Forecast replacements of smart meters

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1 Executive summary

1.1 Background

As part of its price reset proposal for the 2026-31 regulatory control period, Jemena Electricity Networks (Jemena) is proposing to replace a significant portion of its smart meter fleet. The total number of replacements (both pre-emptive and reactive) that Jemena is proposing over the period is 94,632, as set out in Table 1 below.

Table 1: Forecast replacements of smart meters over the 2026-31 regulatory control period

FY2027	FY2028	FY2028	FY2030	FY2031
3,204	13,042	21,193	25,902	31,290

Source: Jemena.

We have been engaged by Jemena to derive an estimate of the prudent number of smart meters within the existing fleet that would need to be replaced over the next regulatory control period, having regard to recent Australian Energy Regulator (AER) guidance and asset replacement planning, Jemena data on historical smart meter failures and the age profile of Jemena's smart meters.

1.2 Estimation

Using data provided by Jemena, we attempted to obtain robust estimates of failure rates using Weibull distribution models, in line with AER practice note on asset replacement planning. We focussed on the most popular smart meter model within Jemena's network, a single phase single element meter accounting for around three quarters of installed meters, with low failure rates observed. However, the resulting estimates were either unable to capture recent increases in failure rates among older smart meters (which would materially understate the likely number of failures over the forthcoming regulatory control period), or resulted in implausibly high forecast failure rates. We deemed the results unsuitable for reliably forecasting failure and replacement of smart meters.

The underlying issue was the small sample size of meters that have reached the age at which point the failure rate appears to increase considerably. This means that a substantial degree of non-linear extrapolation is required in order to estimate the failure of installed smart meters during the 2026-31 regulatory control period. We caution against this due to the relatively poor model fit of various Weibull distributions using the maximum likelihood estimation approach, suggesting that the underlying failure is not well modelled by the Weibull functions considered.

As an alternative we suggest consideration of simple linear extrapolation, adopting a conservative increase in the failure rate compared to Weibull or other parameterisations.

1.3 Key findings

We find that the number of smart meters that would likely need to be replaced over the 2026-31 regulatory control period—either pre-emptively or reactively—in order for Jemena to comply with its regulatory and reporting requirements is higher than Jemena has proposed to replace.

This suggests that Jemena's proposed volume of replacements is conservative, and that Jemena is not proposing an overly risk-averse level of replacements.

We forecast that, without pre-emptive replacement of older smart meters, Jemena will fail to meet the mandatory reporting requirements for smart meters in Victoria. In order to satisfy the meter data reporting requirement in expectation (setting aside the potential for failures to be more frequent than modelled and expected in June 2031), Jemena would need to pre-emptively replace 92,601 model 22305 smart meters, which results in only 22,841 reactive replacements of smart meters. That is, Jemena would need to replace, either pre-emptively or due to failure, 115,442 model 22305 smart meters during the 2026-FY2031 regulatory control period (around 37% of the model 22305 smart meters expected to be in service as at FY2031).

The high degree of pre-emptive replacement is due to the mandatory meter data reporting requirement in Victoria, which requires 99.9% of meters to be able to report within 24 hours. The relatively high rate of failure towards the end of the regulatory control period, due to a large share of smart meters being relatively old at that point, and a 10-business day replacement timeframe under the National Electricity Rules (NER), cause Jemena to violate the requirement unless it undertakes substantial pre-emptive replacement of smart meters.

We note that reporting requirement was imposed on Jemena. Similarly, the age distribution of smart meters, heavily skewed towards older meters with associated high failure rates, is a consequence of the rapid and widespread (rather than staggered) initial rollout of smart meters following the mandated rollout of smart meters in Victoria.[1] Jemena did not choose either of these circumstances. However, it must prudently manage its assets within those constraints. A prudent replacement policy that aims to comply with Victorian meter data reporting requirements, and which accounts for the age profile of Jemena's assets, requires significant pre-emptive replacement of smart meters.

1 In 2006, the Victoria Government mandated the rollout of electricity smart meters to all households and small businesses across Victoria under the Advanced Metering Infrastructure program.

2 AER guidance

The AER's 2024 industry practice note on asset replacement planning explains that using past failure data as a common method of predicting the probability of failure for an asset or asset class:

> *A common approach to predicting an asset/asset class' probability of failure is to use past failure data to derive a relationship between an asset's age and its probability of failure at that age. This is typically done by fitting the historical 'time to fail' data to a statistical distribution and two approaches are common: use of a Weibull distribution or using the Crow-AMSAA approach, as described below.*[2]

Further, the AER notes that the Weibull probability methodology is commonly used where a single source of failure is the dominant source of failure. Under the Weibull distribution approach, the failure rate (which is the probability of failure expressed as a function of time), is estimated using the following two-parameter equation:

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1},$$

where:

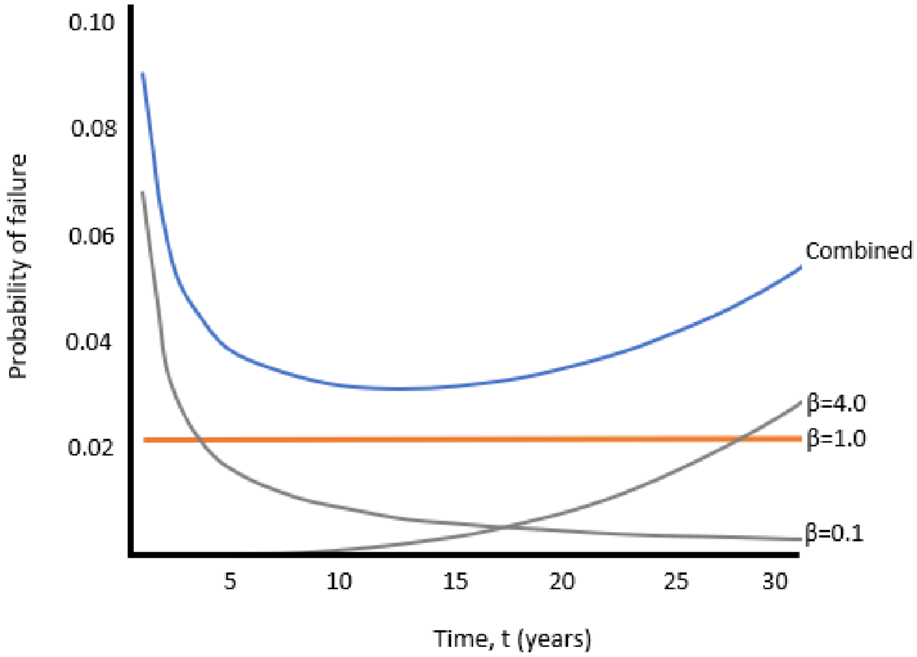
- t represents time;
- η is a scale parameter that measures the expected life of the asset; and
- β is a slope parameter for the Weibull function that reflects the rate (e.g., increasing, constant or declining) of failure.

The AER practice note goes on to provide an illustrative example that shows that multiple Weibull functions can be combined to obtain more realistic estimates of asset failure rates (see Figure 1).

The AER notes the parameters of a Weibull distribution may be estimated using a number of statistical techniques, including least squares, the weighted least square method, the maximum likelihood method and the method of moments. The AER explains that in most applications the maximum likelihood method will provide good estimates of Weibull function parameters, and that in cases with very small sample sizes, the weighted least square method may provide good estimates.

2 AER, Industry practice application note – Asset replacement planning, July 2024, p. 43.

Figure 1: Alternative Weibull functions



Source: AER, Industry practice application note – Asset replacement planning, July 2024, p. 44.

The AER practice note focuses on the use of historical data from the Network Service Provider (NSP) in question to estimate failure rates for that NSP. This may be feasible if the NSP has sufficient data on relatively old assets, such that large enough samples of failing assets exist to derive statistically reliable estimates of failure rates. However, if as in Jemena's case, the NSP has a relatively small population of 'older' assets, reliable Weibull distribution estimates of assets that are likely to fail over the upcoming regulatory control period will be difficult to obtain.

As we explain in section 4, in these circumstances alternative approaches need to be explored to estimate prudent replacement rates, including pre-emptive replacement of assets that have a high probability of failure once they reach a certain age.

3 Weibull estimation

3.1 Overview of approach

The AER's practice note sets out guidance on the process that should be followed by an NSP when estimating asset failure rates empirically, for instance, using a Weibull distribution approach (see Table 2)

Table 2: AER recommended process for estimation of asset failure rates

Steps	Description
1. Collect asset end of life failure data	Asset failure data is derived from either the NSP's own records or from industry data sets or a combination of the two. The objective is to obtain sufficient age-at-failure data for the asset class or individual asset to be statistically valid as a basis for deriving the probability of failure time series for that asset or asset class.
2. Inclusion of asset replacement data	The age of assets at replacement data points can also be considered. However, this data must be treated differently to age-at-failure data because it pre-empts asset failure and implicitly creates a circularity because it depends on past replacement strategies and criteria.
3. Select failure distribution methodology	Typically, Weibull distributions are applied for assets with wear-out characteristics and single mode failures are contemplated. Alternatives can be selected, but evidence needs to be provided to support the selection and application.[57] This step is a critical input to the application of software tools for deriving the modelling parameters (i.e. such as β and λ)
4. Derive probability of failure distribution parameters	Several NSPs use off-the-shelf software[58] for this step. The modelling approach selected should be commensurate with the failure modes of the asset class.
5. Generate probability of failure time series function	The output of step 4 is the probability of failure in a time series for the asset class (i.e. if data from the whole asset class population was the basis of the input data) or for individual assets (i.e. if the input data was applicable to a single asset). The results of step 4 should be tested against the actual failure data and the parameters adjusted as necessary to achieve a reasonable correlation between predicted and actual failure rates.
6. Calibrate probability of failure function to individual assets	Considering the importance of having sufficient data points to derive representative probability of failure time series, typically data from a whole asset class population is used. Individual asset probability of failure time series can be derived from the population results by calibrating the population average and variance with individual asset information.

Source: AER, Industry practice application note – Asset replacement planning, July 2024, p. 46.

3.2 Data

We received from Jemena data on installed meters, meter failures, and scrapped meters. These files contained data on:

- All historical installations of smart meters ("Complete export from SAP011124 with installed date.xlsx") (Installation spreadsheet);
- Historical asset meter failures ("ZAEC Faulty meter report IW39 – update with meter models.xlsx") (Failure spreadsheet); and
- All meters that have been removed from service ("List of SECURE meter Scrapped to date_15 Nov 2024.xlsx") (Scrapped spreadsheet).

Each meter is identified by the model and serial number as in columns A and C of the Installation spreadsheet ("Material" and "Serial no.") and columns N and O of the Failure spreadsheet ("Material" and "Serial number").

To determine the age of the meters we use the installation date. For surviving meters still in use, we obtain this information using the "Inst. Date" variable from the Installation spreadsheet, but for meters that have already failed we obtain this information from the "Earliest Install Date" variable in the Failure spreadsheet. To determine the failure date of the failed meters we use the earliest of the two variables in the Failure spreadsheet: "Created on" and "Bas. start date". Noting that some meters appear multiple instances in the Failure spreadsheet (for example due to being inaccessible requiring a further work order), we take the earliest failure date observed.

We have been provided with data on meters that have been scrapped, for example due to being taken out of service but not viable for installation due to advanced age. As these meters have neither failed nor survived in the usual sense, we remove any meters identified as having been scrapped without failing to avoid overstating or understating the probability of failure.

This results in a sample of 399,817 smart meters installed, with 76% of these being model 22305 smart meters, a type of single phase meter. The second most prevalent smart meter is the model 22311, a three phase meter, accounting for 13% of installed smart meters. Table 3 summarises the various models of smart meters installed historically by Jemena, but excluding all smart meters that were taken out of service before they failed.

Table 3: Sample of smart meters installed

Model	Category	Number installed
22305	Cat1	304,375
22306	Cat2	8,358
22308	Cat5b	3,603
22310	Cat6a	2,469
22311	Cat4	53,325
22312	Cat3	27,687

Source: Frontier Economics of Jemena data

Examining the failure by meter model (Table 4), we find that model 22305 has a substantially lower cumulative failure rate than other meter models. Only 1.2% of installed model 22305 meters have failed since installation, which is a lower failure rate than that of other meters despite having a higher average age than other meter types. The exception is the model 22312 smart meter with similar failure rate and age, which is also a single-phase meter. Model 22311, a common three phase meter, has experienced more than twice the failure rate despite having a significantly lower average age across the portfolio.

Table 4: Comparison of failure rates and ages of smart meter models

Model	Proportion failed	Average age (years)
22305	1.2%	10.8
22306	3.3%	9.4
22308	8.9%	9.2
22310	7.3%	8.3
22311	2.8%	8.8
22312	1.2%	10.3

Source: Frontier Economics of Jemena data

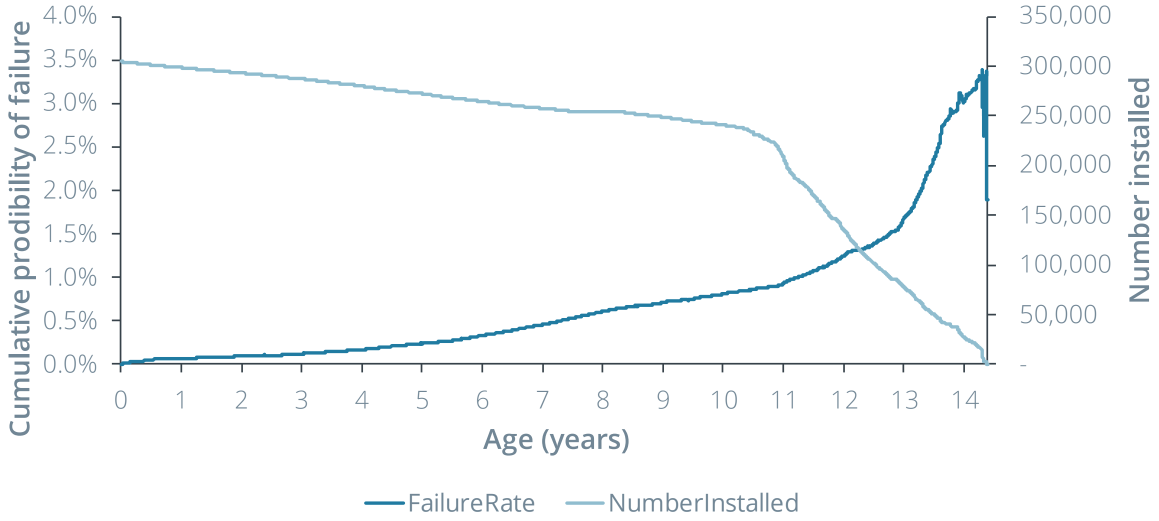
3.3 Estimation

We begin by attempting to estimate the failure rate distribution of the model 22305 smart meters (single phase meters). As shown above, these meters account for over 75% of smart meter installations within Jemena's network.

The empirical cumulative distribution function is shown below in Figure 2. This shows the share of installed meters that have failed, based on age in years since installation. As expected, the distribution tends to increase over time, with a more rapid increase from around 13 years.

On the same figure we also present the number of meters that were installed at least X years prior to the sample date (October 2024). For example, around 300,000 model 22305 meters had been installed at least zero days prior to October 2024, with around 210,000 of these installed at least 11 years prior to October 2024 (coinciding with the end of the initial deployment of smart meters). However, only 77,000 meters have been installed for at least 13 years, and only 27,000 have been installed for at least 14 years.

Figure 2: Empirical failure distribution and age distribution



Source: Frontier Economics analysis of Jemena data.

We first attempted to estimate a Weibull failure function using maximum likelihood estimation. We parameterised the Weibull distribution as being represented by a failure rate of the form

$$f(x;\beta;\eta) = \frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1}$$

Where, as explained in section 2, $\beta > 0$ is a shape parameter and $\eta > 0$ is a scale parameter.

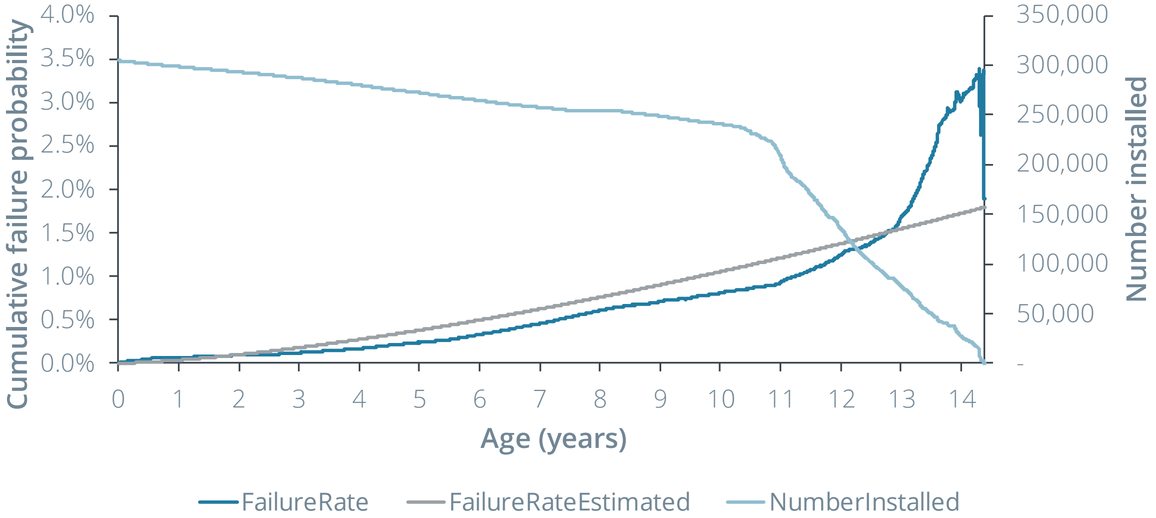
We obtained estimates of the Weibull distribution shown below in Table 5. These parameter estimates result in an estimated failure probability function as shown by the grey line below in Figure 3.

Table 5: Parameter estimates – maximum likelihood estimation – Single Weibull

Coefficient	Estimate	Standard error
Scale parameter - η	218.1	10.2
Shape parameter - β	1.476	0.023

Source: Frontier Economics analysis of Jemena data

Figure 3: Maximum likelihood estimation results – Single Weibull



Source: Frontier Economics analysis of Jemena data.

We observe that the estimated function fails to capture the recent increase in failures for meters 13 years and older. This is likely due in part to a relatively small sample size of meters of these ages and perhaps an underlying failure distribution that may not closely follow a Weibull distribution.

In an attempt to improve the fit of the model to the data, we also considered a joint double Weibull distribution (akin to the illustrative example provided in the AER's practice note), whereby there are two factors that can cause a meter to fail, each following a separate Weibull distribution, albeit independently drawn and potentially with different Weibull parameters. The resulting estimates of the two underlying Weibull distributions are provided in Table 6.[3]

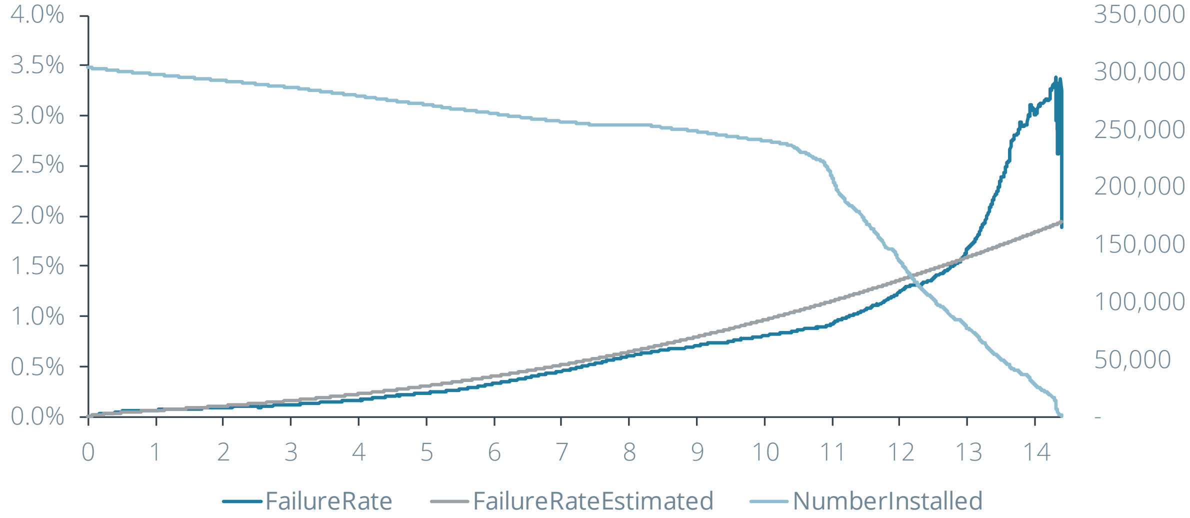
Table 6: Parameter estimates – maximum likelihood estimation – Joint Double Weibull

Coefficient	Estimate	Standard error
Scale parameter of Weibull 1 - η_1	495,343.6	n/a
Shape parameter of Weibull 1 - β_1	0.57	0.01
Scale parameter of Weibull 2 - η_2	89.7	3.4
Shape parameter of Weibull 2 - β_2	2.23	0.04

Source: Frontier Economics analysis of Jemena data.

[3] We note that the scale parameter of the first underlying Weibull distribution was not sufficiently identified, so that a standard error was not obtained.

Figure 4: Maximum likelihood estimation results – Joint double Weibull



Source: Frontier Economics analysis of Jemena data

The resulting distribution is broadly similar to the single Weibull model estimated above, and again does not reflect the observed increase in failure rates from 13 years of age.

We attempted alternative Weibull specifications, including joint triple Weibull distributions, and allowing some of the underlying distributions to commence not from zero years of age but from later on in the life of a smart meter, but were unable to yield good fits of the data, in particular failure from 13 years of age.

The inability to match observed failure rates from 13 years of age is a key concern as it is meter failure from 13 years of age that is likely to be a key driver of Jemena's smart meter replacement over the 2026-31 regulatory control period. The average age of the model 22305 smart meters is currently 11 years, so will be around 13 years in the first year of the FY2026-FY2031 regulatory control period and even higher throughout the regulatory control period. Furthermore, the empirical failure distribution suggests that failure rates will increase as the cumulative distribution function curves upwards at around 13 years.[4] Ultimately, a substantial degree of extrapolation would be required to accurately forecast the amount of failure in the upcoming regulatory control period.

Given the inability of maximum likelihood estimation of the broad class of Weibull distributions to match failure for ages 12 through 14 years, we conclude that it is inappropriate to rely on these estimated distributions. Doing so would likely significantly understate the number of replacements that Jemena is likely to need to undertake in order to both replace failed meters and ensure that it complies with its regulatory and reporting requirements for smart meters, which we discuss in more detail in section 4.

As an alternative we applied the weighted least squares method to the distribution using a double Weibull approach, weighting by the number observed for each age category.[5] We attempt this approach because the AER's practice note recommends the weighted least squares method

[4] Noting that that the estimated failure rates are somewhat volatile at around 14 years of age due to the small sample.

[5] To be specific, for each age in days x we compare the fitted cumulative distribution to the empirical distribution, square the difference and multiply by the number of meters observed to have been installed at least x days prior to the observation date. We then sum up over all days observed in the data and find the four parameter estimates to minimise the weighted squares of differences.

when dealing with small sample sizes. The results of this estimation are presented below in Table 7.

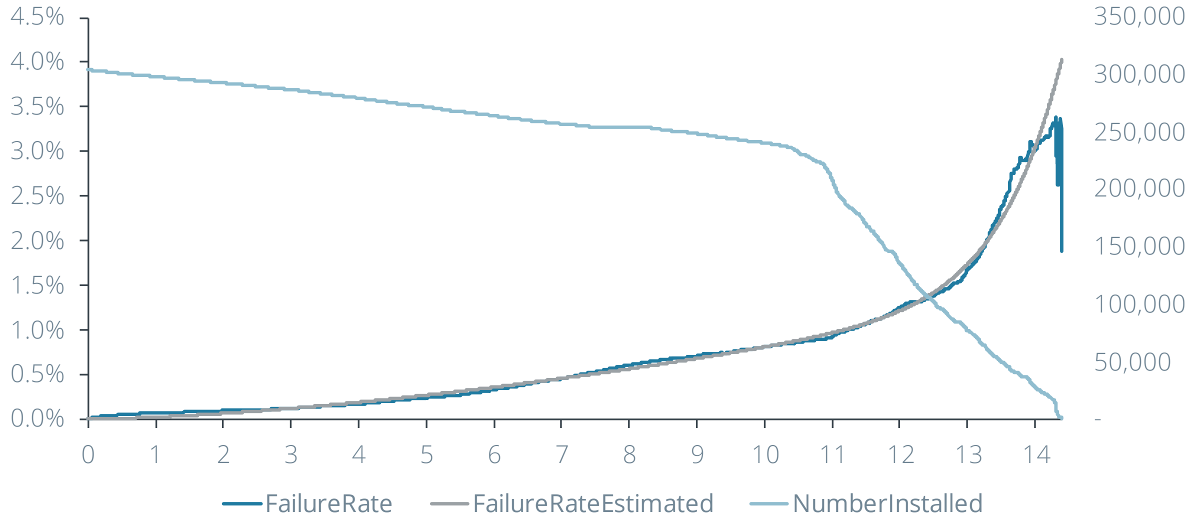
This yielded a closer match for the data, particularly at the upper end of the observed age distribution.[6] The resulting parameter estimates are provided in Table 7 and the failure distribution is shown in Figure 5.

Table 7: Parameter estimates – weighted least squares estimation – Joint Double Weibull

Coefficient	Estimate	Standard error
Scale parameter of Weibull 1 - η_1	209.36	2.15
Shape parameter of Weibull 1 - β_1	1.59	0.01
Scale parameter of Weibull 2 - η_2	18.06	0.03
Shape parameter of Weibull 2 - β_2	15.91	0.11

Source: Frontier Economics analysis of Jemena data

Figure 5: Estimation results - Weighted least squares – Double Weibull



Source: Frontier Economics analysis of Jemena data

However, the resulting failure rates were extremely high beyond the ages observed, with the oldest 36,000 of installed meters having a 100% probability of failure by June 2031. Further, over 180,000 of the 300,000 installed model 22305 meters would be forecast to fail by June 2031, well above Jemena forecasts. We do not recommend forecasting replacements on the basis of these results, which involve a substantial degree of extrapolation of a highly non-linear function, which is likely to overstate the number of required replacements.

6 Estimated parameters of (209.4,1.59,18.1 and 15.90) for $(\eta_1, \beta_1, \eta_2, \beta_2)$.

4 Extrapolation

4.1 Estimation

One alternative to estimation of parametric Weibull failure rates is simple extrapolation of the observed empirical failure rate distribution.

Using the cleaned model 22305 data, as discussed in Section 3, we derived the cumulative failure rate for each half year between, from 0.5 years to 14.0 years. We did not derive the cumulative failure rate as at 14.5 years as only 159 meters were observed that had been installed at least 14.5 years prior to the observation date in October 2024.

For each age, Table 8 below provides the size of the sample used to estimate the failure probability, the cumulative failure probability, and the probability of failure in each half-year.

Table 8: Age and failure probability distribution

Age	Sample size	Cumulative failure estimate	Estimated probability of failure during half year
0.0	304,375	0.000%	
0.5	301,195	0.054%	0.054%
1.0	298,618	0.068%	0.014%
1.5	295,734	0.078%	0.011%
2.0	292,958	0.093%	0.015%
2.5	290,070	0.099%	0.005%
3.0	287,011	0.121%	0.022%
3.5	283,380	0.145%	0.024%
4.0	279,839	0.167%	0.021%
4.5	275,690	0.205%	0.038%
5.0	272,286	0.239%	0.034%
5.5	267,925	0.270%	0.032%
6.0	264,418	0.332%	0.061%
6.5	260,477	0.389%	0.057%
7.0	257,365	0.455%	0.066%
7.5	254,281	0.529%	0.074%
8.0	254,156	0.606%	0.077%

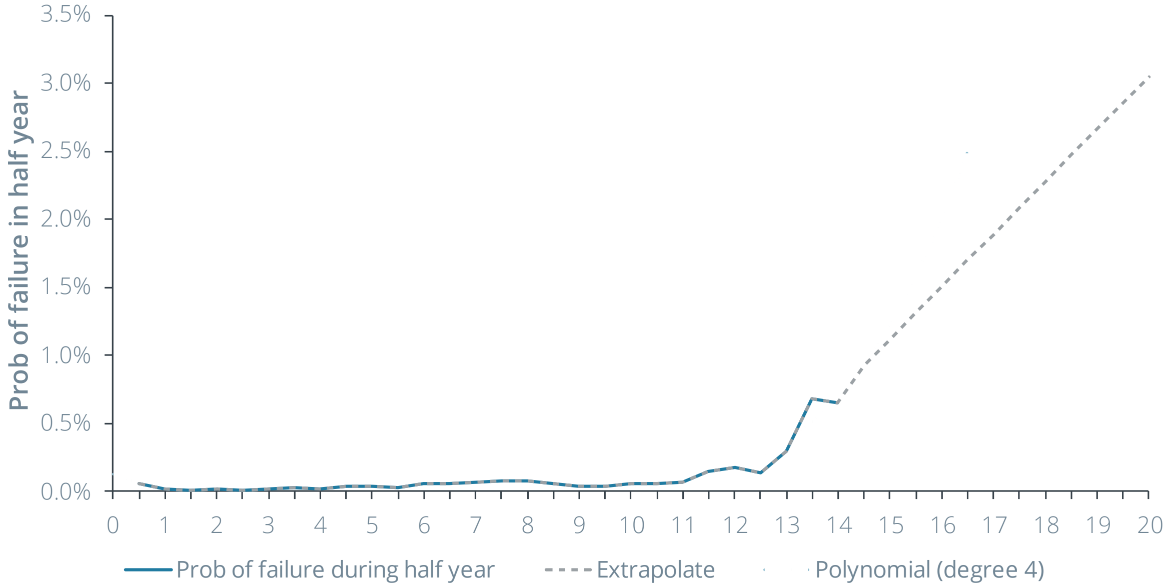
Age	Sample size	Cumulative failure estimate	Estimated probability of failure during half year
8.5	252,200	0.665%	0.059%
9.0	248,738	0.707%	0.041%
9.5	244,454	0.747%	0.041%
10.0	240,782	0.807%	0.060%
10.5	233,310	0.862%	0.055%
11.0	208,552	0.927%	0.065%
11.5	169,555	1.072%	0.145%
12.0	135,790	1.246%	0.174%
12.5	101,767	1.384%	0.138%
13.0	76,974	1.678%	0.295%
13.5	50,214	2.362%	0.683%
14.0	27,178	3.013%	0.652%

Source: Frontier Economics analysis of Jemena data.

The failure rate curve is presented in Figure 6. This figure demonstrates the increase in the failure rate from year 11 onwards. The figure also presents two fitted curves – a polynomial curve (of degree 4) fitted to the entire range and a linear extrapolation.

To obtain the linear extrapolation we applied a linear regression model to the observations from 12.5 years to 14.0 years. This resulted in a failure rate that is below the polynomial curve at all points.

Figure 6: Empirical failure distribution and extrapolation



Source: Frontier Economics analysis of Jemena data.

This failure probability distribution can then be applied to the population of meters[7] to generate expected failures of meters, by installation date.

On this basis, we find that the expected number of model 22305 meters that will fail during the FY2026-FY2031 regulatory control period is 44,432, as set out in Table 9.

Table 9: Model 22305 failures without pre-emptive removal of meters

Period	Number of failures	Proportion of installed meters
FY2027	4,990	1.61%
FY2028	6,831	2.19%
FY2029	8,871	2.84%
FY2030	10,847	3.47%
FY2031	12,893	4.12%
FY2027-FY2031	44,432	14.18%

Source: Frontier Economics analysis of Jemena data

The failure rate of the installed meters increases substantially through the regulatory control period, from 1.6% in FY2027 to 4.1% in FY2031. This rise reflects the aging population of meters and the relatively substantial increase in failure probability from 11 through to 20 years since installation; the oldest meters in the population would be 21 years old as at June 2031. Based on

[7] Both meters currently in service and meters forecast to be installed for new connections for each year through to FY2031.

the extrapolated failure distribution, approximately 34% of those oldest meters would have failed by that point.[8]

4.2 Pre-emptive replacement

We note that Jemena is subject to performance requirements for reporting set by the Victorian Department of Primary Industries.[9] In particular, Jemena is required to report all data from 99.9% of meters within 24 hours after midnight.[10] That is, if a sufficient proportion of meters have failed and have not yet been replaced, Jemena will be in violation of the meter data reporting requirement. The number of business days to replace a meter is therefore a key factor in whether Jemena will meet its regulatory reporting requirements. We note that according to the National Electricity Rules (NER) there is a 15-business day replacement timeframe, however, the relevant timeframe for replacement is 10 business days as per NER 7.8.10 (3) and the National Electricity (Victoria) Act 2005.[11]

During the last month of the regulatory control period, June 2031, we forecast that 1,110 meters will fail, compared to 313,310 meters installed, or 0.35% of installed meters. Based on a 10-business day replacement timeframe, this results in 0.177% of meters being unable to report within 24 hours after midnight.[12] That is, Jemena would be expected to violate the meter data reporting requirement.

This indicates that Jemena will need to pre-emptively replace part of its aging portfolio of model 22305 smart meters in order to satisfy the 99.9% reporting requirement.[13] If Jemena were to wait until those meters were to fail before replacing them, it would not be compliant with its regulatory obligations.

To find the number of smart meters that will, in expectation, need to be pre-emptively replaced in order to meet the reporting requirement in June 2031, we consider an upper limit on age as at the start of June 2031. Any smart meter that will be above that upper limit is pre-emptively replaced, as the failure rate of those meters will exceed that of other meters. We then find the number of meter failures during June 2031 and find the proportion that will be inactive based on the 10 business day replacement timeframe. This is compared to the 0.1% limit as per the reporting requirement.

We estimate that Jemena will need to retire any meter that is 7,050 days old (19.3 years old) as at June 2031 in order to meet the reporting requirement in expectation. This implies that Jemena would need to make 92,601 pre-emptive replacements. Note there is uncertainty around the true number of replacements required. The estimated number of replacements represents the *expected* number meters that need to be replaced pre-emptively in order for Jemena to comply with its reporting requirements. As failure is a stochastic process, there is a 50% chance that the actual number of failures could exceed expected number of failures so that the reporting requirement is violated for some or all days in June 2031. Since it is mandatory for Jemena to comply with its obligations, the consequences of replacing too few smart meters and breaching its regulatory requirements are asymmetric.

8 We note that this figure is well under 50%. The linear extrapolation becomes less reliable beyond the expected lifetime as the probability density cannot increase monotonically.

9 Department of Primary Industries, Advanced Metering Infrastructure – Minimum AMI Functionality Specification (Vicotria), September 2008.

10 See 4.1(a)(2) of Minimum AMI Functionality Specification Victoria Release 1-1.

11 See Victorian Government Gazette No. 346, 12 October 2017.

12 This can be calculated as 0.354%*(10/20), reducing the share that fail within a month by the fraction of a month that that a failure is not remedied.

13 We note that other type smart meters, which account for a small share, typically have higher failure rates.

The number of estimated pre-emptive replacements is also conservative because we have assumed a linear extrapolated failure curve. If the true failure curve is non-linear to some degree (e.g., in line with the polynomial function in Figure 6), then the number of required pre-emptive replacements in order to comply with Jemena's regulatory obligations would be understated.

The large number of required pre-emptive replacements considerably reduces the number of reactive replacements (i.e., replacements due to meter failures) to 22,841 failures over the course of the upcoming regulatory control period, or 115,442 replacements in total for the model 22305 smart meters.

As a sensitivity, we considered the impact on total replacements of alternative extrapolations. If we extrapolate the trend from 12 to 14 years instead of 12.5 to 14 years we obtain 91,533 total replacements, due to lower rate of failure (and, as a consequence, a higher pre-emptive replacement age). We note that these are the forecast required replacements of model 22305 smart meters.

Table 10: Model 22305 failures with pre-emptive removal of meters

Period	Number of failures	Proportion of installed meters
FY2027	2,136	0.69%
FY2028	3,239	1.04%
FY2029	4,555	1.46%
FY2030	5,799	1.85%
FY2031	7,113	2.27%
FY2027-FY2031	22,841	7.29%

Source: Frontier Economics analysis of Jemena data.

While the number of meters to be pre-emptively replaced is more than double the number of meters that would ordinarily have failed, we note that this level of pre-emptive replacement occurs for two reasons:

- The mandatory 99.9% reporting requirement; and
- The age distribution of Jemena's smart meters is heavily skewed towards older smart meters.

If aging smart meters are not pre-emptively replaced, we forecast that the bulk of the meters currently installed will be aged between 17 and 20 years old towards the end of the 2026-31 regulatory control period, as shown in Table 11.[14] As a consequence of the age distribution, Jemena will expect relatively high failure rates compared to a hypothetical DNSP with a more uniform distribution of smart meter ages.

[14] The age distribution of currently installed meters as at June 2031 removes meters that are forecast to fail prior to June 2031.

Table 11: Age profile of smart meters currently installed – October 2024 and June 2031

Age (years)	October 2024	June 2031
0	5,775	-
1	5,616	-
2	5,863	-
3	7,106	-
4	7,554	-
5	7,812	-
6	6,977	2,067
7	3,175	5,641
8	5,332	5,430
9	7,740	6,395
10	32,361	7,603
11	71,642	7,713
12	58,206	7,396
13	49,148	5,940
14	26,339	1,734
15	-	7,241
16	-	7,539
17	-	49,179
18	-	58,217

Source: Frontier Economics analysis of Jemena data.

The age profile of meters was not chosen by Jemena as it was compelled to rapidly rollout smart meters in the initial deployment commencing FY2011 in response to the Victorian mandate. However, the age distribution combined with the reporting requirement compel Jemena to pre-emptively replace large numbers of smart meters. We consider that this is a prudent replacement strategy, given the age profile of Jemena's smart meters and regulatory obligations that it must operate under.

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