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AUSGRID RISK QUANTIFICATION

INDEPENDENT VALIDATON REPORT

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CutlerMerz Pty Ltd
ABN 16 607 833 590
201 Sussex Street
Sydney NSW 2000 Australia
T +61 2 9006 1024
www.cutlermerz.com

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Contents

Executive Summary

Ausgrid is responding to concerns raised by the AER in its draft determination on Ausgrid's 2019-24 regulatory submission. A key part of the response is to provide clarity and to demonstrate the reasonableness of Ausgrid's risk appraisal that forms the basis for its investment benefit evaluations.

This report provides the outcomes of a validation of the risk appraisal process that was undertaken by CutlerMerz. The objective is to provide assurance regarding the main building blocks applied in the quantification of asset risk. An assessment was made of the method, inputs and parameters, and outputs associated with determining probability of failure, probability of consequence, and the value of consequence.

Overall, Ausgrid's approach is consistent with the risk quantification methods currently being used by power networks in Australia and reasonably follows the Australian Energy Regulator's Industry Practice application note[1]. Whilst the MS Excel models themselves have been recently created, the underlying methodologies being used to calculate the three components (PoF, PoC and VoC) are established and consistent with the practice used within the industry. The input data being used in the model is predominantly sourced from Ausgrid's systems and records. Where data is not available from internal systems, Ausgrid has sourced and used data from industry sources. Based on our review of the input data being used in the modelling process, we are confident that the data is reasonable and valid.

Probability of Failure (PoF)

Ausgrid forecast the probability of asset failure by applying the following statistical analysis methods:

- Weibull analysis for discrete assets, and
- A modified CROW-AMSAA for linear assets

Five to six years of historical failure data was used to determine the forecast parameters. Normalised adjustment factors were used to determine the PoF for each asset class based on asset health and failure characteristics.

We consider that the method and logic applied by Ausgrid in calculating probability of failure is consistent with industry practice and is the most appropriate method to use given the data and information available to Ausgrid at the current time.

Probability of Consequence (PoC)

Ausgrid determined the likelihood that an asset failure would result in a consequence through a two-step process. The first step was to determine an incident conversion rate (ICR). The ICR is determined from historical data on asset failures resulting in a consequence. For example, if 100 assets fail over the assessment period and one failure results in a safety consequence, the safety ICR is 1%. The second step is to determine the probability of severity (PoS) of the consequence. The PoS is aligned with Ausgrid's risk framework whereby a probability is assigned to each severity level in the consequence range based on historical asset failure consequences and asset characteristics.

A model was developed that implements the defined method for determining the ICRs using Ausgrid's incident data where available. The determination of ICRs is supported by industry data in cases where no incident data is available (e.g. LV dedicated mains). The calculated ICRs are highly dependent on the parameters applied in categorising and classifying incidents and consequences, as well as on the accuracy of the incident data recorded in Ausgrid's systems. A reasonableness test was performed by comparing the ICRs against peer network data. The purpose of the comparison was to identify any areas for further investigation. We did not identify any calculation issues in the model and outcomes.

[1] *Draft Industry Practice application note, Asset Replacement Planning*, September 2018, Australian Energy Regulator

The application of and basis for the PoS factors are consistent with industry practice and considered reasonable. The PoS factors have been determined based on an initial PoS calculated from historical incidents in each severity and adjusted to reflect Ausgrid's appetite for a similar event occurring within a defined time period for each severity level (e.g. 1 in 100 years for a severe event to 1 in 3 years for an insignificant one).

The method, technique, and input data applied by Ausgrid in determining the PoC is considered reasonable for providing a credible risk appraisal.

Value of Consequence (VoC)

VoC has been determined by valuing the highest severity level for each consequence and applying a logarithmic scale to establish values across the declining levels of consequence severity. This approach compares with that applied by peer utilities and is supported by academic research. The input data and parameters have been informed by national and international industry experience and closely implemented in the model.

The method, technique, and input data applied by Ausgrid is consistent with industry practice and provide a uniform and transparent approach to the calculation of VoC. The VoCs used by Ausgrid are therefore considered reasonable for providing a credible risk appraisal.

Ausgrid's approach to determining the PoF, PoC, and VoC applied in its risk appraisal process aligns with industry practice, relies on appropriate input data, and the outcomes are considered suitable for calculating risk.

1 Introduction

Ausgrid is responding to the AER's draft decision on its distribution determination for the 2019–24 regulatory control period. The response includes a review of Ausgrid's cost-benefit analysis method as it relates to replacement capital expenditure to provide the AER with further assurance on the analysis approach and the strength of the proposed investments.

Ausgrid evaluates the strength of its proposed investments by assessing the level of risk that the investments mitigate. The process involves an assessment of the probability of asset failure, the probability and severity of the consequence, and the value of the consequence.

This document provides the findings and outcomes of a validation performed on Ausgrid's approach to risk quantification.

1.1 Objective

The objective of the validation is to provide assurance regarding the robustness of the process, appropriateness of the input data, and the reasonableness of the outcomes for each of the main components of the asset risk appraisal.

1.2 Context

The method for determining and evaluating risk is based on the principles of ISO31000: Risk Management and considers risk in terms of the likelihood and consequence of an asset failure. The method has been developed in a series of asset class risk quantification models that support Ausgrid's risk-based decision making and informs its replacement investment requirements and prioritisation. A total of 19 models have been developed covering key asset classes and sub-asset classes as applicable.

Ausgrid identified some areas where additional support was required so that the analysis could be appropriately calibrated. CutlerMerz were able to provide support to improve the robustness of Ausgrid's CBA modelling.

1.3 Validation Approach

The validation approach is structured to systematically assess the method, inputs and parameters, and outputs of Ausgrid's risk quantification process to determine its appropriateness for use in appraising benefits from the proposed investment.

The validation followed a three-step process:

1. Review:

   A review of the model template was undertaken in conjunction with key Ausgrid personnel to develop an understanding of the framework of the model, the key inputs and assumptions, the calculation methods, and the outputs.

2. Validate:

   The validation focused on the three key areas of risk quantification: probability of asset failure, likelihood of consequence, and the cost of consequence. Its aim was to assess the appropriateness of the:
   - Method and logic that was applied
   - Data sources and parameters
   - Modelled approach and parameters
   - Modelled outputs

   The findings for each key area are summarised in an overall assessment of the appropriateness of the approach and outcomes for delivering credible risk quantification outcomes.

Where possible, the outcomes have been assessed against relevant industry experience to evaluate the reasonableness.

3. Report:

   This report documents the findings of the validation.

2 Probability of Failure (PoF)

2.1 Method and logic validation

Probability of failure is the probability that an asset will experience a failure each year. Ausgrid used statistical approaches to forecast the probability of failure for each asset based on the current asset base and recent historical failure data.

Ausgrid has applied one of two correlation analysis methods depending on the type of asset:

- Weibull analysis for discrete assets (such as poles, switches), and
- A modified CROW-AMSA analysis for linear assets (such as overhead mains and underground cables), consistent with modern methods.

Each of these methods generates a probability of failure that depends on time, which can be generalised as asset age.

The use of the Weibull distribution and CROW-AMSAA is well established for forecasting asset failures. There is substantial literature supporting the use of these two approaches for electricity distribution network assets[2].

For each asset class, both an upper bound and a lower bound PoF function are calculated. A customised PoF is then determined for each asset based on several PoF adjustment factors. Up to five PoF adjustment factors are identified that affect the failure rate of an asset. These are used to determine the unique PoF for the asset within the lower and upper PoF range.

2.1.1 Weibull parameter estimation

The Weibull function has two parameters that require estimation, β and η. These parameters determine the characteristics of the Weibull distribution and therefore the PoF of the asset at any particular age. The Weibull function used in the modelling is:

$$\rho_n = \frac{\beta}{\eta}\left(\frac{T_n}{\eta}\right)^{\beta-1}$$

Ausgrid has estimated these parameters using the Median Rank method and Simple Linear Regression. Six years of historical data are used for each asset class modelled with Weibull. Both methods are documented and researched[3] for determining the parameters of the Weibull distribution from historical data.

The failures included in the Weibull estimation were filtered for their relevance, but in general all conditional and functional failures have been used.

2.1.2 CROW-AMSAA parameter estimation

The CROW-AMSAA function has two parameters that require estimation, β and λ. As with the Weibull distribution, these parameters determine the characteristics of the CROW-AMSAA distribution and therefore the PoF of the asset at any particular age. The CROW-AMSAA function used in the modelling is:

$$\rho_n = \lambda\beta {T_n}^{\beta-1}$$

Ausgrid estimated β using a linear regression approach. The log of asset age or time was regressed on the log of cumulative defects per kilometre using six years (five years for Consac/HDPE and LV Dedicated mains) of failure data.

[2] Refer to Ausgrid's methodology document for relevant reference material.
[3] ibid

From the regression, β is the regression coefficient on the log of cumulative defects. The λ is a scale parameter that is derived from the intercept term in the regression as $e^{intercept}$.

2.1.3 PoF upper and lower bounds

The approaches for calculating the parameters above are statistical in nature. This allows the calculation of upper and lower bounds for what the 'true' parameters are.

Ausgrid used the 95% confidence upper and lower values for the β parameters to generate the upper and lower bounds of the PoF functions. In the Weibull approach, η is a function of the β parameter so both parameters have an upper and a lower bound value. In the CROW-AMSAA approach only the β parameter changes.

2.1.4 PoF adjustment factors

Adjustment factors are applied to shift the PoF between the upper and lower bounds. The adjustment factors are characteristics of the individual assets that are known to change the likelihood of a failure. The adjustment factor is used to determine the specific PoF within the upper and lower bounds. To ensure that the adjustment factors do not shift the overall asset class PoF from the mid-point of the upper and lower bound, the adjustment factors are normalised to ensure that the distribution is symmetrical.

The models allow a maximum of 5 adjustment factors each with its own associated weighting. Adjustment factors are given a value from 1 to 5 based on their influence on the PoF. This approach results in a maximum possible of 3,125 (5^5) different combinations of score outcomes if all five adjustment factors are used and given a different weighting.

Adjusting the PoF to account for known asset characteristics that affect the asset's PoF is likely to result in more accurate modelling of the asset base as characteristics beyond the age of the asset can be taken into account. The adjustment approach is considered reasonable as it does not result in the overall asset class mean PoF changing, but elevates and depresses the PoF of individual assets between the upper and lower bounds within the asset class.

2.1.5 PoF normalisation

The effect of the PoF adjustment factors can result in an increase or decrease in the expected number of failures. The historic failure data used to calculate the PoF functions can also result in an initial step change in the number of expected failures in the first year of the model.

The PoF functions are normalised to account for these changes and ensure that the model forecasts the correct number of failures.

The η parameter of the Weibull and λ parameter of the CROW-AMSAA are adjusted to ensure that the expected number of failures in FY19 is equal to the average number of failures over the preceding six years (five years for Consac/HDPE and Dedicated mains). This approach is similar to that used by the AER in the Calibrated Lives scenario of the Repex Model.

Both the η and λ parameters are 'scale' parameters and act to shift the function up or down while retaining the shape, which is β.

The method and logic applied by Ausgrid in calculating probability of failure is aligned with industry practice and is likely to result in a reasonable determination of the probability of failure of an asset.

2.2 Data source and parameter validation

Datasets used by Ausgrid include:

- Current asset base from Ausgrid's corporate EAM system SAP and GIS

- Failure data for previous five to six years from Ausgrid's corporate EAM system SAP.

For each asset class the failure data was filtered to remove failures that were not relevant to informing the model.

Failure modes that do not contribute to functional asset failures were removed from the data.

The data applied in calculating probability of failure is consistent with data applied in other areas of the risk appraisal and provides for uniformity in the quantification process.

The approach of filtering the failure data is consistent with industry practices and considered appropriate.

The input data and parameters are generally aligned with industry practices and considered appropriate for providing credible risk appraisal outcomes.

2.3 Model logic validation

The probability of failure is used in the models to calculate the total number of expected asset failures. Each expected failure is associated with a level of realised risk that is aggregated to calculate total risk.

The probabilistic nature of the model results in no particular asset failing with certainty. The probability of failure, rather, represents the likelihood of an asset failure that can be expected to be realised in a given year. This approach is mathematically sound and reasonable.

The logic underlying how probability of failure is used in the models is reasonable.

2.4 Model parameter validation

The parameters were generated using empirical data and an appropriate technique. However, despite this approach it is still possible to generate parameters that are not reasonable estimates of the true population parameters.

2.4.1 Weibull

The Weibull distribution is made up of two parameters. The first is β, which determines the shape of the PoF curve. The β parameter follows the rules:

- $\beta<1$, PoF decreases with time/age
- $1<\beta<2$, PoF increases with time/age at a decreasing rate (logarithmic like PoF curve)
- $\beta=2$, PoF increases linearly with time/age (straight line PoF curve)
- $\beta>2$, PoF increases exponentially with time/age

Of the above values for β, it is expected that the true population β is greater than 2. This is because assets tend to fail more as their condition worsens, which can be approximated by the passage of time, or asset age.

The η parameter determines the characteristic age of failure. The Weibull distribution will always result in 63.2% of assets failing by age η. The mean life of the assets is also dependent on the shape of the distribution so is a function of η and β. The mean life has been calculated in Table 2 below.

Table 1 below shows the parameters of the Weibull distributions that were generated by Ausgrid.

Table 1: Weibull Parameters (average)

Model Asset Category	RIN Asset Group/s	β	η
High Voltage CBD Isolator and Earth Switches	Switchgear	2.76	89
Circuit Breakers (excludes switchboards):	Switchgear		
Sub-transmission		1.50	20
High Voltage		1.92	32
Low Voltage		2.26	45
High Voltage Fuse Switches	Switchgear	2.38	68
Sub-transmission Isolator and Earth Switches	Switchgear	1.79	50
CBD Distribution Transformers:	Transformers		
Chamber transformers		3.06	57
Underground transformers		4.70	54
High Voltage Drop-out Fuses	Switchgear	1.68	51
Sub-transmission Towers	Poles	14.28	62
High Voltage Underground to Overhead Connection	Poles, Underground Cables	1.90	79
Poles*	Poles	4.17	70
Low Voltage Overhead Service Lines	Service Lines	2.83	102
High Voltage Air Break Switches	Switchgear	1.75	32
Major Transformers	Transformers	3.78	86
Pole Top Substations	Overhead Conductors, Poles, Switchgear, Transformers	4.17	70
Distribution Substations (Kiosks and Chambers)	Switchgear, Transformers, Underground Cables		
Outdoor enclosures (excluding transformer & switchgear)		3.78	41
Kiosks (excluding transformer & switchgear)		1.80	37
Outdoor enclosure transformer		3.67	57
Kiosk transformer		2.85	66

*** Replacement modelling only, does not include staking**

Seven of the asset categories have β<2. This may indicate that the empirical data used to generate the Weibull parameters is biased and not reflective of the true population failure rates.

Some of the asset categories are known to have been impacted by early life failures due to manufacturing defects present in some manufacturer/model combinations. This would contribute to values for β of less than 2.

Table 2 shows the calculated mean life for each asset category and the approximate mean life used in two scenarios of the AER's Repex model.

Table 2: Weibull Implied Mean Life Comparison

Model Asset Category	Implied Mean Life (years)	AER Repex Mean Life* (Historical)	AER Repex Mean Life* (Calibrated)	RAB Life
High Voltage CBD Isolator and Earth Switches	79	65	65	47
Circuit Breakers (excludes switchboards)	28	68	68	47
High Voltage Fuse Switches	58	62	62	47
Sub-transmission Isolator and Earth Switches	44	41	41	47
CBD Distribution Transformers	59	61	63	46
High Voltage Drop-out Fuses	45	62	62	47
Sub-transmission Towers	57	49	49	55
High Voltage Underground to Overhead Connection	70	75	81	58
Poles#	63	66	75	52
Low Voltage Overhead Service Lines	91	71	71	52
High Voltage Air Break Switches	10	67	67	47
Major Transformers	~	~	~	46
Pole Top Substations	~	~	~	52
Distribution Substations (Kiosks and Chambers)	~	~	~	46

***Approximated asset categories**
 # Replacement modelling only, does not include staking
~ Not possible to calculate

Due to the differences in asset categories between the Ausgrid models and the AER Repex model, only high-level consideration can be given to the comparison; however, from the analysis, a few outlier results are observed, notably circuit breakers and high voltage air break switches.

The differences are in themselves not considered a significant issue due to the model aligning the first-year modelled failures with the historical average. It is noteworthy that the two asset classes that differ materially tend to be those asset classes where the repair versus replace ratio is relatively high. Given the mechanical nature of circuit breakers and high voltage air break switches, repairable failures tend to be more frequent than failures requiring complete asset replacement. As these failure types are included in the calculation of the PoF (not just failures that result in asset replacement), it is not necessarily unreasonable that the calculated mean life (which includes repairable failures) is lower than the AER mean life, which represents the asset replacement age (as does, to an extent, the RAB life).

2.4.2 CROW-AMSAA

The CROW-AMSAA failure function is made up of two parameters. The first is β, which determines the shape of the PoF curve. The β follows the same rules as the β in the Weibull approach:

- $\beta<1$, PoF decreases with time/age.
- $1<\beta<2$, PoF increases with time/age at a decreasing rate (logarithmic like PoF curve)
- $\beta=2$, PoF increases linearly with time/age (straight line PoF curve)
- B>2, PoF increases exponentially with time/age.

The second parameter, λ, is the scale parameter and shifts the PoF curve up and down.

Table 3 shows the parameters of the CROW-AMSAA formula for the asset classes where this approach was used.

Table 3: CROW-AMSAA Parameters

Model Asset Category	RIN Asset Group	β	λ
Low Voltage CONSAC / HDPE	Underground Cables	3.11	7.72E-06
Low Voltage Underground Reactive	Underground Cables	2.09	3.00E-04
High Voltage Underground Reactive	Underground Cables	1.98	6.73E-04
High Voltage Overhead Lines	Overhead Conductors	3.67	9.88E-07
Low Voltage Dedicated Mains	Overhead Conductors	1.22	5.69E-02

Two asset categories using the CROW-AMSAA approach have β<2. The HV Cables β is close enough to 2 to be effectively linear. The β on Dedicated Low Voltage Dedicated Mains is very low and indicates that all assets have a close to random failure characteristic with very old assets having a marginally higher probability of failure. Given the specific details of this asset class the result is not unreasonable.

The majority of the PoF parameters used by the model are within expected ranges. Some values were identified that were not consistent with our expectation; however, the approach of normalising first-year failures is expected to reduce the impact of these anomalies.

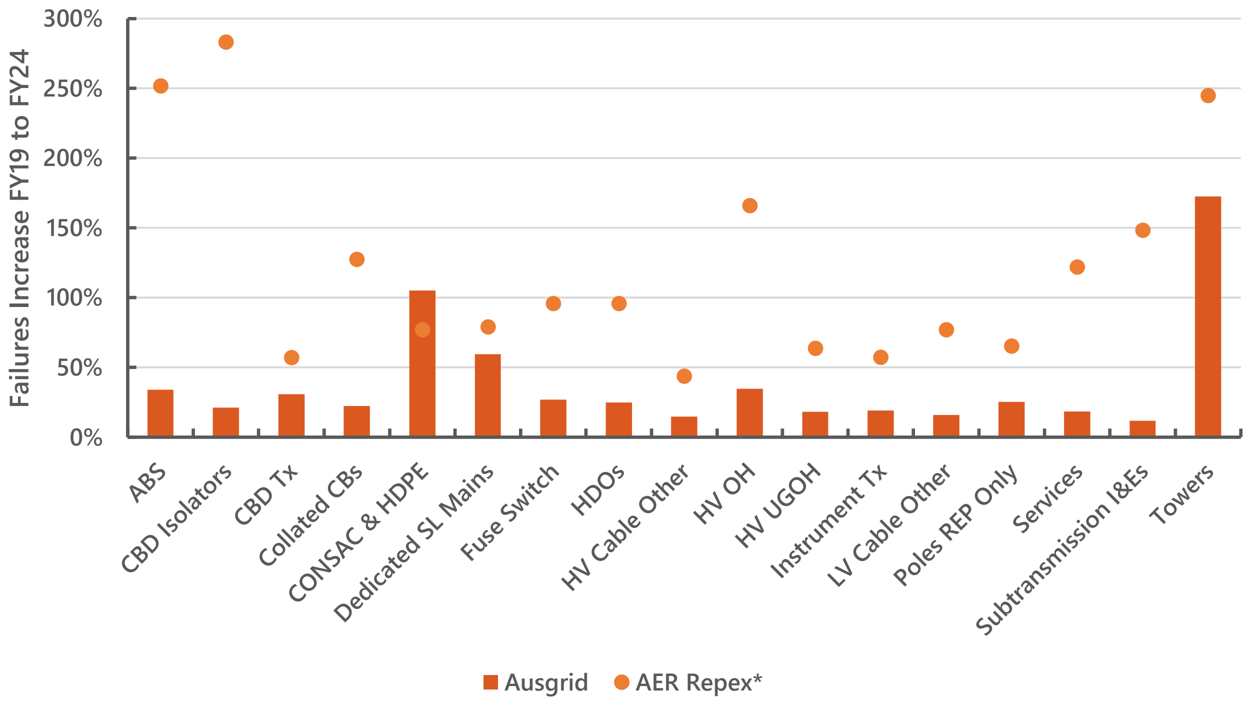
2.5 Model output validation

As the PoF model is normalised to always start with the historical failure rate, the FY19 modelled outcomes are considered reasonable. There is some risk of bias due to the historical data not reflecting changes in the condition of the assets and/or the possibility of an unusually high or low level of failures during the time period used; however, this approach aligns to that used elsewhere in the industry, most notably in the AER Repex model calibrated scenario. Therefore, we consider that the initial modelled PoF is not unreasonable.

To validate the outcomes of the PoF model over time, we have considered the equivalent results that can be derived from the AER Repex model using the Calibrated scenario. The chart below shows the change in the number of failures between FY19 and FY24 using both the Ausgrid modelled outcomes and the AER Repex model[4].

[4] FY24 failures / FY19 failures - 1

Figure 1 – Growth in Modelled Failures Over Time



***Approximate asset class matches used. The AER Repex model uses different asset categories that do not exactly align to the asset categories used in the Ausgrid modelling.**

AER Repex model equivalent values were estimated by adding six years to the age of every asset and using the first-year replacement volumes result.

Across all asset classes with the exception of CONSAC & HDPE, Ausgrid's model results in a lower number of failures (or replacements) than that predicted by the AER Repex model. As much broader asset categories are used for the AER Repex model, it is reasonable to expect that if other LV cables were removed and CONSAC & HDPE modelled separately, the AER Repex model would produce a higher value for this asset category.

The Towers asset class is a notable outlier against the other asset classes, both from the AER Repex outcome and Ausgrid's model. The modelled result for Towers is due to a very high β of 14.28 being applied which causes a higher increase in failures for each additional year of age. As the data used in the model has been based on actual data available from Ausgrid's systems, the result is not considered unreasonable. Furthermore, it is noted that all but a very small percentage of towers are repaired rather than replaced and therefore the result is likely to indicate that tower refurbishment is likely to be required going forward, as opposed to tower replacement.

3 Probability of Consequence (PoC)

Where PoF represent the probability of an asset failing, PoC represents the probability that an asset failure converts into a consequence of particular severity.

3.1 Method and logic validation

Probability of consequence is the predicted likelihood that an asset incident will result in a consequence type and severity. Ausgrid determined the PoC through the method of calculating Incident Conversion Rates for each asset class and consequence, and multiplying it by the probability of severity.

$$PoC = incident\ conversion\ rate\ \times probability\ of\ severity$$

PoCs have been calculated for six main risk categories: worker safety, public safety, environment, fire, loss of supply and financial. For loss of supply risk and financial consequences, the PoC is embedded in the value of consequence calculation and is based on historic data of the number of failures resulting in unserved energy and the number of failures requiring replacement as opposed to repair.

Incident Conversion Rate (ICR)

ICR is the ratio of the number of asset incidents attributed to a consequence type as a fraction of the total number of incidents within an asset class.

$$ICR = \frac{n_{incidents\ attributed\ to\ consequence}}{n_{incidents,assetclass}}$$

Where the dataset contains incidents reported over a period of more than one year, the ICR is divided by the total years in the period to achieve an annualised percentage.

The ICRs applied by Ausgrid have been calculated based on asset functional failures and the number of these failures that converted into a consequence type related to each of the main risk areas. To maintain consistency with the PoF calculation, assets where the data indicated that the asset condition required urgent repair or replacement and that had not been actioned at the time of the data extract were included in the denominator. This approach would act to suppress the ICR value and is considered conservative. The risk areas and associated consequence types included in the assessment are provided in Table 4.

Table 4: Risk consequence types

Risk area	Consequence type
Worker safety	Electric shock, Physical impact
Public safety	Electric shock, Physical impact
Environment	Oil spills and leaks, Noise, Flora and fauna impacts
Fire	Fire incidents caused by network assets

Probability of Severity (PoS)

For each of the risk areas, five severity levels have been used that align with Ausgrid's corporate risk framework: insignificant, minor, moderate, major, and severe. For each severity level, a probability of occurrence (severity) is applied based on the potential of an incident converting into that level of consequence severity. The initial PoS is calculated based on historical incidents in each severity and adjusted considering known incidents within the industry. The method used to adjust the PoS value enables a reasonableness test to be applied through consideration of the years until the next event of each consequence severity. Table 5 provides an example of typical PoS factors applied for each of the main risk areas for one of the asset classes, and the associated expected number of years until the next event.

Table 5: Typical PoS factors

Severity	Worker and Public Safety		Environment		Fire	
	Probability of Severity (PoS)	Years until event	Probability of Severity (PoS)	Years until event	Probability of Severity (PoS)	Years until event
Severe	0.009	229.5	-	-	-	-
Major	0.050	41.3	0.001	2,065.7	0.001	1,652.5
Moderate	0.150	13.8	0.150	13.8	0.050	33.1
Minor	0.300	6.9	0.300	6.9	0.100	16.5
Insignificant	0.5	4.2	0.549	3.8	0.8	1.9

PoC Adjustment

To differentiate between PoCs associated with different types of assets within an asset class, PoC adjustment factors have been applied. These factors provide a weighting within an asset class based on asset characteristics. For example, oil-filled circuit breakers are allocated a higher PoC weighting than air-insulated circuit breakers in the worker safety and environmental risk areas.

The PoC adjustment factors were reviewed and are considered reasonable.

3.2 Data source and parameter validation

Datasets were provided by Ausgrid and addressed the risk areas of worker safety, public safety, environmental incidents and fires. In order for data sources to be validated for use within the PoC analysis, the following was assessed:

- Worker Safety dataset based on internal employee recorded incidents
- Public Safety dataset based on call centre incident records
- Environmental dataset based on worker recorded incidents
- Fire dataset based on worker recorded incidents

Data cleansing was undertaken to identify and remove incident categorisation and duplication anomalies. This process involved an automated cleansing followed by a manual review and verification by Ausgrid subject matter experts.

Assets with conditional failures that remain unrectified have been included in the ICR calculations to account for the risk associated with these failures and maintains consistency between the datasets used to calculate the ICRs and the probability of failure.

Significant near misses were included within the incident count. This is not considered unreasonable.

3.3 Model validation

The ICR calculation model has been developed to implement the proposed method and logic. Incidents in each of the risk areas were categorised by the relevant asset class and consequence.

The following criteria were applied in the categorisation of incidents:

- Worker Safety incidents caused by network asset failures that led to electric shocks or physical impacts to Ausgrid network workers/contractors
- Public Safety incidents caused by network asset failures that led to electric shocks or physical impacts to public safety
- Environmental incidents caused by network asset failures that led to oil spills or leaks, noise in excess of allowable levels or impacts to flora and fauna.

  More specifically:

  - Oil spills caused by a failed transformer, part thereof or other switchgear not performing in its intended operation. The failure would need to have resulted in Ausgrid responding with action to carry out either a transformer/part replacement or maintenance work to rectify the leak
  - Noise incidents attributed to an asset, mainly transformers requiring replacement or maintenance, where noise assessments had measured that the noise exceeded acceptable levels
  - Oil leaks from installed cables
  - Where Ausgrid assets have failed and caused a direct impact to flora and fauna. Flora and fauna present either in, on, or near equipment that are impacted were not considered as incidents.
- Fire incidents caused by network asset failures. These include incidents where the fire spreads beyond the network (escaped) and fires that are confined to the network (confined).
- Incidents that were not considered in the ICR calculations:
  - Incidents in which network assets had not failed or failed but were rectified without any safety impacts to workers, the general public, the environment or fire event
  - Impacts to worker safety, public safety, environment or fire events resulting from equipment during transportation or from vehicles/scissor lifts/ EWPs
  - Noise complaints due to scheduled and unavoidable nightworks
  - Fires events from existing grass fires, lightning strikes or vehicles.

3.4 Model parameter validation

The following parameters were used in the classification of incident types. It has been assumed that these are caused by Ausgrid asset failures and require replacement or maintenance as a part of rectification works:

- Worker Safety incidents, further classified by:
  - Electric shocks of any severity that affect Ausgrid network workers/contractors are assumed to be an impact to worker safety
  - Physical impacts of any severity that affect Ausgrid persons (injury other than electric shocks) or property are assumed to be a physical impact to worker safety.
- Public Safety incidents, further classified by:
  - Electric Shocks of any severity that affect public persons are assumed to be an impact to worker safety

- Physical impacts of any severity that affect public persons (injury other than electric shocks) or public property are assumed to be a physical impact to worker safety.

- Environmental incidents, further classified by:
  - Oil leaks or spills of any quantity from Ausgrid assets (e.g. pole transformers, substations, cables) are assumed as an environmental impact
  - Noise impacts are assumed to be caused by failed transformers or transformers requiring maintenance
  - Other impacts are assumed to include SF6 leaks.
- Fire incident assumptions include:
  - That they are either contained within the asset or escaped from the asset
  - Incidents with unclear descriptions related to pole fires are assumed to be contained within the asset
  - Incidents with unclear descriptions related to grass fires due to Ausgrid assets are assumed to be escaped from the asset.

3.5 Model output validation

An assessment between the ICRs established using empirical data and the ICRs applied in the risk quantification models was performed. Minor variances between the ICRs were identified. These related mostly to differences in data cleansing criteria and minor data errors. Where insufficient data was available, incident data has been based on similar assets and industry average data where available. It is not appropriate to directly compare one distribution network's ICR against another as all networks have unique characteristics that have the potential to make the results of the comparison misleading. Notwithstanding the limitations of a direct comparison, we did compare Ausgrid's ICRs to ICR data we have on other Australian distribution networks to assess the reasonableness of the modelled ICR outcomes and to identify areas of potential further investigation.

Comparable data was not available for all the asset classes and risk categories identified by Ausgrid. Where comparisons were possible, these have been considered representative of the overall reasonableness of Ausgrid's ICRs. The outcomes of this reasonableness test are provided in the figures below. The comparison revealed that Ausgrid's modelled ICRs generally fall within or below the industry range for worker, public and fire safety. The worker and public safety conversion rates shown in Figure 2 and Figure 3 include both electric shock and physical impact incidents to allow for a comparison with industry data. Fire conversion rates shown in

Figure 4 includes both contained and escaped fire for comparison against industry data. Insufficient industry data was available to perform a comparison on environmental incident conversion rates.

Figure 2 – Worker safety ICR comparison (includes electric shock and physical impact)

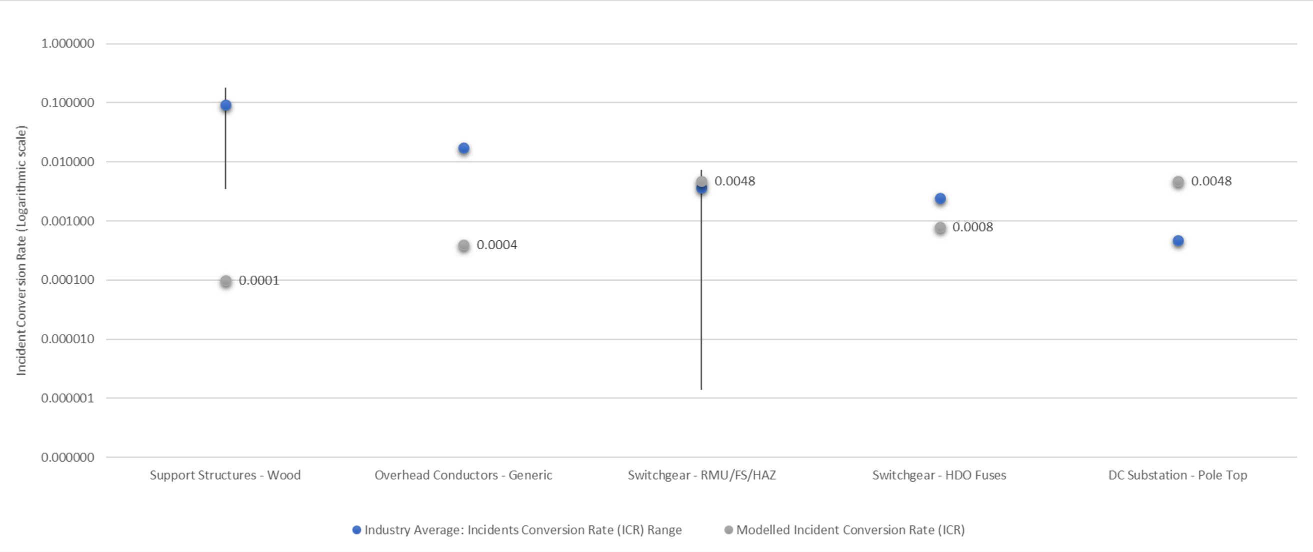


Figure 3 – Public Safety ICR comparison (includes electric shock and physical impact)

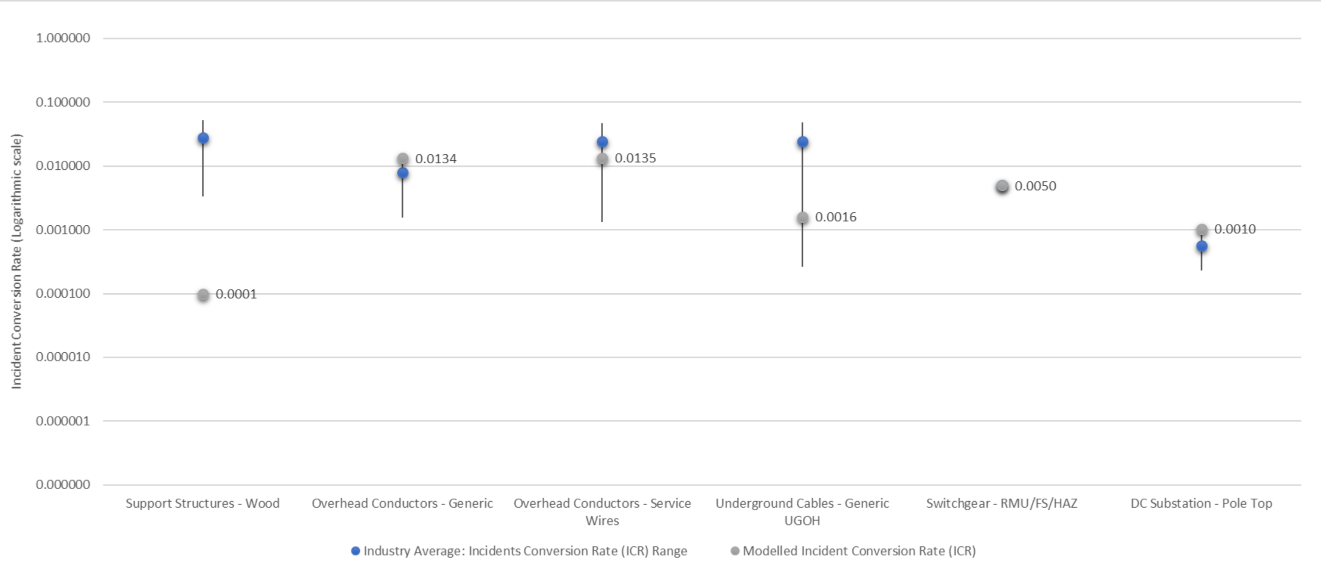
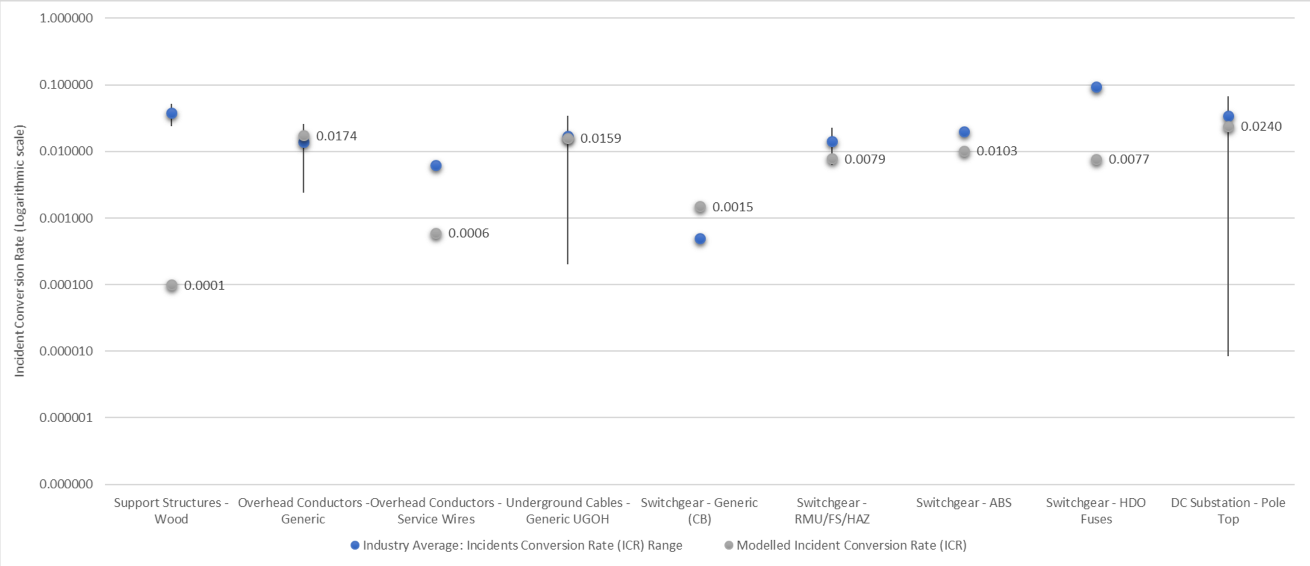


Figure 4 – Fire ICR comparison (includes contained and escaped fires)



3.6 PoC Validation

The validation of the PoCs applied in the quantification of risk in the Ausgrid network is summarised as follows for each of the key areas considered:

Method and logic

- Applying a combination of incident conversion rates, probability of severity and a weighted adjustment based on asset characteristics is a reasonable approach for calculating PoC. The PoC for worker safety, public safety, environmental and fire were able to be quantified through this method.

Data sources and parameters

- The accuracy of the ICR and subsequent PoC calculation approach is highly dependent on the categorisation and classification of incidents and consequences across asset classes and the reliability of incident data. A reasonableness test of the calculated ICRs against industry data did not identify significant systemic calculation issues and Ausgrid's values appear reasonable.

- The application of and basis for PoS factors applied in the PoC calculations are not considered inappropriate for achieving credible outcomes.

Modelled approach and parameters

- The ICR models implement the approach and parameters and the input data has been based on incident records captured in Ausgrid's network over the past six years, strengthened with industry data where appropriate.

PoC outputs

- The approach, parameters and input data applied in determining the PoCs are likely to result in a reasonable determination of the probability of an incident in Ausgrid's network converting into a worker safety, public safety, fire, and/or environmental consequence.

- The calculated PoCs are therefore considered reasonable for providing a credible risk quantification.

4 Value of Consequence (VoC)

The VoC is used to determine an economic cost of consequence from network events.

4.1 Method and logic validation

The approach to determining the economic value of consequence involves valuing the highest severity level for each consequence and applying a logarithmic scale to establish values across the declining levels of consequence severity. This approach is supported by academic research (Duijm, 2015; Prem, Ng et al., 2010; Levine, 2012) and the European Railway Agency's approach (European Railway Agency, 2008) and is consistent with the practice of comparable electricity utilities within Australia.

Ausgrid eliminates safety risk so far as is reasonably practicable (SFAIRP) and where it is not reasonably practicable to eliminate risk, risk is reduced as low as reasonably practicable (ALARP). Ausgrid defines ALARP as that point where the cost of further mitigation is grossly disproportionate to the value of the risk being mitigated. This approach is consistent with the requirements of *AS5577 Electricity Networks Safety Management System*.

Disproportionality factors (DFs) have been established for each severity level based on ranges proposed by the United Kingdom's Health and Safety Executive.

The VoCs for safety, environment, and fire applied in the risk quantification are provided in Table 6 along with the safety DFs.

Table 6: Safety, Environment, Fire: Value of Consequence and Safety Disproportionality Factors

Severity	Worker and Public Safety	Environment	Fire	Safety Risk Disproportionality Factor
Severe	$4,469,292	$10,193,119	$66,000,000	x 10
Major	$446,929	$4,558,501	$6,600,000	x 8
Moderate	$44,693	$1,019,312	$660,000	x 6
Minor	$4,469	$101,931	$66,000	x 4
Insignificant	$447	$10,193	$6,600	x 2

VoCs for loss of supply are based on the value customers place on supply reliability and is calculated as the cost of unserved energy. The cost of unserved energy has been based on the value of customer reliability (VCR).

$$Loss\ of\ Supply\ VoC\ (\$) = \ Average\ load\ lost\ (MW) \times \ Average\ restoration\ time\ (h) \times VCR(\$/MWh)$$

The VoCs for financial costs associated with asset failures considers both capital and operational costs. The VoCs include for a proportion of asset replacement costs, typically less than 10%, with the remainder repair costs. Repair costs have been based on historical costs and asset repair versus asset replacement ratios. Costs associated with a reactive response to the incidents have been included.

Operational costs (and reduced costs due to asset replacement) are included as the cost difference between current planned maintenance expenditure and projected planned maintenance expenditure following investment. Repair costs are calculated separately and based on the percentage of assets repaired using the historical average cost for repair.

4.2 Data source and parameter validation

Public and Worker Safety

The costs associated with safety consequences have been based on the value of statistical life (VSL) that represents the willingness to pay for a reduction in the risk of physical harm. A guidance note published by the Australian Government in 2014 estimated the value of a statistical life at $4.2 million based on international and Australian research. This value was used in setting the value of a severe safety consequence.

The community cost for the major severity level was set at 10% of VSL as determined by applying the disability weighting of the average of long-term injuries, amputations and fractures from the Australian Institute of Health and Welfare (Mathers et al 1999, pp. 202) to the VSL. The severity levels less than major followed a logarithmic scale based on the highest severity.

Ausgrid's basis for and evaluation of safety cost of consequence is considered reasonable.

Safety Disproportionality Factor

Disproportionate Factors (DFs) represent an organisations appetite to spend more than the value of the safety risk avoided to reduce the risk. It is common practice to apply DFs as a means of demonstrating what is reasonably practicable for the management of safety risk. Consistent with the practice of other Australian electricity network businesses, Ausgrid followed guidance from the Health and Safety Executive (UK) that a DF between 2 and 10 can be used. Higher values are used for situations where extensive harm is possible if the risk event were to occur. The DFs applied by Ausgrid in the quantification of risk are provided in Table 6.

Ausgrid's basis for and application of DFs is consistent with industry practice and is considered reasonable.

Environmental

Ausgrid's VoCs for environmental impacts have been based on the cost to undertake environmental clean-up and associated potential fines taking into consideration relevant legislation and previous environmental breaches. The quantification process is described in the Risk Quantification[5] document and considers Tier Two offences under the Protection of the Environment Operations Act (POEO Act) covering the areas of air, noise, water and land pollution. A value of $10.19 million was determined for a severe consequence based on the worst oil leak rate experienced in the last five years, the associated cost of ground water impact, the offence cost.

The cost for the major severity level was set at 45% of the highest severity as determined applying Ausgrid's corporate risk matrix and subsequent severity levels were established using a logarithmic scale.

Fire

Ausgrid has applied the economic cost for fire that was calculated by CutlerMerz for another NSW network business. The valuation was developed from comprehensive research conducted into establishing the value of a catastrophic bushfire in NSW.

Reports prepared for NSW DNSPs for insurance purposes investigated the major differences between states with respect to bushfire risk. The conclusions from the investigation and modelling was that NSW had a significantly lower risk of catastrophic bushfires than Victoria. Key findings from the investigation were:

- NSW did not have any extreme bushfire potential zones whereas Victoria, Tasmania and Western Australia did

[5] Risk Quantification, Document No D19/794

- The regular occurrences of meteorological conditions that are conducive to fire starts on extreme bushfire prone days occurred in Victoria but not in NSW. When combining both factors, Victoria is exposed to "Extreme" bushfire risks which are not present in NSW
- “Extreme” bushfire potential zones have 3-5 times greater frequency of house damage than a “Very High” zone
- 30% of all historical bushfire losses are in “Extreme” bushfire potential zones
- 90% of properties destroyed are within 100 metres of bushland. Victoria has over 9,500 houses within 100 metres of bushland in an “Extreme” bushfire potential zone, whereas NSW has none
- Loss-causing bushfires have a similar frequency in Victoria and NSW at approximately 1 in 3 years. However, Victoria has a greater magnitude of bushfire losses and severe fire days than NSW
- Victoria has experienced the greatest percentage of bushfire related building damage over the last 110 years

Fire consequence modelling using the Phoenix RapidFire model developed by the University of Melbourne and carried out by Professor Tolhurst delivered results broadly consistent with the above observations.

The valuation of the economic costs associated with 2009 Victorian bushfires estimated the cost at $4,369 million ($4.4b in 2009 dollars) with the average cost for each fire that broke out in the order of $330 million. A Regulatory Impact Statement (RIS) associated with proposed policy changes in Victoria following the 2009 fires investigated a range of data and information and found that the average cost per fire over $10 million was in the order of $300 million.

Combining the analysis following the 2009 Victorian fires with the NSW investigations into bushfire risk, it is expected that, on average, a catastrophic fire in NSW is likely to cost between $66 million and $110 million (using the value of $330 million for extreme zones and moderating by 3 to 5 times based on the frequency of damage between extreme (Victoria) and very high (NSW) bushfire zones).

The cost of a major bushfire was set at 10% of the value of a severe fire reflecting findings from the VBRC/RIS with the remaining consequence levels determined through the application of the logarithmic scale.

Loss of Supply

Ausgrid applied the Value of Customer Reliability (VCR) to establish the cost of a loss of supply. The VCR values have been based on AEMO’s 2014 VCR report[6]. The VCR used by Ausgrid for urban and rural type customers compares with AEMOs state-wide VCR for NSW and the VCR for CBD compares with AEMO’s VCR for large commercial businesses as shown in Table 7.

Using VCR in the calculation of loss of supply cost is a common industry approach.

Table 7: Value of Customer Reliability

AEMO	AEMO VCR ($ / MWh)	AUSGRID VCR ($ / MWh)
NSW Average (excluding direct connects)	$41,200	$40,729 (Urban & Rural)
NEM Average (excluding direct connects)	$48,100	$47,494 (CBD)

[6] AEMO, *Value of customer reliability review, final report*, September 2014, escalated to October 2018 dollar value using June 2018 CPI index.

Financial

The financial consequence cost associated with an asset failure has been limited to those costs related directly to the asset restoration with other event-related costs captured in the risk areas of safety, loss of supply, environmental and fire as appropriate. It has been defined as the repair or replacement cost to return the asset to its pre-fault state.

The unit cost applied in each asset category has been determined as a weighted average of historical repair and replacement costs.

4.3 Model validation

The risk quantification model closely implements the predefined method and logic applying the tested input data and parameters. It provides a consistent and transparent quantification approach across the asset classes.

4.4 VoC Validation

The validation of the PoCs applied in the quantification of risk in Ausgrid's network is summarised as follows for each of the key areas considered:

Method, data sources and parameters

- The approach, input data, and parameters applied in the development of Ausgrid's VoCs are consistent with industry practice and informed by national and international industry experience.

Modelled approach and parameters

- The implementation of the VoCs is consistent with practices applied by other utilities in Australia and provide a uniform and transparent method for quantifying risk.

VoC outputs

- The approach, parameters and input data applied in determining the VoCs are consistent with industry practice.

- The calculated VoCs are therefore not considered unreasonable for providing credible risk appraisal outcomes.