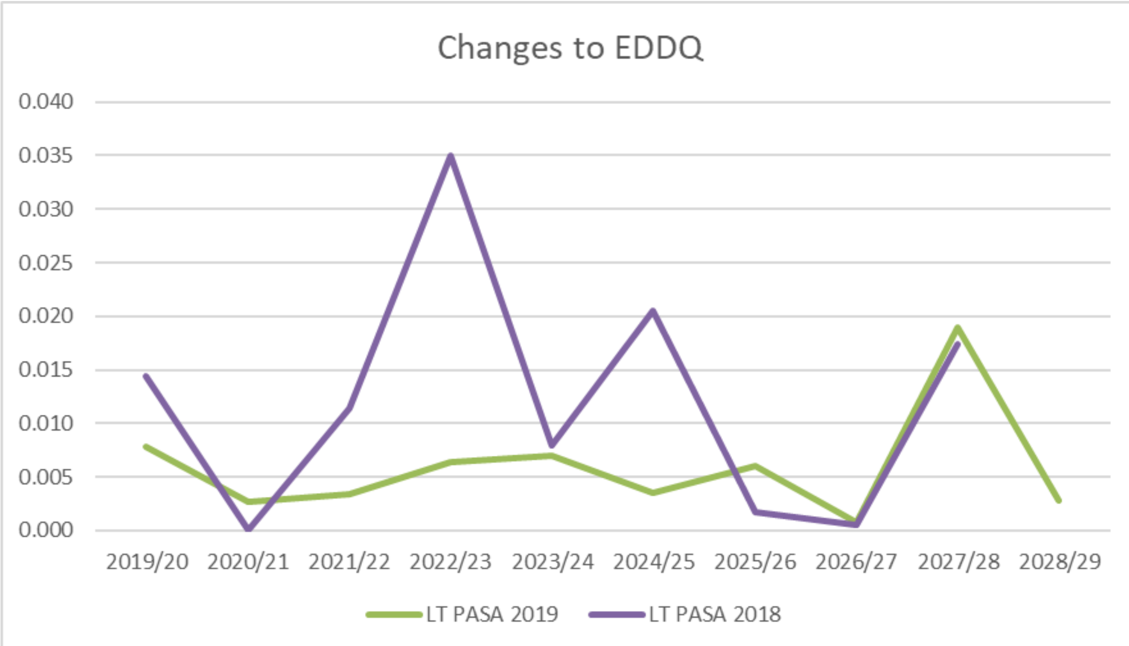
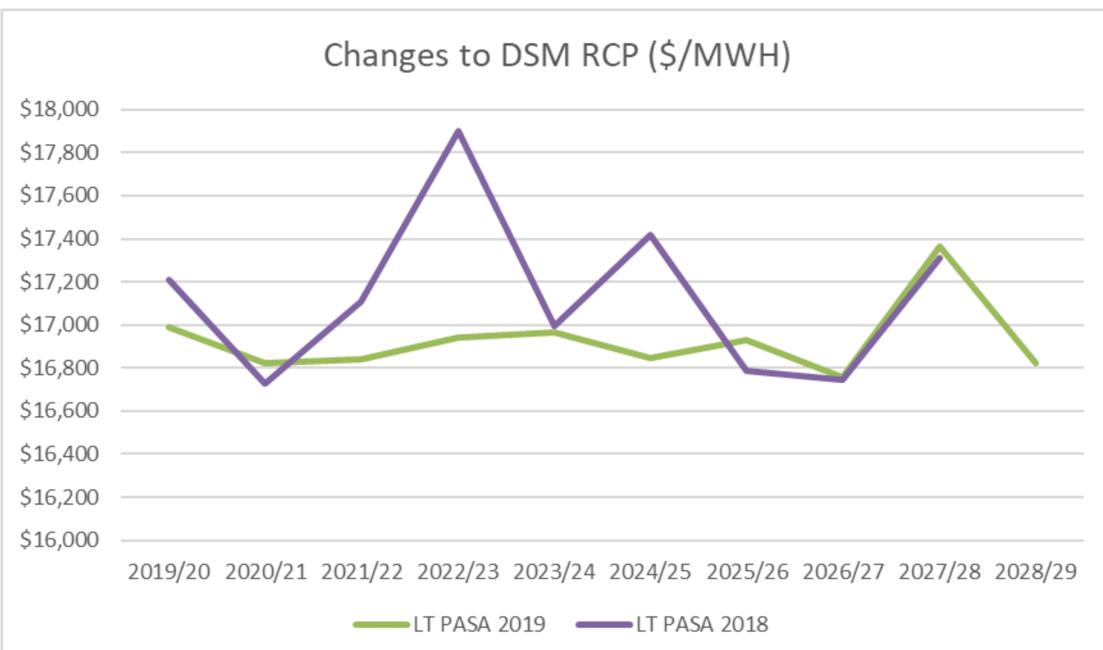


Figure 9: Comparing 2018 and 2019 Long Term PASA DSM RCP values



The highest EDDQ occurs in 2027/28 for the reasons noted in Section 3.1; namely a lower capacity margin (relative to other years), due to higher than usual planned outages for that year.

EDDQ is otherwise low with limited variation across the years. This is a reflection of the fact that unserved energy is very low under the reliability scenario to begin with (see Table 13). This combined with the fact that there are only two facilities (with a combined CC assignment of 66 MW over the Long Term PASA horizon) means that not running these DSPs has a minimal impact on the level of unserved energy.

APPENDIX A MODELLING ASSUMPTIONS

In this section we set out:

- Assumptions about Capacity Credits allocated to facilities over the Long Term PASA horizon
- Planned and forced outage assumptions
- Demand assumptions

A.1. CAPACITY CREDITS

The amount of capacity credits assumed by facility is summarised in this section.

As noted in Section 2.4, for each year of the Long Term PASA Study Horizon, we assume reserve capacity (generating capacity and DSM) equals the forecast peak quantity plus reserve margin and Load Following Ancillary Services (LFAS) quantity determined by MR 4.5.9(a). To do this we pro-rate the capacity credits (provided by the AEMO and Market Participants) for each facility so that the total number of capacity credits in a given year sum to the forecast peak component given by MR 4.5.9(a) for that year as follows:

$$\widehat{CC_i} = CC_i{}^{33} \times \frac{10\%\ POE\ peak + Reserve\ Margin + LFAS}{\sum_{j \in all\ facilities} CC_j}$$

For generators that have a commencement date before the beginning of the first capacity year for which they have been assigned capacity credits, we have modelled the plant commencing when its capacity obligations begin.

[33] For scheduled generators CC_i denotes the Capacity Credits the facility is applying for. For non-scheduled (intermittent) generators, CC_i denotes the average annual facility generation (based on historic or participant provided generation data). We do not use the Relevant Level value for CC_i as this would underestimate the total available annual generation from an intermittent facility (noting that the Relevant Level is a measure of intermittent generator performance in peak load intervals only).

A.2. Planned and forced outage assumptions

A.2.1. Planned outages

Planned outage assumptions have been developed using the methodology described in Section 2.4.4.

Briefly, Market Participants provided planned outages were validated by comparing the "capacity gap" (the level of available capacity minus the forecast load[34] in each period) to a Planning Margin analogous to that used by System Management (See Section A.4). Where the Planning Margin exceeded this capacity gap, participant outages were to be shifted until the planning margin was satisfied for each period.

As mentioned in Section 2.4.4, the planning margin was satisfied in all periods using the original participant provided outage schedule. We have therefore made no modifications to the outage schedule and have used participant provided outages 'as-is'.

A.2.2. Forced outages

Forced outage rates (FOR) are based on the historical 36 month average for existing plants. This is a departure from our previous assumptions which used a ten-year average. We have used a 36 month average FOR to align with MR 4.11.1(h) and MR 4.11.1D, which may affect a facility's capacity credit assignment if their 36 month average forced outage rate exceeds certain thresholds.

We have assumed a FOR of 0.1% for facilities with zero historic FOR. Assuming a FOR of 0% is unrealistic as equipment is unlikely to have a zero failure rate.

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 off 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.

A.3. Demand assumptions

In this section, we set out:

[34] Scaled to the Medium Term PASA (Refer to Table 6)

- The RCT and annual energy consumption forecasts
- The base year LDCs which are used as a basis to forecast load shape and hourly load over the Long Term PASA Study Horizon
- The seasonal distribution of peak periods between the five base year LDCs.

A.3.1. RCT and demand forecasts

Table 21 summarises:

- The peak forecast component of MR 4.5.9(a) (which has set the RCT in every Capacity Year of the Long Term PASA Study Horizon)
- The 50% and 10% POE peak demand forecasts (expected scenario)
- The annual energy consumption forecast (expected scenario).

Table 21: RCT and demand forecasts

Capacity Year	Peak forecast component of Planning Criterion MR 4.5.9(a)	50% POE peak forecast	10% POE peak forecast	Expected annual energy consumption (MWh)
2019/20	4414	3,758	4,007	18,241,450
2020/21	4470	3,813	4,063	18,267,580
2021/22	4482	3,819	4,075	18,124,527
2022/23	4481	3,822	4,074	17,977,902
2023/24	4485	3,826	4,078	17,845,426
2024/25	4486	3,832	4,079	17,760,672
2025/26	4499	3,847	4,092	17,683,313
2026/27	4524	3,860	4,117	17,622,475
2027/28	4535	3,876	4,128	17,566,216
2028/29	4559	3,897	4,152	17,542,936

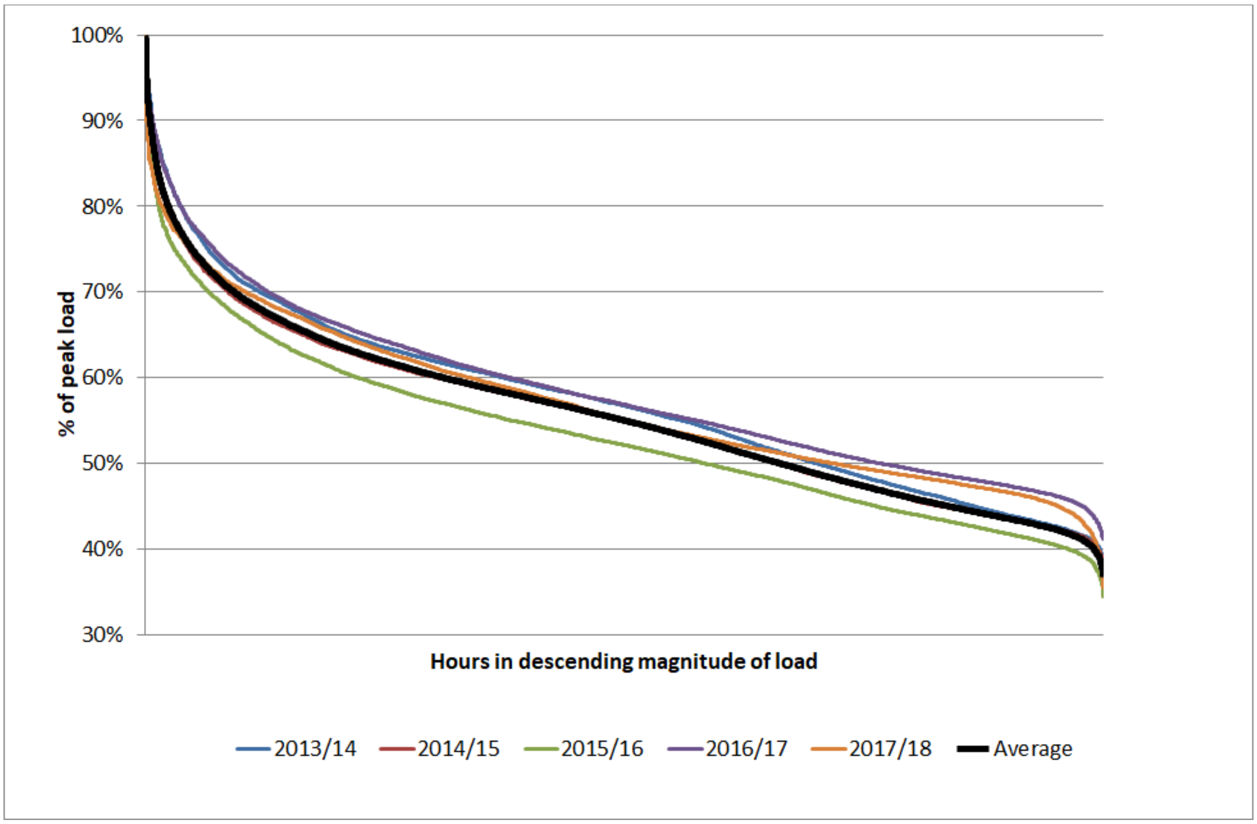
A.3.2. Base year load duration curves

We use the TT30GEN dataset from AEMO's website to calculate historical hourly load. Additionally:

- NLMQ values for Greenough River and Mumbida are added on as these are excluded from the TT30GEN dataset (These values were included for 2018/19 capacity cycle, but this was not the case for years prior to this).
- Curtailments (due to generation shortfall) are also added on to get gross load.

The load duration curves for the past five capacity years are summarised in the figure below.

Figure 10: Base year load duration curves



A.3.3. Seasonal distribution of peak periods

The use of five base load curves and chronologies has introduced a source of variation in the seasonal distribution of peak periods.

Table 22 summarises the percentage of top 50 peak periods in each season across the load curves:

Table 22: Seasonal Distribution of Top 50 Peak Periods by LDC

Season	2013	2014	2015	2016	2017
Summer	94%	98%	80%	46%	28%
Autumn	6%	2%	20%	24%	44%
Winter	0%	0%	0%	30%	28%
Spring	0%	0%	0%	0%	0%

The 2013 and 2014 load curves are summer focused with an overwhelming majority of peak periods occurring in the Summer months (94% and 98% respectively). However, the 2016 and 2017 load curves are much more likely to have peaks occurring in the autumn and winter months. The 2017 load curve in particular, has the majority of peaks occurring in autumn.

A.4. Planning Margin

The minimum generation capacity requirement prescribed by MR 4.5.12(b) and used in the planned outage scheduling in Section 2.4.4 is modelled by assuming a Planning Margin equivalent to applying the Ready Reserve Standard defined in MR 3.18.11A and the Spinning Reserve requirement in MR 3.10.2.

We have assumed a Planning Margin of 518 MW for the Planned Outage Scheduling.

For the minimum generation capacity calculation under MR 4.5.12(b), it is necessary to scale the Planning Margin based on the ratio of the RCT to total capacity credits for a given year. This is because the use of an unscaled planning margin, with *scaled* capacity, overestimates the contingency implied by the planning margin. It is therefore more appropriate to use a planning margin with the generator's capacity scaled by the RCT for each year.

The scaled planning margin assumptions for the minimum generation capacity calculation are summarised below in Table 23

Table 23: Scaled Planning Margin Assumptions for MR 4.5.12(b)

Capacity Year	Unscaled Planning Margin	Scaling Factor	Scaled Planning Margin
2020/21	518	0.8504	440.5036
2021/22	518	0.8126	420.9467