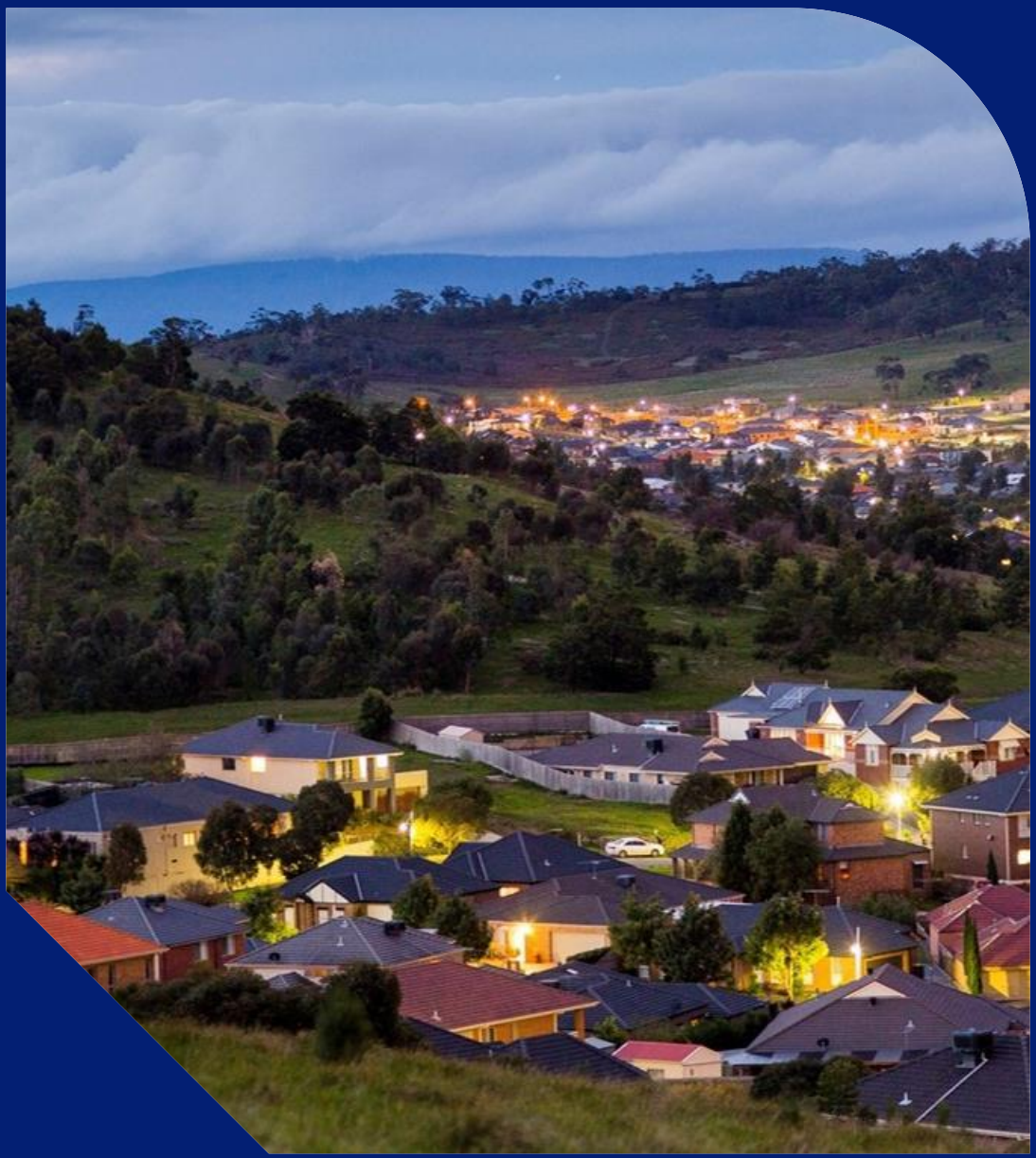
AusNet

Asset Risk Assessment Overview

Asset Management System



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1. Purpose

Understanding asset risk underpins the development and optimisation of inspection regimes, maintenance schedules, refurbishment and replacement programs, short-term and long-term CAPEX and OPEX forecasts, and work prioritisation.

The purpose of this document is to outline methodologies that enable lines of business to make objective data-driven and evidence-based replacement and maintenance investment decisions.

The document is not intended to be prescriptive for every asset class, instead it details organisationally approved methods. The unique characteristics of an asset class will determine the most appropriate specific methods used.

2. Scope

This document outlines methodologies to quantitatively assess asset risk and risk treatments within AusNet's:

- Regulated businesses - Electricity Transmission, Electricity Distribution, and Gas Distribution
- Unregulated businesses

The methodologies align with the broader AusNet Enterprise Risk Management (ERM) framework as a more specialised approach to asset-level risk quantification.

Project delivery risks (including budget, schedule, safety in design, etc.) are excluded from the scope of this document. Given this is a quantitative asset level risk it is not intended to be an enterprise risk framework.

This document is regularly updated to reflect new asset classes and operating contexts. Version 4 applies to the asset classes listed in Appendix A.

AusNet's risk management system is based on **AS ISO 31000 – Risk Management Guidelines**, ensuring effective risk management to support stakeholders including owners, employees, customers, suppliers, and communities.

- **Risk** is defined as "*the effect of uncertainty on objectives*".
- **Uncertainty** is captured through the probability of failure.
- **Consequence** refers to the "*outcome of an event, with positive or negative effects on objectives*", and includes:
    - Safety (Employee and Public)
    - Environmental
    - Bushfire
    - Customer and Market (due to unavailability of network elements)
    - Financial

AS ISO 31000's structured and internationally recognised approach contains three core components:

Principles – Risk management should create and protect value, be integrated across the organisation, and tailored to its context.

Framework – Enables integration into governance, strategy, and operations, with leadership driving commitment, clear responsibilities, and resource allocation.

Process – Involves the systematic application of policies, procedures, and practices to the activities of communicating and consulting, establishing the context and assessing, treating, monitoring, reviewing, recording and reporting risks.

Figure 1 illustrates the risk management process as defined by AS ISO 31000, which underpins the methodology described in this document:

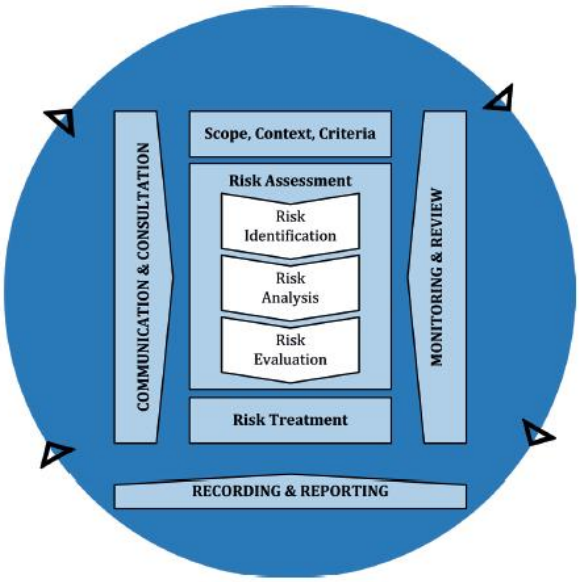


Figure 1: Risk Management Process[1]

The risk management process ensures that risks are identified, understood, and managed in a consistent and transparent manner, supporting better decision-making and improved outcomes.

The remaining subsections of section 2. describe how the six components of the risk management process—shown in Figure 1—are applied within AusNet's asset risk methodology. Together, they form the basis of the scope for overall document.

2.1. Communication and Consultation

The key stakeholders required to understand asset risk are the business lines (Distribution, Transmission, Gas and Unregulated), Corporate risk management group and the AusNet Executive Leadership Team (ELT) who provide overall oversight and decision-making.

Subject matter experts for various asset classes are consulted and provide information on defining and evaluating asset risk.

2.2. Scope, Context and Criteria

Scope, Context and Criteria relating to the risk management process. This document presents AusNet's approach to asset-level risk quantification across its electricity transmission, electricity distribution, gas distribution, and unregulated businesses. It encompasses all physical network assets and considers risks throughout the asset lifecycle—from planning and operation to maintenance and decommissioning. The approach is designed to integrate with enterprise risk reporting processes while maintaining the necessary granularity to support asset-specific decision-making. The methodologies outlined are intended to inform investment planning, maintenance prioritisation, regulatory submissions, and compliance with safety and reliability obligations. Corporate risks that are not directly related to asset condition or performance are outside the scope of this assessment.

The process supports AusNet's strategic objectives and is aligned with the broader Enterprise Risk Management (ERM) framework. It complements ISO 55000-aligned asset management practices and leverages existing systems such as SAP, GIS, and SCADA. The approach also builds on the organisation's internal capabilities in engineering, analytics, and risk management to drive consistent and objective decision making.

Risk appetite which is established by the Board helps to define thresholds that determine tolerable levels of risk across consequence categories. A calibrated 5x5 risk matrix, consistent with the ERM framework, is used to combine likelihood and consequence, providing a structured basis for prioritisation and treatment decisions.

[1] AS ISO 31000

Externally, the risk quantification methodologies are designed to meet the expectations of key stakeholders, including the Australian Energy Regulator (AER), Energy Safe Victoria (ESV), the Environment Protection Authority (EPA) Victoria, consumers and the broader Victorian community.

Australian Energy Regulator (AER) – As per the National Electricity Objective (NEO) promotes efficient investment in networks for the long-term interests of consumers.

Energy Safe (ESV) – Requires AusNet to minimise safety risks as far as practicable.

Environmental Protection Authority – Require AusNet to minimise pollution or waste as far as reasonably practicable.

The quantified risks from this document can be used to support those requirements.

2.3. Risk Assessment

Risk assessment is the process which includes risk identification, risk analysis, and risk evaluation.

Risk Identification

In the context of this methodology, risk identification is about understanding how assets fail, what causes the assets to fail, and the effect of the assets failing.

Failure Mode and Effects Analysis (FMEA) and Failure Modes Effects and Criticality Analysis (FMECA) are the techniques employed to identify the risks of the network systems and equipment. These techniques subdivide the systems into elements (or subsystems) and for each element, pinpoints the ways in which it might fail, what causes failure, and the effects of the failure.

This understanding is then used to design strategies to prevent adverse consequences or enhance positive ones.

Risk Analysis

Risk analysis is undertaken to understand the nature of the risk and its characteristics. The factors considered in this methodology are

- the probability of failure of functional failure and consequence
- the nature and magnitude of consequences

Historical data analysis, machine learning, Event Tree Analysis (ETA), and Fault Tree Analysis (FTA) are used in this process to understand consequence and likelihood.

Sections 4. and 5. detail the methodologies used to quantify probability of failure and consequence of failure. Respectively they quantify the uncertainty of consequence, collectively they allow the risk to be analysed quantitatively.

Risk Evaluation

This stage as an evaluation of the risk to understand if it is broadly acceptable, or whether it requires an intervention to reduce the risk. Section 6. describes the methodologies use to evaluate the risks.

2.4. Risk Treatment

Risk treatment is the process of selecting and implementing options for addressing risk. Risk treatment options will include the following

- changing the likelihood (maintenance, refurbishment, replacement, etc.)
- changing the consequence (redesign, spares, contingency plans, etc.)
- retaining the risk (inspection/testing, monitoring, etc.)

From a financial consideration, risk treatment plans can be either Capital Expenditure (CAPEX) or Operational Expenditure (OPEX). CAPEX plans include asset replacement, redesign, and refurbishment. OPEX plans cover inspections, measurements, routine maintenance, and testing.

CAPEX plans will be supported by an economic assessment.

2.5. Monitoring and Review

Risk management processes are continually refined to improve the quality and effectiveness of the process, implementation and outcomes. This is considered a living document to be republished when a major improvement or new consideration has been added.

Actual outcomes are compared with predicted risk assessment, and the result of the comparison will drive the need for further improvement or enhancement.

2.6. Recording and Reporting

The outcomes of the risk management process can be reported using a risk matrix dashboard. This dashboard typically displays a 5×5 Consequence/Likelihood matrix for each consequence type (e.g. safety, financial, environmental), as well as a combined consequence matrix to support broader decision-making. The matrix helps identify appropriate interventions, such as asset replacement, adding redundancy, or mitigating specific consequences.

In addition to matrix visualizations, the dashboard can present key risk metrics including Probability of Failure (PoF), Consequence of Failure (CoF), and overall Risk values. These can be contextualized with asset-specific information such as asset type, performance history, and estimated intervention costs, enabling more informed and strategic asset management decisions.

3. Abbreviations and definitions

Table 1 - Important Acronyms

ACRONYM	FULL FORM
ACR	Automatic Circuit Reclosers
AER	Australian Energy Regulator
CBMO	Circuit Breaker Minimum Oil
CBVU	Circuit Breaker Vacuum Type
COF	Consequence of Failure
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DF	Disproportionality Factor
DFA	Distribution Feeder Automation
DNO UK	Distribution Network Operators UK
DSI	Death or Severe Injury
EUE	Expected Unserved Energy
FFDI	Forest Fire Danger Index
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode, Effect and Criticality Analysis
HBRA	Hazardous Bushfire Risk Area
HSE	Health and Safety Executive
IRU	Ignition Risk Unit
LBRA	Low Bushfire Risk Area
LOC	Likelihood-of-Consequence
LTI	Loss Time Injury
MIP	Market Impact Parameters
NPV	Net Present Value
POF	Probability of Failure
REFCL	Rapid Earth Fault Current Limiter
SME	Subject Matter Expert
VBRC	Victorian Bushfire Royal Commission
VCR	Value of Customer Reliability
ZSS	Zone Substation

Some key definitions of terms used often this document are tabulated for clarity:

Table 2 - Important Definitions

Term	Definition
Method	A method is a specific procedure or technique used to accomplish a task or solve a problem.
Methodology	A methodology is the systematic framework that defines how methods are selected, applied, and evaluated.
Probability of Failure (PoF)	For the purpose of the document PoF is the conditional probability of failure. That is, the probability that an asset will fail within a specified period, given that it has forecast to survive up to the beginning of that period.
Target	In machine learning, the target is the specific outcome the model is trained to predict — such as a catastrophic failure, SF6 leak, or major failure notification. The model uses historical data to learn patterns associated with this outcome and applies them to predict future occurrences.
Feature	In machine learning, **features** are data points that describe and differentiate assets - such as voltage, location, notification history, or operational characteristics. These features help the model learn what distinguishes failed assets from healthy ones and are then used to predict failures in assets currently in service.

4. Probability of Failure

An asset is deemed to have failed when it does not meet the functional requirements for which it was acquired. A combination of measurements, observations, failure history, and performance history are used to determine both the probability of an asset failure (PoF) and the remaining life.

Within this document, PoF is defined as a conditional probability of failure, meaning the probability an asset will fail in a specified period, given it had survived to the start of that period – usually the period is 12 months. Equation 1 shows the calculation of conditional probability of failure used for survival models.

$$PoF_{(t)} = \frac{F_{(t+\delta t)} - F_{(t)}}{1 - F_{(t)}}$$

Equation 1: Conditional Probability of Failure

Where:

PoF = conditional probability of failure
F = Cumulative distribution function (CDF)
t = current age or current effective age (t is treated as the first of January in the year t)
δt = time-period - commonly 1 year, or 1 effective year

The method of producing PoF values into the future can be generalised as 'Covariate Weibull' analysis or 'Condition Adjusted Weibull' analysis. This means the PoF is based on time-based Weibull distribution, with age or characteristic age adjusted up or down depending on the level of deterioration relative to the population.

An asset class will use one of five methods to produce either an initial PoF value – that is the conditional probability of failure within the next 12 months - or a health score. The specific methodology will depend on the complexity of the asset, the population of the assets, failure history, measurement data, and observation data. Table 33 lists the five methods with guidance for how to assign a method based on the attributes of the asset. The table lists the models in descending order of model complexity and richness of data, and ascending order of SME influence.

Table 3 - Methods used to produce initial PoF

Model	Method	Asset Population	Data	Asset Complexity	Key Benefit	Output
Machine Learning (ML)	Supervised learning model actively **trained by SMEs** using asset features (e.g. construction, location, measurements) and failure history to predict failures. Predictions **validated with standard statistical tools** (e.g. ROC, SHAP).	Large (>>1,000)	Differentiating features Failure History	Low	Predictive modelling based on proven statistical methods. Maximizes available data. Trained by SMEs.	Initial PoF
Health Score (HS)	Applies rules to measurements. **Heuristic** thresholds.	Small (<1,000)	Well Established Measurements	High	Based on direct measurements	Health Score
Hybrid ML/HS	Combine ML and HS outputs for different failure modes	Medium/ Large (>1,000)	Failure history/ measurements relating to specific failure modes	High	Integrates strengths of ML and HS approaches	Health Score and Initial PoF
Health Score - simple	Similar to previous condition method – condition score treated as single health index relating to initial age in Weibull distribution	Medium/ Large (>1,000)	Replacement History and expert observations	Low	Simple	PoF
Time-based Weibull	Probability Distribution based on historical failures	Medium/ Large (>1,000)	Failure History or industry heuristic	Low/ Moderate	Allows failure prediction with minimal data	PoF

Increased model complexity reflects the ability of a model to incorporate variables beyond time, which is suitable when such variables have a proven impact on the probability of failure.

'Health Score Simple' and 'Weibull' methods are already in the time domain, and future PoF values can be estimated by projecting 't' in the future. ML produces a PoF but need to be converted to the time domain to project PoF into the future. HS outputs are in a 'health score' domain and to produce an initial PoF and PoF into the future the outputs either need to be converted to time domain or correlated to the time domain.

Table 4 summarises three methods currently developed to produce future PoF values from initial PoF or health score. It is noted that more sophisticated methods exist, and they will be explored in future issues of this document.

Table 4 - Methods to Project PoF from HS and ML

Method	Description	Application
HS-based Weibull	Use HS at failure as the input to Weibull analysis instead of time (t) to produce a characteristic health score - η_{HS} - and a shape parameter – β. Fit Weibull distribution to HS instead. Determine δHS in one of two ways: **Regress health score on age** in 1 year – plot age + 1 on the x-axis and health score on the y-axis and produce trend line. Take a **ratio of health score** to characteristic health score $$F(HS) = 0.63 \cdot \frac{HS}{\eta_{HS}}$$ **Trend HS inputs** and directly produce HS values into the future. With HS and future HS the conditional probably equation can be applied as $$PoF_{(HS)} = \frac{F_{(HS+\delta HS)} - F_{(HS)}}{1 - F_{(HS)}}$$	HS
CDF Alignment	Construct a cumulative distribution function (CDF) F(HS), or $F(t)_{ML}$, and align it with the time-based Weibull CDF F(t). Alignment between F(HS), or $F(t)_{ML}$, to F(t) can be achieved in one of two ways: 1. **Fix age (t), adjust η(t)** until F(t) = F(HS) to produce an **individual characteristic age.** 2. **Fix η(t), adjust age (t)** until F(t) = F(HS) to produce an **effective age** Creating a **F(HS)** can be achieved by (2) from HS-based Weibull – take a ratio of HS to η_{HS} of the defined 63% F(η). Where the model produces **PoF(age)**, a CDF is produced with a lookup table of PoF to F(t) and selecting F(t) where PoF of the model matches the PoF in the lookup table. The resulting value of 't' is the effective age. Alternatively, the lookup table uses the age of the asset for t and produces a F(t) and PoF for every combination of characteristic age (η), the effective characteristic age is the value of η where PoF from the model equals the PoF from the lookup table.	HS, ML and Hybrid
HS-to-Time Regression	**Regress age on health score** - plot health score on the x-axis and age on the y-axis and produce trend line. Use health score to produce an equivalent age (t), then run standard time-based Weibull analysis.	HS

Notes:

- For linear regression as the fit improves, the HS becomes more of a proxy for age.
- Most value from a health score comes when there is a greater spread of values around the mean, or as the regression increases in order (eg square or cube functions)
- The order of the regression should be kept low (3 or less), higher values run the risk of overfitting – ie characterising noise

Figure 2 shows an example of regression of health score on age to determine a health score at a different time.

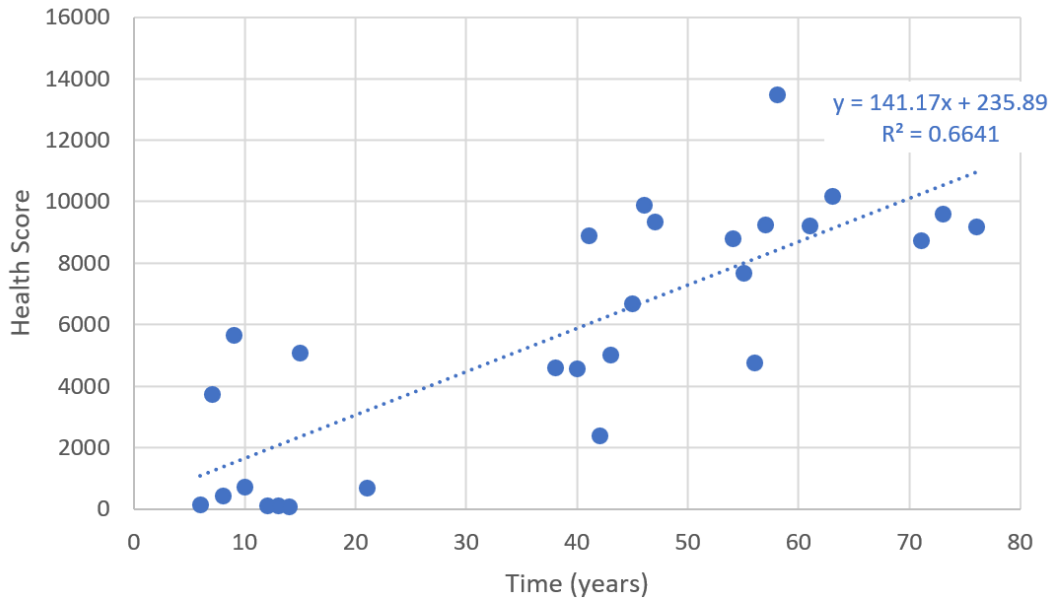


Figure 2 - Health Score vs Time

Where the available data is insufficient to produce a valid failure distribution and no reference distribution parameters can be identified, two practical approaches can be taken:

- Identify an incipient or minor failure mode for which data exists. Redefine this state as the "failure" and perform an event tree analysis. This method uses available data to establish the probability of the initial event, then evaluates the sequence of subsequent events—along with their probabilities and assumptions—that must occur to result in the original failure of interest.
- Apply a qualitative method to convert a health score into a PoF. This approach relies on expert judgment, condition assessment frameworks, or scoring systems to estimate failure likelihood, therefore it should only be used as a last resort.

The following subsections expound on how each method results in a PoF projected into the future.

4.1. Machine Learning (ML)

The machine learning modateel approach is an **SME trained advanced predictive model**. It is a data-driven analytical approach used to estimate the probability of asset failure based on historical performance and asset characteristics. This method identifies patterns and relationships within large datasets to produce risk scores for individual assets. It does not rely on predefined rules, instead it adapts to the data, allowing for more nuanced and scalable insights.

The specific method used at AusNet is the Random Forest Machine Learning model. The model is trained using historical asset data, including measurements, observations, maintenance notifications, environmental and operational conditions, construction type, age, etc. These data points are used to define a **target variable or target**, which represents a specific **functional failure**.

Once the target is established, historical failure events that meet this definition are analysed across all available **features**. The model evaluates the prevalence and influence of each feature in past failures to understand their predictive power.

For assets currently in service, the same features are assessed. Each feature contributes either positively or negatively to the likelihood of failure:

- **Positive influence**: increases the asset's probability of failure.
- **Negative influence**: decreases it.

The Random Forest model aggregates these influences across all features to produce a **Probability of Failure (PoF)** for each asset. This method is particularly effective in complex engineering systems where causal relationships between features and failures are not fully understood. Unlike a single decision tree, which assumes a clear and deterministic path from features to outcomes, Random Forest builds multiple decision trees using randomly selected feature subsets, improving generalisation and robustness.

To ensure the model aligns with engineering expectations and avoids spurious relationships, subject matter experts (SMEs) review the influence of input features on model predictions. This review helps identify which features are genuinely driving outcomes, assess whether these relationships are causative or coincidental, and determine if any features should be excluded. Although Random Forest models do not explicitly model correlations, they can still learn from coincidental patterns in the data, which may compromise reliability. As part of the SME sense-check stage, invalidated features are removed, and the model is retrained. This process is often iterative, with SMEs exploring different combinations of features—such as age, condition, loading, and environmental factors—to ensure the model produces a well-distributed and representative estimation of Probability of Failure (PoF). Through this refinement, the model becomes more generalisable, less prone to overfitting, and more aligned with domain knowledge. The standardised statistical validation techniques, explained in section 4.1.3. , are key strengths of the machine learning approach.

4.1.1. Benefits and Limitations

This type of model is more sophisticated than traditional heuristic models, because it:

- Learns from historical target data and asset features without required pre-defined rules
- Handles large and complex data sets
- Captures non-linear relationships and interactions between features
- Reduces SME bias
- Better identifies subtle patterns and trends
- Is more robust to missing data and noise

Most importantly, well-established analytical methods are used to assess the effectiveness and suitability of the model and guide refinements. The Receiver Operator Curve (ROC) and Shapely Additive Explanations (SHAP) methods, described in 4.1.2. are the key methods used.

Random Forest Machine Learning may be a suitable approach when the asset population is large, and the available data (i.e. failure history and asset features) is rich. It requires data science expertise, computational resources, and structured SME-led training. Like other data-driven models, it learns from historical patterns, which means it may not immediately detect step changes or emerging failure modes until sufficient new data becomes available.

To get the best value, it's important to apply ML where the data supports it and where predictive insights will meaningfully inform decisions.

4.1.2. Training and Validation

Figure 3 show the process of defining a target, training correlations, and producing predictions of the target:

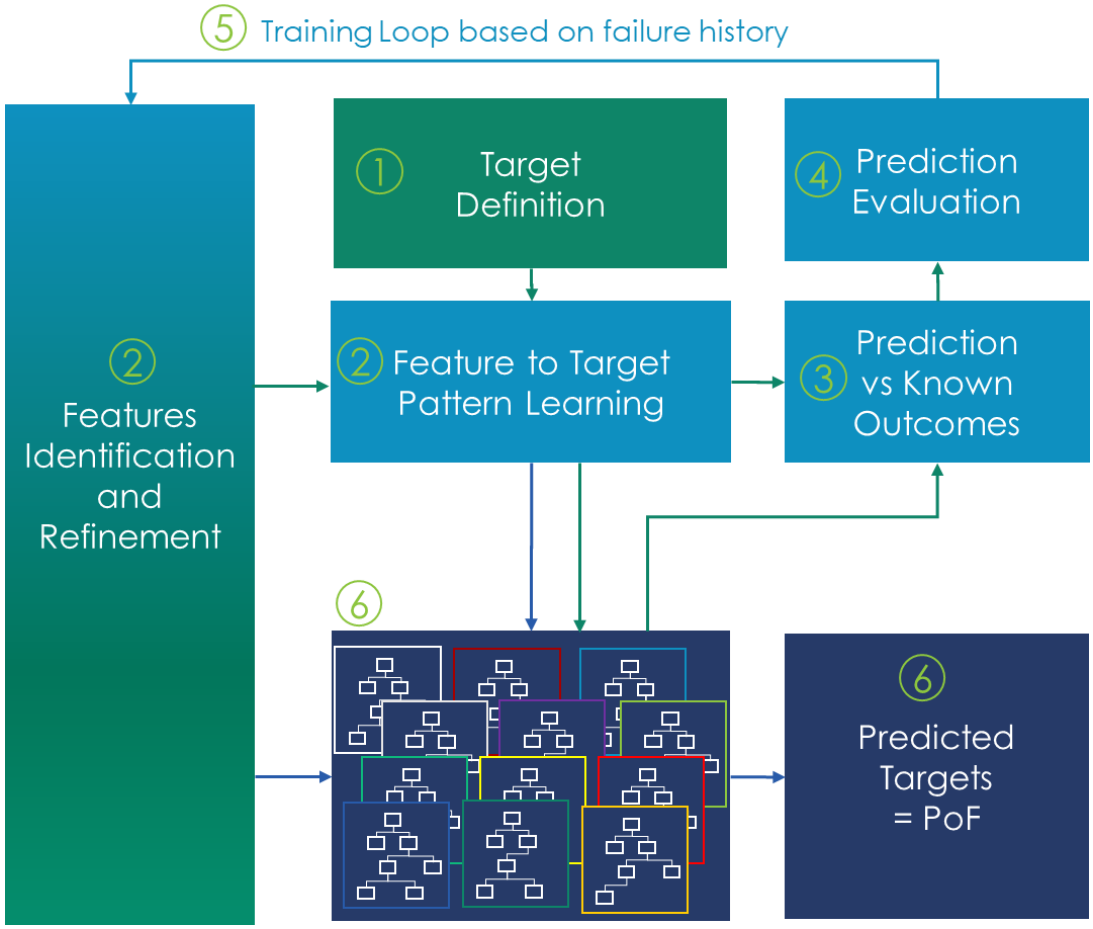


Figure 3 - ML Prediction and Training Loop

The process follows the annotated numbers:

1) Define the **Target**
    a. Identify the **functional failure mode** of interest, and **criteria** to determine when an asset has experienced this failure.
    b. Label historical asset data accordingly to create a **binary target variable** ('failed' or 'not failed').
2) **Feature Preparation** and **Pattern Recognition**
    a. Compile a comprehensive list of features associated with the asset fleet in to be modelled (eg. construction, environment, observations, measurements, etc)
    b. Set aside a 'hold-out' set of assets that have failed for validation purposes.
    c. Run the model on the remaining set of failed assets to learn patterns between features and failures.
3) **Predictions on Hold-out Set** – apply the model to the hold-out set to generate failure predictions for a set of assets that have failed – the outcomes were excluded during the training, therefore the model is trying to predict these outcomes using the data provided in the training stage.
4) **Model Evaluation** and **Feature Influence**
    a. Evaluate model performance on the hold-out set using ROC curves (this method is described in section 4.1.3. to assess how well the model distinguishes between failed and non-failed assets – is the model effective enough?

b. Use SHAP plots to interpret feature importance and understand which variables most influence predictions (this method is described in section 4.1.3.

5) Re-training

a. If SMEs determine that influential features don't align with known engineering or causal mechanisms remove the features and re-run step 2, 3, and 4.

b. If ROC curves are insufficient no clear improvements can be made rethink the model – is the target definition good enough? Is ML still appropriate given the data set?

6) Production Run

a. Once validated, apply the final model to all in-service assets.

b. Generate a Probability of Failure (PoF) for each asset over the next year based on its current feature profile.

4.1.3. Testing and Calibration

One major benefit of this method is that each iteration of the model can be validated using standard statistical tools. The approach uses two such tools - the Receiver Operating Characteristic (ROC) curve and SHAP (Shapley Additive exPlanations) plots. These tools help assess how well the model performs and provide transparency into how predictions are made, supporting both model improvement and stakeholder confidence.

ROC curves

ROC curves help to evaluate how will a model distinguishes between true and false outcomes across all probability bands.

Based on the input features and failure target a model produces a probability score, e.g. 0.1, indicating a 1 in 10 chance the asset will fail in the next year. This prediction is then compared to the actual outcome – whether the asset failed or did not fail.

For all predictions in the hold-out set, the PoF values are ordered from highest to lowest, along with their corresponding outcomes – 1 for true (failure) or 0 for false (no failure). Each prediction is plotted against the accumulated sum of true outcomes as a percentage of the total sum of true outcomes (true positive rate). This results in a plot that starts in the bottom left and ends up on the top right, as per Figure 4:

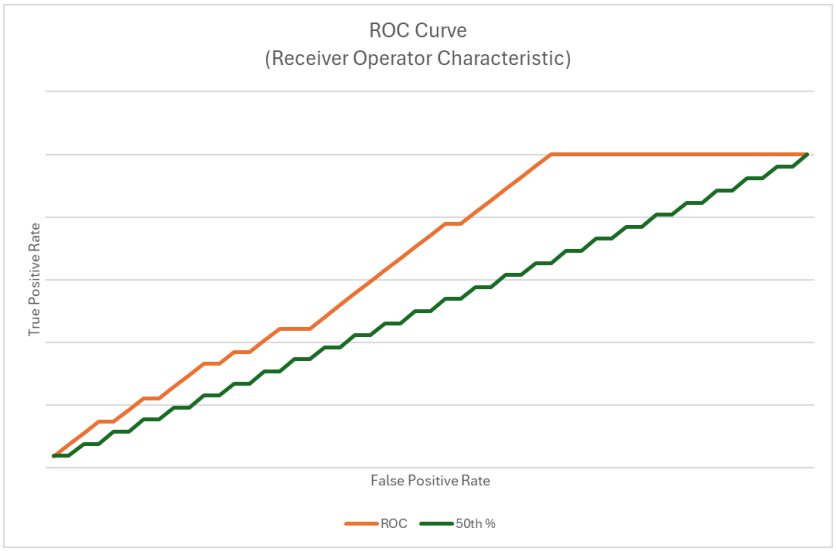


Figure 4 - ROC Curve Example

The orange plot shows outcome for a sample data set, while the green line represents a model with no predictive power – equivalent to a random guess. The green plot is as good as tossing a coin, whilst the orange is weighted based on the predictive power of the ML model.

The area under the green curve is 0.5, whereas the area under the orange curve is 0.66, this indicates the orange curve is a better predictor than the green curve. The area under the curve - **AUC** – provides a single metric to evaluate to a mode's ability to distinguish between true positives and false positives across all probability bands. A

'perfect' predictor will have an AUC of 1 and be a curve that 'hugs' the left vertical and top horizontal axis. Figure 5 shows three set of ROC curves with the resulting distributions of true and false outcomes as histograms with bins representing a range of probability values:

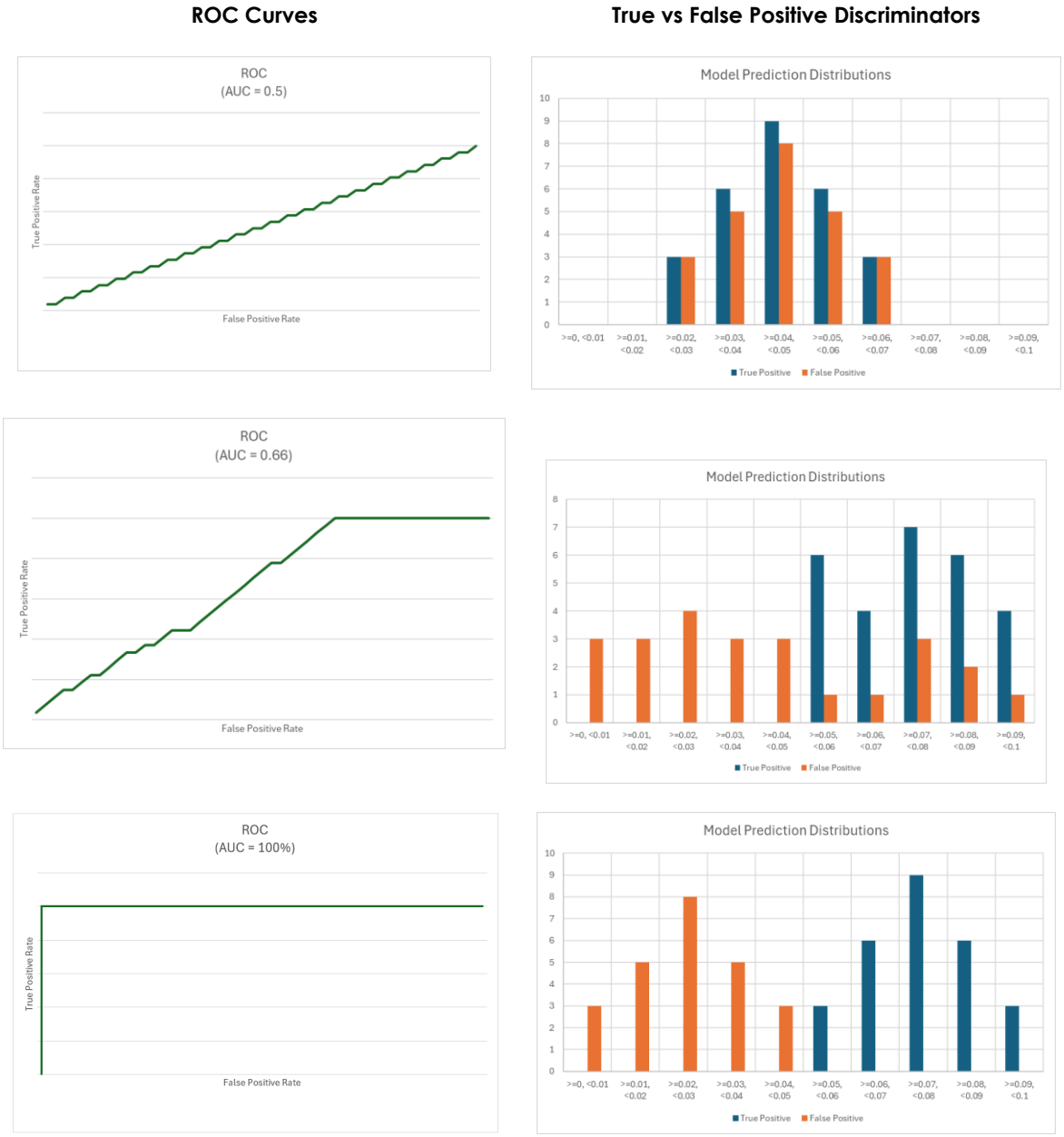


Figure 5 - ROC Curve vs True & False Positive Discrimination

With an AUC of 50% the distributions of predicted probabilities for true positives and false positives are almost identical, indicating the model cannot reliability distinguish between the two. At the other end of the scale, with an AUC of 100%, the two distributions are completely separated, and all true positives can be identified. An AUC of 66% can be viewed as better than tossing a coin, but the model will still produce false positives as there is an overlap between the false positive and true positive distributions.

The aim of this tool is to train the model to maximise AUC. The example shows that the model should be retained because it still contains uncertainty. The acceptable level of uncertainty depends on the effort required to improve and the benefits that an improved model would provide.

SHAP Plot

The SHAP (SHapley Additive exPlanations) plot is a visualization tool to interpret how individual features influence a model's prediction.

Figure 6 presents a sample SHAP plot generated from the Circuit Breaker Mechanism model.

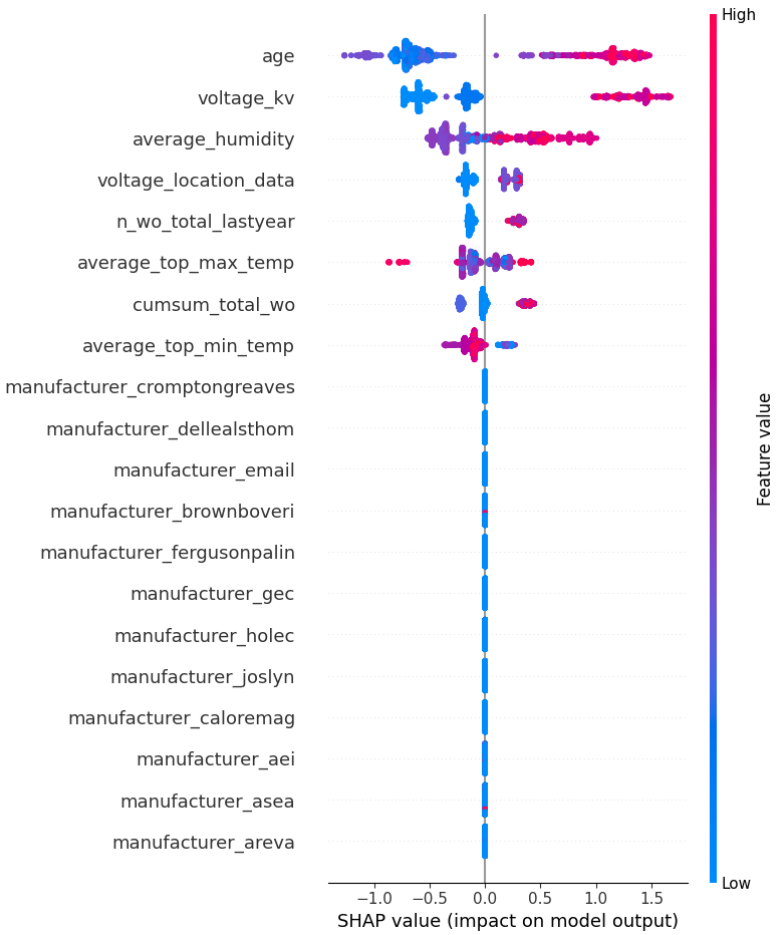


Figure 6 - Sample SHAP Plot

Chart explanation:

Dot cloud: Each dot represents a single prediction for a given feature. All predictions are shown for each feature, providing a view of how that feature behaves across the dataset.

Dot **colour**:

Red indicates a high feature value – or 'true' for binary features

Blue indicates a low feature value – or 'false' for binary features

SHAP Value: Measures how much a feature contributes to shifting a prediction from the model's average prediction, ie how influential it was.

Positive SHAP value increases the predicted probability of failure

Negative SHAP value decreases the predicted probability of failure

Order (vertical axis): Features are ranked by their average absolute SHAP value, meaning those at the top have the greatest overall influence on the model's predictions—regardless of whether that influence increases or decreases the PoF.

In the example, **asset age** is the most influential feature. Low asset age (blue dots) tends to reduce the predicted PoF, while high asset age (red dots) increases it. This aligns with expected degradation patterns.

The top eight features show a clear influence over the prediction, whereas the binary feature such as 'is a specific manufacturer' or not exhibit minimal impact on the prediction.

The SHAP plot provides transparency into the model behaviour allowing SMEs to:

Identify which features drive predictions.

Validate that model behaviour aligns with known engineering or causal mechanisms.

Recognise when a feature's influence may result from coincidental or non-causal patterns in the data. While Random Forest models do not explicitly model correlations, they can still learn from spurious patterns or inherent correlations that affect predictions.

This is the SME sense check stage, if features have been invalidated, then they are removed from the training set of features, and the model is rerun with a more acceptable set of features.

4.1.4. Translating to Time Domain

The PoF output from a ML is the probability an asset will fail within the next 12 months. As the predictions are applied to in service assets, this is inherently a conditional probability. As a predictive model that isn't rooted in a causal system, or a historical failure distribution degradation cannot be directly extrapolated. The one method that can be used to do a time domain to estimate failures into future years is method 2 from Table 4 – CDF alignment. Using Weibull analysis to create an effective age or individual characteristic age, the PoF is extrapolated into the future by increasing the value of t which is either an effective age or chronological age base on the method used.

4.2. Health Score (HS)

Heath scores are used as a covariate to time when producing PoF from a failure distribution. A health score reflects whether an asset is degrading in a manner consistent with its age and cohort.

Factors influencing asset health include:

time in service

operating stress – usage intensity or load relative to rating, eg high operations, high loading

stress from physical environmental, eg corrosion

inherent asset robustness – ie quality of specification, design, material quality, manufacturing standards and installation practices – apparent from failure history

A health score is an aggregation of health indices. Each health index is an indication of how a measurement or observation impacts likelihood of occurrence of that failure mode by assigning it a 1 to 5 value – 1 indicating low likelihood and minimal degradation, 5 indicates a high likelihood of occurrence or high level of degradation.

The index is assigned to a measurement or observation based on SME developed heuristic thresholds. This reflects a correlation between measurements and observations and historical failure.

Health indices serve as indicators of failure modes, and a single failure mode may be associated with multiple health indices. Conversely, a health index may indicate multiple failure modes. Health indices that point to the same general failure mode are grouped together, and for simplicity, the highest health index within the group is used as the representative indicator for that failure mode.

4.2.1. Aggregation of Health Indices

For complex assets, such as power transformer, there are several failure modes that can result in a major failure. To create a single failure prediction the health indices, need to be combined into a single health score. Two common methods used for this purpose are the **Non-Linear** and **Weighted Average** aggregation methods – the two methods are subsets of the methods described in the CIGRE Technical Brochure 761 – Transformer Condition Assessment.

Non-linear Aggregation

1 to 5-in each category are then combined into a score of 1 to 5 by taking an average or maximum of the factors. The four categories are then aggregated using a nonlinear methodology to determine the health score.

$$HS_{NL} = \sum_{n=0}^{k-1} x_n i^n$$

Equation 2: Non-Linear Health Score Calculation

Where:

k = number of levels,

i = number of failure modes,

x = count of failure modes within the same health index

The non-linear nature of the method is effective in capturing high individual health indices, where an averaging method may 'hide' poor health indices in an overall score. By avoiding a manual weighting the method removes one layer of potential SME bias.

The method requires a complete set of health inputs - the results can be greatly impacted if not all defined failure modes have been assigned a health index. If missing health indices can be completed or imputed, then the Weighted Average Aggregation method may be more appropriate.

Weighted Average Aggregation

This method requires more understanding of the interaction between failure modes and the relative criticality of each. Each failure mode is assigned a relative weighting which is multiplied by the highest health score for that failure mode. The resulting scores are summated to produce an overall health score.

$$HS_{WA} = \frac{\sum_{i=1}^{n} W_{FMi} \cdot HI_{FMi}}{\sum_{i=1}^{n} W_{FMi}}$$

Equation 3 - Weighted Average Health Score Calculation

Where:

n = number of failure modes

W_{FM} = Weighting per failure mode

HI_{FM} = The maximum health index per failure mode

The weighted average aggregation method is intuitive and less affected by missing data. It has a higher reliance on SME knowledge of the relative importance of failure modes. The non-linear method is preferred if a complete list of health indices can be produced.

4.2.2. Testing and Calibration

Measurements and observations are objective and directly recorded and follow international and internal guidelines – such as 'IEC60599 – Guide to the Interpretation of Dissolved and Free Gas Analysis' and 'LPP 09-06 – Condition Assessment of Overhead Lines'. The level of testing and calibration is primarily aimed at the ability of the health index thresholds to:

- rank the assets from worst to best health in a way that is consistent with SMEs expectations and historical failure patterns
- identify conditions under which an SME would consider an asset unfit for service without corrective action

4.2.3. Translating to Time Domain

A health score is a relative measure that allows the asset to be ranked within a population, it can't be used to make quantitative decisions until converted to a PoF. The health score model requires a failure distribution for an initial PoF to be assigned. The same failure distribution is used to predict a PoF into the future.

All methods described in Table 4 can be used to translate:

- a health score to a time-based Weibull distribution, or,
- a Weibull distribution fitted to a health score to a time.

Using health score to adjust a Weibull characteristic age, shape parameter, or fit a Weibull curve directly to a health score assumes:

- A robust scoring methodology
- Health score increases predictably with age
- A robust failure history data set

4.3. Hybrid (ML/HS)

A hybrid model utilises initial PoF values produced in accordance with sections 4.1. and 4.2. The primary purpose is to incorporate additional failure modes to an ML model, where the failure mode has minimal failure history, but a rich set of measurements and observations.

For example, circuit breakers have a sufficient failure history to run a ML model for interrupters, auxiliary controls, and insulation dielectric, but not for bushings. Bushings followed the data set and heuristic rules developed for power transformers.

When aggregating PoF values from different failure modes the union rule from probability theory is applied to avoid double counting overlapping failure contributions:

$$\mathrm{P(A\ U\ B)} = \mathrm{P(A)} + P(B) - P(A \cap B)$$

Equation 4 - Union rule

In this context:

$$PoF_{combined} = PoF_{ML} + PoF_{HS} - (PoF_{ML} \cdot PoF_{HS})$$

Equation 5 - Union of PoF

Where:

PoF_{ML} is the PoF resulting from a ML model predicting failure modes with sufficient failure history

PoF_{HS} is the PoF resulting from a health score model

PoF extrapolation is undertaken using one of the methods in Table 4. It is noted that the failure distribution utilises history of failure resulting from all failure modes.

4.4. Health Score - Simple

This is a simplified version of the health score, where a score is assigned to an asset based on single health index which is based on a simple measurement or overall observation score. It is a means of classifying assets based on their likelihood of failure health index based on the observed condition of an asset.

It is a means of incorporating condition observations into a time-based Weibull analysis. It is also useful where the Weibull data is limited.

4.4.1. Testing and Calibration

It is based on applying assumed values and calibrating a predicted number of failures each year against historical replacement volumes. Figure 7 shows a sample – with dummy data – of the calibration method:

Health Score	Count of Assets	Remainig Service Potential	Remaining Life	Effective Initial Age	Eta	Beta	PoF	Predicted Failures
1	400	70	32	13	45	3.5	0.38%	1.53
2	200	35	16	29	45	3.5	2.65%	5.30
3	100	25	11	34	45	3.5	3.79%	3.79
4	76	15	7	38	45	3.5	5.18%	3.94
5	24	5	2	43	45	3.5	6.84%	1.64

Sum Predicted Failures	16.20
Percentage of Fleet	2.03%

Figure 7 - Expected Failure to Replacement Volume Calibration

The steps are:

1) **Propose Weibull Parameters -** Eta and Beta values are proposed
2) **Define Remaining service potential (RSP)** – for the five health indices, as a percentage of the characteristic life (Eta) – effective initial age is Eta minus RSP.
3) **Input Asset Count** – per health index
4) **Calculate PoF** – Use Weibull formula with Eta, Beta and RSP to calculate PoF for each health index group (Health Score)
5) **Estimate Failures per Health Score** - multiply the count of assets by the PoF for each health score group
6) **Compare with Historical Replacements** – sum predicted failures per health score group and compared with the historical replacement volumes
7) **Refined Parameters** - adjust eta, beta or RSP until the expected failures aligns with the number historical replacements.

The replacement volumes exclude replacements due as augmentation as far as possible. Historical failures and planned replacements become the replacement volumes. The assumption is made that the planned replacements were made because it was believed that they would have failure shortly afterwards – ie right censored failures.

4.5. Weibull

Where the only thing known about an asset class is time in service, or a health score method is not robust enough, time-based Weibull analysis is appropriate.

Weibull values can be calculated using historical failure data if the correlation coefficient (ρ) and goodness of fit (ε) are of an acceptable minimum value. A model where $\rho > 0.75$ and $\varepsilon < 0.3$ represents an acceptable trend and fit, otherwise Weibull parameters can't be trusted.

If there is insufficient data to create a trustworthy set of Weibull parameters, values must be sought from industry standards and have a clearly stated rationale why an assumed value was used.

5. Consequence of Failure

Failure of an asset has the potential to result in several types of consequences including safety, bushfire, environment, customer, market, and financial losses. Table 5 is a summary description for each type of failure considered at AusNet.

Table 5: Consequence Types

Consequence Types	Descriptions (including but not limited to)
SAFETY	Threat to health and safety of public and/or employees
ENVIRONMENT	Sulfur hexafluoride (SF6) uncontrolled discharge
	Oil spills
BUSHFIRE	Bushfire damage and safety hazard
CUSTOMER and MARKET	Loss of Supply to customers
	Impact on energy market
	Breach of regulatory obligations
FINANCIAL	Emergency response and repairs
	Asset replacement costs
	Collateral damage
	Service revenues impacts
	Customer compensation payments
	Network performance penalties
	Compliance costs

A monetary value of consequence following an asset failure (cost of failure) is calculated using the cost of consequence and the probability that the consequence will occur (likelihood of consequence).

There are two distinct types of consequences – **event-based** and **state-based.** Event-based consequences can be quantified as a product of cost of consequence of an event as per Equation 6.

$$CoF = LoC \times CoC$$

Equation 6 - Likelihood of Consequence x Costs of Consequence

Where:

CoF = consequence of failure

LoC = likelihood of consequence

CoC = cost of consequence

State Based consequences are dependent on the availability of other assets as well as the asset of interest. They instead are quantified as an overall unavailability multiplied by a rate – usually a dollar per time-period. Table 6 summarises the two different types of consequences.

Table 6 - Event-driven vs State-driven Consequences

Attribute	Event-Driven	State-Driven
Description	Discrete failure event	Based on system or asset unavailability
Typical consequence types	Safety, Environment, Collateral, Financial	Customer outage, market constraint
Quantification method	LoC x CoC	Unavailability x Rate
Time Dependency	Instantaneous, time horizon T1	Time-dependent, time horizons T2 and T3, based on system state

The distinction is important because overall system availability is dependant of PoF, whereas event-based is independent of repair time. To compare the two either:

- Compare the resultant risk values.
- Create an equivalent CoF is created by dividing state-driven risk by PoF. Note, this is only valid for the first year of analysis, availability changes over with changing PoF, meaning the equivalent cost is not consistent over time.

The remainder of section 5. details the consequence of failure for different types of consequences:

5.1. Safety Consequence of Failure

Safety consequences are event-based consequences and are quantified as the product of LoC and CoC.

Cost of Consequence

The Safety lens incorporates all potential health and safety effects that could impact the public and employees. It includes the possibility of injury, incapacity, and/or death. There are two sources of potential costs that could result from a safety consequence:

- Death or Severe Injury (DSI)
- Lost Time Injury (LTI)

The value of DSI is obtained from the Australian Government Best Practice Regulation Guidance Note "Value of statistical life" and the value of LTI is quoted from Safe Work Australia's "The Cost of Work-related Injury and Illness for Australian Employers, Workers, and the Community".

DSI as of 2024 is $5.7M[2] and LTI as of 2013 is $162,780[3] per incident. LTI is Indexed at 3% p.a. over 10 yrs to give a value of $225,000 in 2024 dollars.

[2] Australian Government, Office of Best Practice Regulation, *Best Practice Regulation Guidance Note: Value of Statistical Life,* Value of statistical life | The Office of Impact Analysis

[3] Safe Work Australia, The Cost of Work-related Injury and Illness for Australian Employers, Workers and the Community: 2012–13, https://www.safeworkaustralia.gov.au/system/files/documents/1702/cost-of-work-related-injury-and-disease-2012-13.docx.pdf

Safety costs are further modified by a Disproportionality Factor (DF) which recognises the high-risk nature of the electricity industry. The value is a guide when identifying reasonably practicable costs of mitigation. "The greater the risk, the more should be spent in reducing it, and the greater the bias should be on the side of safety"[4]. This methodology applies a similar factor as proposed by the UK distribution networks, known as distribution network operators or DNOs.

Table 7 shows the applicable disproportionality factors for safety consequences in this methodology. The scenario used is based on the credible outcome associated with each type of failure – for example, multiple fatalities resulting from a bushing failure is a credible outcome, therefore a DF 6 is appropriate. Appendix B provides more background in this method.

Table 7: Applicable Disproportionality Factors

Scenario	Disproportionality Factor
Public Trespass	1
Single Fatality (public or worker)	3
Multiple Fatality (public or worker)	6

Note: VSL values are based on a 2007 quantification with an applied consumer price index (CPI) of 3%. If extrapolating a stated VSL a CPI value of 3% is appropriate.

Likelihood of Consequence

Details of LoC for safety events are recorded as event trees in the addendum to this document (*AMS 01-09-02)*.

5.2. Environmental Consequence of Failure

Environmental consequences are event-based consequences and are quantified as the product of LoC and CoC.

Cost of Consequence

The Environmental lens covers consequences relating to the environment which includes contamination and pollution. The potential costs arise from the effects of bushfire, uncontrolled release of oil or gas, and waste generated when assets fail.

5.2.1. Oil

Discharge of oil into land and/or water bodies can lead to ecosystem disruptions. The environmental cost of oil leakages is determined by the Environment Protection Australia (EPA) through penalty units, and the cost per penalty unit is determined by the Department of Treasury and Finance. Significant oil leak that creates a risk to environment would result in a penalty of 10,000 penalty units[5] at $197.59 per penalty unit as of the 2024-25 financial year[6]. This resulting in $1,975,900 per environmental incident.

The Department of Treasury and Finance adjusts the penalty rate annually, so the latest published value can be used at the time of assessment.

Costs for remediation as well as penalties for failure to meet improvement notice also apply, however for the purposes of risk modelling, the penalties above are considered sufficient.

[4] Energy Networks Association, DNO Common Network Asset Indices Methodology, https://www.energynetworks.org/assets/images/Resource%20library/DNO%20Common%20Network%20Asset%20Indices%20Methodology_v2.0%20Draft%20Final.pdf

[5] Section 25(2), Part 11.5, Chapter 11, Environment Protection Act 2017, Authorised Version 5 June 2024, https://content.legislation.vic.gov.au/sites/default/files/2024-06/17-51aa015-authorised.pdf

[6] https://www.gazette.vic.gov.au/gazette/Gazettes2024/GG2024S225.pdf, Published 7 May 2024

5.2.2. Sulfur hexafluoride (SF6)

Uncontrolled discharge of SF6 can lead to costs associated with ozone layer protection and greenhouse gas emissions.

The amended value of emission reduction (VER) from July 2024 specifies an escalating carbon credit unit spot price, with the initial value of $33/tonne CO2-e (equivalent CO2). The in-force version of National Greenhouse and Energy Reporting Regulations (NGERS) 2008[7] stipulate CO2-e values consistent with the IPCC's Fifth Assessment Report (AR5)[8] - sulfur hexafluoride (SF_6) is 23,500 times more potent than CO_2 in terms of its greenhouse effect.

Likelihood of Consequence

Details of LoC for safety events are recorded as event trees in the addendum to this document (*AMS 01-09-02*).

5.3. Bushfire Consequence of Failure

Bushfire consequence is treated as an event-based consequence because it is independent of PoF. Bushfire consequence was previously included within environmental consequences. While it is primarily quantified by the extent of loss the built environment, it also represents a significant safety hazard.

Cost of Consequence

The cost of consequence associated with bushfires is calculated using the expected house loss, and the bushfire loss value. The financial impact of bushfires is sourced from the Victorian Bushfire Royal Commission 2009 VBRC - Final Report (royalcommission.vic.gov.au), Bureau of Meteorology, and CSIRO.

For transmission lines, bushfire cost of consequence is based on Phoenix RapidFire estimates, which incorporate both safety and housing impacts.

Table 8: Fire Estimated Costs[9]

Forest Fire Danger Index (FFDI)	FFDI $k per house[10]
70_re	437
100_r	1,118
1400_r	2,914

Table 9: Fire Estimated Fatalities

Category	Housing	Fatality
LBRA	0.2	1
HBRA	1	3
REFCL	4.6	6

[7] **Australia. Department of Climate Change, Energy, the Environment and Water.** *National Greenhouse and Energy Reporting (Measurement) Determination 2008*. F2025C00729. Canberra: Federal Register of Legislation, 1 July 2025. Available at: https://www.legislation.gov.au/F2008L02230/latest/text.

[8] **Intergovernmental Panel on Climate Change (IPCC).** *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Edited by O. Edenhofer, R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel, and J.C. Minx. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014. Annex II: Metrics & Methodology. Available at: https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_annex-ii.pdf. [ipcc.ch]

[9] **Tolhurst, K. G., Shields, B. J., & Chong, D. M.** *Phoenix: Development and application of a bushfire risk management tool*. University of Melbourne / Bushfire CRC. Retrieved from https://www.researchgate.net/publication/284304908_Phoenix_Development_and_application_of_a_bushfire_risk_management_tool

[10] Values shown as of 2025. They were escalated with CPI from 2020 values in version 3 of this document. The 2020 values were in themselves escalated per CPI from the original values from 2010 resulting from the initial implementation of the Phoenix Rapidfire fire loss consequence model.

Codified	19.8	10

Likelihood of Consequence

Details of LoC for safety events are recorded as event trees in the addendum to this document (*AMS 01-09-02)*.

5.4. Financial Consequence of Failure

Financial consequence represents the direct economic impact to the organisation arising from an asset failure event. It reflects costs that are incurred to respond to, repair, replace, or otherwise manage the failure and any associated service or performance impacts.

Financial consequence is treated as an event-driven consequence. The relevant cost components are applied only where they are applicable to the specific asset class, failure mode, network context, and consequence scenario.

Key drivers of financial consequences include:

- **Emergency response and repair costs** – immediate costs associated with attending the failure, making the site safe, restoring service, and undertaking emergency or temporary repairs.
- **Asset replacement costs** – the cost to replace the failed asset or component with a functionally equivalent asset, including associated labour, materials, plant, access, commissioning, and project delivery costs where applicable.
- **Collateral damage costs** – costs associated with damage to adjacent or dependent assets caused by the initiating asset failure, and costs associated with restoration of property damage.
- **Service revenue impacts** – revenue not recovered during an outage or supply interruption, where this is applicable to the relevant network or asset class.
- **Customer compensation payments** – payments made to customers under applicable guaranteed service level or interruption compensation obligations and payments made to landowners for revenue lost due to disruptions caused by asset failure on crops or livestock.
- **Network performance penalties** – financial impacts associated with business disruption, and failure to provide network support.
- **Compliance costs -** investigation costs and potential penalties, financial impacts arising from regulatory reportable incidents and regulatory requirements.

Financial consequence does not include impacts that are already captured under other consequence categories, such as safety, bushfire, environmental, or customer consequences, unless those impacts create a direct financial liability that is separately defined and not double-counted.

5.4.1. Unit Cost Inputs

The cost of consequence for financial impact is calculated using unit cost inputs relevant to the failure scenario. These may include:

- Emergency response cost
- Repair cost
- Replacement cost which may be annualised
- Collateral damage cost
- Lost revenue
- Customer compensation
- Network performance penalty
- Investigation costs and regulatory penalties

5.4.2. Consequence Factors

Financial consequence is determined by identifying the cost components that are triggered by the failure scenario and applying the relevant unit costs.

Asset Replacement Cost

- Asset replacement cost represents the total cost to replace the failed asset or component with a functionally equivalent asset. It may include materials, labour, plant, access, commissioning, disposal, and project delivery costs where these are relevant to the asset class and replacement scenario.

Emergency Response and Repair Cost

- Emergency response and repair cost represents the cost of responding to the failure, restoring a safe condition, and completing temporary or permanent repairs. This may include field response, switching, isolation, fault location, temporary works, specialist resources, and repair materials.

Collateral Damage Cost

- Collateral damage cost represents the cost to repair or replace other assets damaged as a direct result of the initiating asset failure and costs associated with restoration of damaged surrounding property. This should only be included where the causal relationship between the failed asset and the damaged assets is credible and defined in the consequence scenario.

Revenue Loss

- Revenue loss represents service revenue that is not recovered during the outage or interruption period. This factor should only be applied where the network, asset class, or regulatory arrangement allows a direct revenue loss to be attributed to the failure event. For electricity networks, this factor may not apply in the same way as gas or other revenue-linked services and should be assessed based on the relevant regulatory and commercial context.

Customer Compensation

- Customer compensation represents payments made to customers due to unplanned sustained interruptions or other service performance obligations. These payments should be applied using the relevant jurisdictional thresholds, rates, and eligibility rules. Payments may also be made to landowners for disruptions to revenue due to crop or livestock damage

Network Performance Penalties

- Network performance penalties represent financial impacts associated with failure to meet service performance requirements. These penalties should only be included where the failure scenario contributes to business disruptions and failure to support the network.

Compliance costs

- Investigation costs and penalties, financial impacts arising from incidents that are reportable under safety regulatory requirements.

Likelihood of Consequence

The likelihood of consequence defines the conditional probability that a financial consequence will occur, given that the asset failure has occurred.

Where the financial consequence is certain following failure, the LoC may be assigned as 1.0. Where the financial consequence depends on the failure scenario, network configuration, operating condition, customer impact, collateral damage, or regulatory threshold, the LoC should be determined using an event tree or other approved conditional probability method.

Details of financial consequence LoC event trees should be recorded in the addendum to this document, AMS 01-09-02, where applicable.

5.5. Customer and Market Consequence of Failure

The consequence arises from customers not being supplied with energy and/or the energy market not dispatching the cheapest generators.

5.5.1. Unit Costs

The cost of consequence resulting from loss of supply is assessed differently across the electricity distribution, transmission, and gas networks.

For the electricity distribution network, the cost is measured using Expected Unserved Energy (EUE), which is influenced by:

- Value of Customer Reliability (VCR)
- Load at risk
- Duration of outage

VCR values, detailed in *Appendix D*, are presented as average rates ($/kWh) per substation. These are based on data published by the Australian Energy Regulator (AER) or derived from customer studies that quantify the value placed on reliability and related benefits.

In the transmission network, the cost of consequence includes both:

- Expected Unserved Energy, and
- Market costs associated with potential, generation redispatch cost, change in emissions cost, demand side management cost

  The latter is estimated using the Market Impact Component (MIC) Parameters model.

For the gas network, cost impacts are not included within the scope of *Issue 43* of this document.

5.5.2. Consequence Factors

Load at risk

Load at risk varies depending on the part of the network impacted by an asset failure. For the distribution network, it is calculated based on the number of affected customers and the average consumption per customer (kW). For the sub-transmission and transmission networks, load at risk is determined by the probability that an asset failure and subsequent events result in a station black - or load-shedding event (MW).

Duration of outage

Outage duration is assessed in three stages:

T1 - Fault: time between initial circuit protection trip operation and automatic switching to reconfigure the network

T2 - Switching: time in which manual switching is carried out to reconfigure the network and minimise risk associated with further asset failure

T3 - Repair: time taken to repair failed asset

These outage durations represent mean time to repair and are used to calculate availability. Typical times of the three stages for the asset classes is shown in AMS 01-09-02.

5.5.3. Electricity Distribution

The energy at risk is estimated using the number of customers interrupted during each of the three outage duration phases considered for the asset class.

The number of customers affected is related to the asset class and circuit configuration. The duration of outage for customers during T1 and T2 will depend on the existence of distribution feeder automation (DFA) and isolating switches.

Distribution Transformers

The customers affected during the T3 outage stage will be equal to the customers directly connected to the transformer. The number of customers per transformer can be obtained from the Kinetiq database.

Pole and Pole Top Assets (conductors, insulators, crossarms)

The customers affected during the T3 outage stage will be equal to the customers in an isolatable section. An isolatable section may have one or more distribution transformers.

Switches and Control boxes

There is likely to be no customers affected during the T3 outage stage

The energy at risk is calculated using the average consumption per customer in an isolatable section or the annual average distribution transformer demand in the isolatable section.

- T1 duration is a function of the feeder circuit breaker, Automatic Circuit Reclosers (ACRs), sectionalisers, and DFA.
- T2 is a function of manual switching operations by the field crew to isolate the faulted assets.
- T3 is the time it takes to repair or replace the failed asset.

$$Customer/reputation\ Cost\$ = ((C\_1 * T\_1) + (C\_2 * T\_2) + (C\_3 * T\_3)) * kW * VCR$$

Equation 7: Customer Cost – Distribution

Where:

- C_1, C_2, C_3 are the numbers of customers interrupted during periods T_1, T_2, T_3 respectively
- kW = Average consumption per customer

5.5.4. Sub-transmission and Zone Substations

In the sub-transmission network (including ZSS), the load at risk (MW) during each of the three outage duration phases is used to calculate the cost of customer consequence. The station load at risk is obtained from data developed by the Network Planners.

- T1 duration is a function of the ZSS protection systems.
- T2 is a function of manual switching operations by the field crew to isolate the faulted asset.
- T3 is the time it takes to repair or replace the failed sub-transmission line asset or station asset.

$$Customer/reputation\ Cost\$ = ((MW\_1 * T\_1) + (MW\_2 * T\_2) + (MW\_3 * T\_3)) * VCR$$

Equation 8: Customer Cost - Sub-transmission

Where MW1, MW2, MW3 are the loads at risk during periods T1, T2, T3 respectively

5.5.5. Transmission

Unavailability of a transmission asset resulting from a failure has two possible effects:

- It can affect DNSP connections limiting supply to zone substations and directly affects customer supply – this is referred to **'customer'** consequence as it is with the distribution network.

Create a constraint on the shared network. This is referred to as **'market'** consequence. Constraints include generation and interconnection constraints on the NEM (national electricity market), network security, increased load shedding risk, changed greenhouse gas emissions, etc.

5.5.5.1. Customer consequences

In the transmission network, customer impact is primarily associated with terminal stations that supply zone substations, forming part of the DNSP-connected network. These stations transfer power through 'B', 'L', 'U', and 'X' type power transformers.

A failure of a transformer, line, or bus at a terminal station has the potential to directly affect customer supply. Other assets within the station—such as circuit breakers, protection relays, and disconnectors—can also contribute to customer impact, but only through their functional association with transformer, line, or bus.

Customer consequence is assessed using two approaches:

- If the failure relates to the transformer bank, the "load duration" method is applied

- If the failure relates to the line or bus, the "station average" method is used

Load Duration

If a failure impacts a single customer connection transformer (including the transformer itself) then the transformer probabilistic planning methodology can be used in line with the AusNet Asset Renewal Planning Guide - AMS 10-24. This method utilises the load duration curve of a station and accounts for the probability that the load will be higher than the capacity of the remaining transformers at any given time.

The 15 minute load (MVA) is obtained from SCADA and a load duration curve is produced by station and transformer type (eg B transformers at BETS, L transformers at BETS). The transformer nameplate continuous ratings (MVA ODAF – oil directed air forced) are stacked from largest to smallest and overload on the corresponding load duration curve for a station of 'k' transformer of the same type. The summated total nominal power rating becomes the 'n' rating, the total minus the smallest transformer becomes the 'n-1', and so on. The total energy (MVAh) within each n state area of the curve becomes the energy at risk (EAR) – the areas are directly calculated from SCADA data.

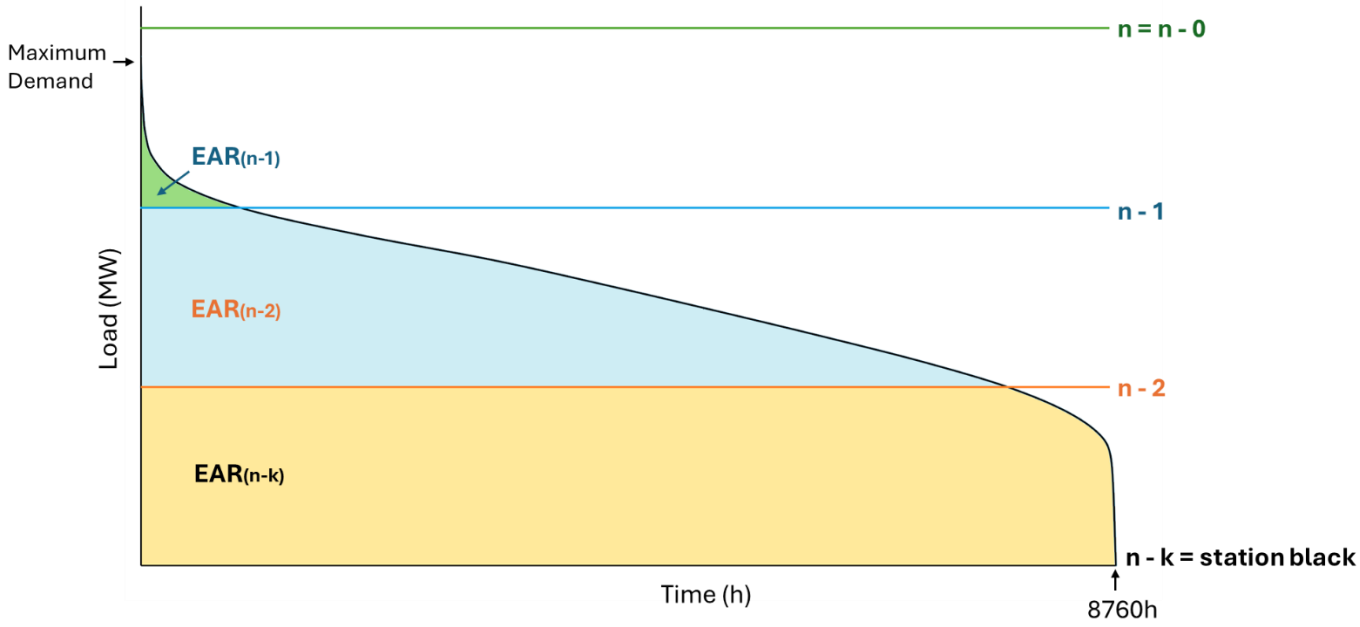


Figure 8 - Load Duration Curve with Transformer Capacity

In the transmission network, the failure of a single transformer automatically places the station in an N-1 state for the T3 period. At most terminal stations, where transformers are fully switched (except Wemen Terminal Station), this means no T2 period occurs for the remaining units. However, at Wemen, a transformer failure results in a T2 outage for the second transformer.

There is also a conditional probability that additional transformers may already be unavailable (due to predicted failures) when the first fails. This can escalate the event to an EAR(N-2) or even EAR(N-k) scenario. For example, in a three-transformer station, if two are unavailable when one fails, the result is a station blackout.

Availability can be described by the equation

$$Availability = A = \left(\frac{MTTF}{MTTF + MTTR}\right)$$

Where:

- MTTF = Mean Time to Fail (conditional MTTF - MTTF given the asset has survived to time t)

- MTTR = Mean Time to Repair (years or portion of a year)

For this calculation, it is reasonable to assume that the failure rate is constant, meaning that:

$$\text{Since } \lambda = \frac{f(t)}{R(t)} \quad \text{then} \quad MTTF = \frac{1}{\lambda}$$

$$Availability = A = \left(\frac{MTTF}{MTTF + MTTR}\right) = \left(\frac{R(t)}{R(t) + f(t)MTTR}\right)$$

Equation 9 – Availability using constant failure rate

Where:

- R(t) = Cumulative Distribution Function - Reliability Function = probability an asset survives to a point in time t.
- f(t) = Probability density function

Target risk of a transformer within a station is the risk of unsupplied load resulting from a transformer of interest within a bank of transformers. This excludes the risk a station may be subjected to from failures of other transformers.

To calculate target risk, the following conditional variable is created:

$$T_j(i) = \begin{cases} 0 & if\ Transformer\ j\ is\ available\ in\ state\ i \\ 1 & if\ Transformer\ j\ is\ unavailable\ in\ state\ i \end{cases}$$

Where:

- i is a counter
- j is a specific transformer in a station of k transformers:

$$j \in \{1, \dots, k\}$$

This variable is created to allow only expected EAR to be calculated where the target transformer is in an unavailable state.

The target risk then follows:

$$Risk_{T_j} = \left(\sum_{i=1}^{k} 1_{\{T_j(i)\}} A_{(n-i)} \cdot EAR_{(n-i)}\right) \cdot PF \cdot VCR$$

Equation 10 - Transformer Target Risk

Where:

- $A_{(n-i)}$ = total station availability for an n-i state
- $EAR_{(n-i)}$ = the energy at risk (MVAh) for an n-i state
- VCR = Value of Customer Reliability ($/MWh) per station
- PF = power factor – is used to convert MVAh from SCADA to MWh to multiply against VCR

The total risk for transformer T_j is calculated by looking at all possible failure scenarios where one or more transformers are unavailable. For each scenario:

- We check if **transformer T_j** is involved
- We consider how likely it is that n−*i* transformers are unavailable (**availability factor** $A_{(n-i)}$)
- We estimate how much energy customers would lose in that scenario (**Expected Unserved Energy**, or $EAR_{(n-i)}$)

Then, we multiply the combined impact by the power factor and VCR.

For service-related consequences—such as supply interruptions—the **Probability of Failure (PoF)** and **Likelihood of Consequence (LoC)** are **intrinsically linked through the calculation of availability**. In contrast, for other consequence types like **Safety** and **Environment**, PoF and LoC are **independent factors**, allowing risk to be represented in the standard form:
Risk = PoF × CoF

Transformer availability is used in **Energy at Risk (EAR)** calculations, therefore, consequence itself varies based on the failure probability, so PoF and CoF are inherently linked. To reflect this, we use the term **"target risk"** to represent the combined impact, capturing both failure likelihood and customer consequence in a unified measure.

The following is an example of a three-transformer station with:

- $A_{(Tr\ 1)}$ = 0.999 => transformer 1 is available 8,751h in a year (or unavailable for 9h)
- $A_{(Tr\ 2)}$ = 0.996 => transformer 2 is available 8,725h in a year (or unavailable for 35h)
- $A_{(Tr\ 1)}$ = 0.998 => transformer 3 is available 8,742h in a year (or unavailable for 18h)
- EAR = the energy at risk (MVAh) for each station state

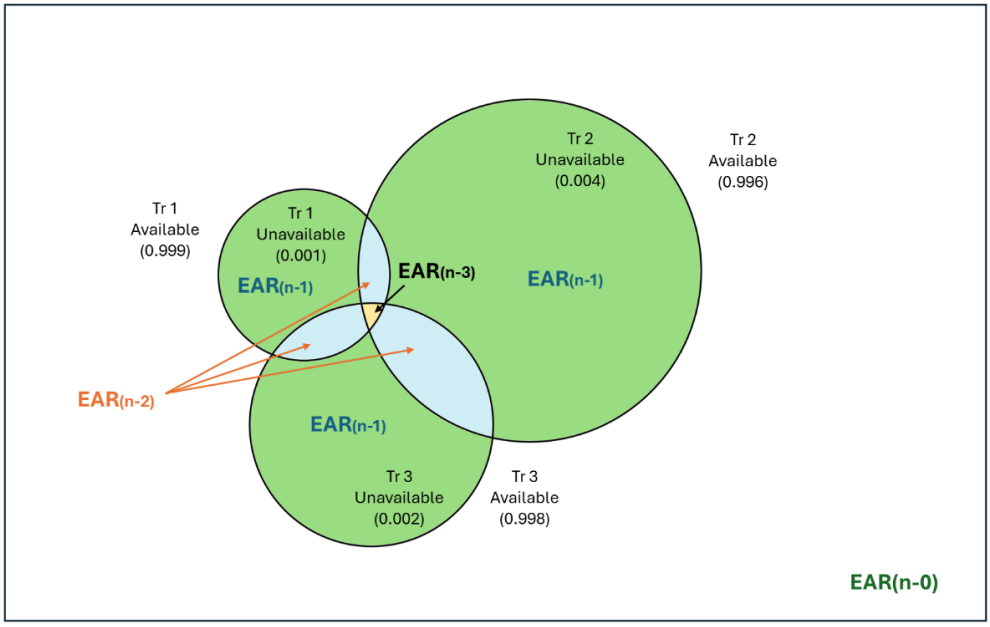


Figure 9 - Three Transformer Unavailability Venn Diagram

The circles represent unavailability of a transformer based on the specified PoF and MTTR values. The area shaded in green is the station state where exactly one transformer has failed (one failure and no more). Multiplying by $EAR_{(n-1)}$ gives the expected energy at risk for the station for an n-1 state.

The area shaded in blue is when two and only two transformers are in an unavailable state.

A station black occurs in the orange shading when all three transformers are in an unavailable state – $EAR_{(n-3)}$. $EAR_{(n-0)}$ is the energy at risk with all transformers in service – a highly undesirable state.

The station availability [Tr 1 Av.) x (Tr 2 Av.) x (Tr 3 Av.)] for all 8 combinations of Available (A) and Unavailable (U) station states are shown in Table 10:

Table 10 - Three Transformer Availability Truth Table

Row	Tr 1 State	Tr 2 State	T3 State	Station State	Tr 1 State Probability	Tr 2 State Probability	Tr 3 State Probability	Station State Probability
1	A	A	A	n-0	0.999	0.996	0.998	0.993013992
2	A	A	U	n-1	0.999	0.996	0.002	0.001990008
3	A	U	A	n-1	0.999	0.004	0.998	0.003988008
4	A	U	U	n-2	0.999	0.004	0.002	0.000007992
5	U	A	A	n-1	0.001	0.996	0.998	0.000994008
6	U	A	U	n-2	0.001	0.996	0.002	0.000001992
7	U	U	A	n-2	0.001	0.004	0.998	0.000003992
8	U	U	U	n-3	0.001	0.004	0.002	0.000000008

For clarity, 'State Probability' is the value used to describe the probability of a transformer, or station, being in the transformer or station state specific in columns 2 to 4. For an asset with an availability value of 0.999, the probability of being A is 0.999, the probability of being a U is 0.001.

The transformer bank is fully available 0.993 (0.999 x 0.996 x 0.998) of the time – or 8,699h.

The four shaded rows show the station configurations possible when the target, transformer 1, is in a failed state. This is used to describe the transformer 1 **target risk**.

When Transformer 1 fails, the risk contribution is calculated across different station states:

1. **n-1 State (Row 5)**
   This is the only n-1 condition where Transformer 1 has failed and the other two are operational.
   - **Station State Probability**: 0.000994008
   - **Risk Contribution**: Multiply this by **EAR(n-1)** to get Transformer 1's n-1 risk.
2. **n-2 State (Rows 6 and 7)**
   These represent scenarios where Transformer 1 has failed **and** either Transformer 2 **or** Transformer 3 has also failed.
   - **Combined Station State Probability**: $0.000001992 + 0.000003992 = 0.000005984$
     This equates to roughly **3 minutes per year**.
   - **Risk Contribution**: Multiply this by **EAR(n-2)** for Transformer 1's n-2 risk.
3. **n-3 State (Row 8)**
   All three transformers have failed.
   - **Station State Probability**: 0.000000008
   - **Risk Contribution**: Multiply this by **EAR(n-3)** for Transformer 1's n-3 risk.

$$Risk_{Transformer\_1\_Target} = (994x10\text{-}6 * EAR(n\text{-}1) + 5.98x10\text{-}6 * EAR(n\text{-}2) + 0.008x10\text{-}6 * EAR(n\text{-}3)) * PF * VCR$$

Equation 11 - Transformer 1 Target Risk

To calculate the risk of transformer and assets that directly impact a transformer the target transformer.

Station Average

Where the impact of an asset failure cannot be mapped to the load duration curve, the impact to consider is a station black. Thus, the cost of consequence is the average load (MVA) of the station. In a similar manner to the above using the MTTR (h) of the asset, availability is determined and the expected load lost is multiplied by the cost

($/MWh). Consequence of failure accounts for all the coincident failures required for an asset failure to cause a station black.

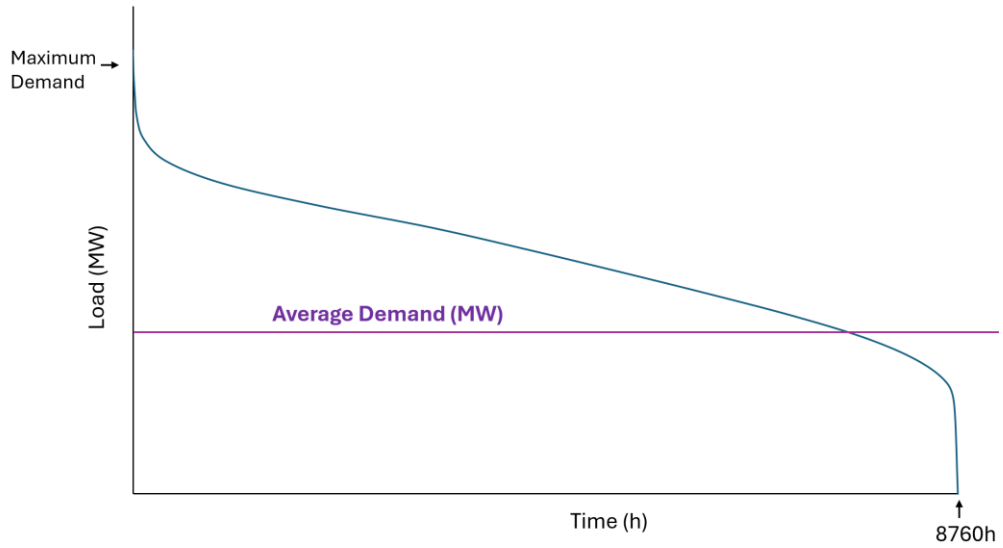


Figure 10 - Load Duration Curve Showing Station Average Load

VCR – per line

For lines feeding terminal stations that have load connection transformers (ie stations with B, L, U, X transformers) the customer methodology can apply. A failure of a line can cause a station black for the stations at both end of the line if there are coincidental failures of the remaining lines supplying each station.

Line availability is consistent with Equation 9, it is based on the failure of the tower with the highest PoF.

Figure 11 illustrates the line and station arrangement for line A-B and Station A and B:

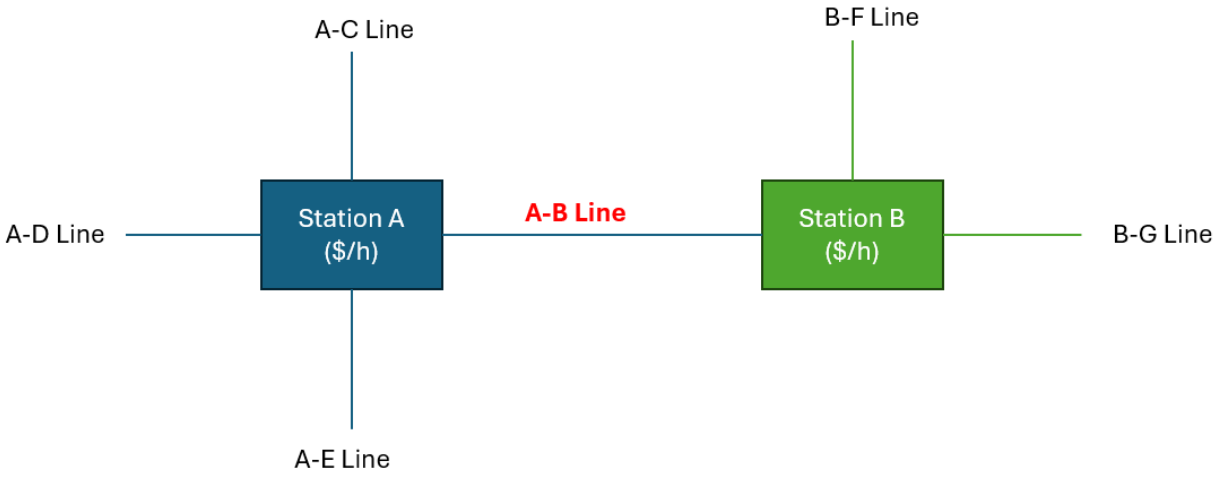


Figure 11 - Coincidental Line Failures

Equation shows the example of the impact of the failure of line A-B on the stations A and B, noting that a:

- station A black results from the coincidental unavailability of lines AC, AD, and AE
- station B black results from the coincidental unavailability of lines BF and BG.

$$AB(\$/h) = [(1 - A_{AC}) \cdot (1 - A_{AD}) \cdot (1 - A_{AE})] \cdot Station_A(\$/h) + [(1 - A_{BF}) \cdot (1 - A_{BG})] \cdot Station_B(\$/h)$$

Equation 12 - Coincidental Line Failures

Where :

- A_{AC},…,A_{BG} = Availability of lines AC to BG in line with Equation 9
- $Station_A$(\$/h) and $Station_B$(\$/h) = cost of station black at Station A and Station B

The generalised equation for any station utilising is shown in Equation 13 using the station naming convention A and B:

$$CoF_{AB}(\$/h) = \prod_{i \in L_A / L_{target}} (1 - A_i) \cdot VCR_A(\$/h) + \prod_{j \in L_B / L_{target}} (1 - A_j) \cdot VCR_B(\$/h)$$

Equation 13 - General Coincidental Line Failure

Where:

- $L_A \in$ {Line 1, Line 2,…,Line m} where m is the total number of lines supplying station A
- $L_B \in$ {Line 1, Line 2,…,Line m} where m is the total number of lines supplying station B
- L_{target} = the target line – which is the effect of a failure that is being assessed – it connects station A and B.
- CoF_{AB} = cost of failure for a line connecting station A and station B
- A_i and A_j = availability for the i set and j set of lines as per Equation 9
- VCR_A and VCR_B = VCR rate for station A and station B black (\$/h)

5.5.5.2. Market Consequences

Market consequence values are produced from specific Detailed Network Studies and the Network Access Guide (NAG).

Detailed Market Studies

Detailed market studies are conducted using advanced energy market simulation platforms (such as PLEXOS), which enable high-fidelity modelling of dispatch, cost, and reliability outcomes across the National Electricity Market (NEM). These studies support scenario-based valuation over multi-year horizons, evaluating combinations of generation sources - including solar, wind, battery, gas, coal, etc. - and transmission configurations under varying policy, demand, and outage conditions. AEMO constraint equations are utilised to account for congestion and curtailment risks caused by network limits, flow conditions, and system stress.

The modelling simulates hourly dispatch and produces both time-weighted and load-weighted least cost market impact forecasts. Modelling doesn't simulate competitive behaviour - it produces is a 'least-cost' output which will ultimately underestimate real world costs but provides consistent base-case value that can used for network planning. The resulting market asset valuation is leveraged to produce market consequence values.

The modelling is comprehensive but requires extensive computational and analytical resources. As a result, this kind of modelling is reserved to develop justification for major and complex projects or high-volume line replacement programs. Where outputs are available, the resulting 10 year projections can be utilised to develop market consequence hourly rates.

Network Access Guide (NAG)

For the majority of network nodes detailed market studies have not been undertaken. They require a more simplistic method, or approximation, so a market value can be assigned to every asset in the shared network.

The NAG provides hourly penalty rates to the majority of shared network nodes for the purposed of planning outages. It is based on the suspended (as of April 2025) Market Impact Component (MIC) that was formerly part of the AER Service Target Performance Incentive Scheme (STPIS). Although, no longer an active scheme, it is considered reflective of economic loss of shared network unavailability, sufficient to estimate loss and rank network nodes with the current mix of generation. For the purposes of assigning market consequence, the MIC penalty value is a proxy for economic loss rather than a financial liability.

The values are produced from historical penalties AusNet has received under the scheme. The dynamic nature of the market and the nature of unplanned outages mean outages could have been taken during favourable or unfavourable conditions – the received penalties reflect this. The values used approximate an average rate based on the historical 'samples', opposed to forecasts produced from detailed market studies, the sampling rate is not comprehensive.

At the time of publishing, a high-level correlation has been undertaken between outputs from detailed market studies and NAG values. The market study outputs fluctuate in comparison to NAG – NAG is overestimated for some nodes, underestimated for others. However, the results are in a similar order of magnitude, showing they are valuing similar impacts.

This directly applies values to major shared network elements, such as transmission lines and transformers. To assign values to all assets, one of the four methods summarised in Table 11 can be used.

Table 11 - NAG Assignment Summary

Method	Name	Application	Summary
1	NAG – element	When NAG values are directly available for network elements - such as transformer and transmission lines.	The hourly NAG values are applied directly to the associated element.
2	NAG – interpolated	Where values have not been assigned to an asset but can be inferred based on network configuration – eg it is part of the same loop or is a direct generation connection.	The interpolated hourly values are applied to the associated element.
3	NAG – derived station	For stations assets - excluding shared network transformers that have been assigned a NAG value, and any assets that directly impact those transformers.	This method assigns a station NAG value by summing the NAG values of the lines supplying the station. This value represents the hourly cost of a station blackout and is first multiplied by the probability of the asset failure leading to black, before being applied to the asset.
4	NAG – derived line	For shared network lines without assigned NAG values.	A value is assigned to a line based on the station NAG values impacted by failure of that line. It is assumed that a station can be supplied by a single circuit, so the station NAG is multiplied by the unavailability of the remaining circuits to derive a line NAG value. This calculation is performed for the stations at both ends of the line and summed.

Note:

- The values produced in accordance Table 11 hourly rates than need to be multiplied by the mean time to repair/restore (MTTR).
- Methods 1, 2 and 4 are CoF values meaning they are already expected values in which the CoC x LoC calculation is already incorporated.
- Method 3 produces a CoC that need to be multiplied by LoC.

The four methods are detailed as follows:

1) NAG - element

Failure of an asset can impact one circuit, as is most common, or two circuits, as in the case for multi-circuit tower failures.

Where an asset affects a single circuit market is calculated using Equation 14:

$$Market\ Impact\ CoC\ (\$/failure) = NAG(\$/h) \times MTTR(h)$$

Equation 14 - Market Impact Cost of Consequence (CoC) – single circuit

Where an asset failure affects more than one circuit – primarily multi-circuit towers – Equation 15 can be used:

$$Market\ Impact\ CoC\ (\$/failure) = NAG\ Circuit\ 1\ (\$/h) \times MTTR\ 1(h) + NAG\ Circuit\ 2\ (\$/h) \times MTTR\ 2(h)$$

Equation 15 - Market Impact CoC - multiple circuits

In the example of multi-circuit tower MTTR - mean time to restore in this case – is 64 hours for circuit 1 and 96 hours for circuit 2. This is the time taken to erect two ERS towers and swap the circuits across the first being energised 64 hours after the failure and the second circuit energised 32 hours later. In the case of degradation-based failure the credible worst-case outcome is that a single tower will fail.

2) NAG - interpolated

The NAG report does not encompass all network elements. Exclusions include base load generators and recent augmentations that have not yet been modelled. Base load generators are excluded in recognition that forced outages on large units—such as coal-fired power stations—are highly disruptive and would not be initiated by AusNet. Instead, the strategy is to align with generator-led outages, and as such, the cost of a network-initiated forced outage has not been valued.

Two methods have been used to interpolate existing NAG values:

- Values have been applied to missing lines within a loop, where the remaining lines are consistently the same
- A ratio was created between the hourly rate of a line connecting a generation connection station and the average generation output. Maximum power generation capacity and capacity factor were obtained from the Open Electricity[11] data recorded from the National Electricity Market (NEM]. The resulting ratio was 0.45 - the interpolation equation is:

$$Interpolated\ Rate\ (\$/h) = 0.45 \times Maximum\ Capacity\ (MW) \times capacity\ factor \times 1{,}000$$

Equation 16 - Interpolated NAG

3) NAG – derived station

The NAG values for all lines feeding a station are summated to produce an overall station NAG $/h. The summated station NAG is multiplied by the LoC to produce the hourly rate. The LoC in this case is the probably that failure of an asset will result in a station black, this is achieved by relating an asset to one of three major station components:

- Transformer (A, F, H, M, P, R, W) – note, assets affecting transformers with a direct NAG value will follow method 1.
- Bus

[11] https://spatial.planning.vic.gov.au/planningwebmaps/RenewablesSummary.html

- Line

The large elements then have a material impact on a station. Methods are detailed in AMS 01-09-02.

4) NAG – derived line

To assign value to a line based on the affected station the assumption is made that a single circuit can supply the station, so the value of a line is the station NAG $/h multiplied by the intersection of unavailability's for the remaining circuits supplying the station. This method follows Figure 11 and Equation 13 substituting station summated NAG for the hourly rate VCR.

5.5.5.3. Map Customer and Market Consequence of Failure to Assets

Sections 5.5.5.1. 5.5.5.2. describe customer and market consequence of unavailability of transformers, stations and lines. These are used as the basis for all stations primary and secondary assets – unavailability of any primary or secondary asset in a station is going to have an impact on a transformer, bus, circuit breaker or line.

Circuit Breakers

Details of method to determine consequence based on station, line and transformer unavailability consequence is recorded in the addendum to this document (*AMS 01-09-02)*.

Buses

Buses are topologically linked to power transformers.

Other Primary Assets

Other primary assets including CTs, VTs, ES/DS, are mapped based on station primary topology.

Secondary Assets

Consists of the secondary systems required for protection including protection systems and systems required to operate protection systems – such as communications assets and auxiliary power supplies. Failure of these devices to work correctly, when required, means that the failure of the primary assets will have a greater impact. The other common way these devices fail is to operate without a valid trigger resulting in an unnecessary customer or market consequence.

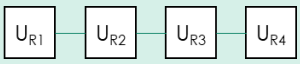
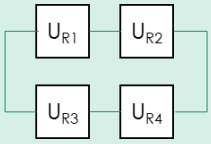
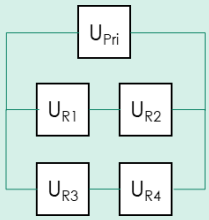
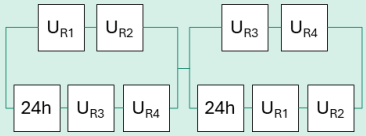
The probability of a failure of protection and communications assets resulting in a primary consequence can be described using reliability block diagrams (RBDs). Table 12 shows four different scenarios for a protection system, where each box represents the unavailability – the portion of the year a protection element is expected to be unavailable in accordance with Equation 9.

Infrastructure Assets

Infrastructure assets—including buildings, fire protection systems, and drainage networks support the safe and reliable operation of electrical assets. When these supporting systems fail, they can initiate cascading effects that compromise both secondary systems and primary systems, ultimately affecting electricity supply to customers.

The resulting customer impact may manifest in several ways. Restricted access due to structural damage or safety concerns can delay fault diagnosis and restoration efforts. Exposure or damage to secondary and/or primary systems—such as from fire or flooding—can lead to station blackouts.

Table 12 - Secondary System Unreliability

Scenario	Description	Impact	Reliability Block Diagram (System)	Rationale
1	Spurious Trip	Element off for MTTR or relay		Relay operates as designed to protect primary asset, despite no valid trigger. Primary asset unavailable for time taken to diagnose and replace/reset secondary asset.
2	Secondary system unavailable, no primary fault	Element off for MTTR of relay		Primary asset switched out if both redundant system (eg X and Y) fail, representing policy to not rely on backup protection. Primary asset unavailable for time taken to restore one redundant system.
3	Secondary system unavailable, primary fault	All remaining elements off for MTTR of relay		If primary asset fails and all redundant secondary systems fail to operate, it is assumed backup protection switch larger system off – eg one PT fails and protection fails, backup switches all PTs out. Impact of relay failure is a larger system outage, when it should have been contained to a smaller system.
4	No secondary redundancy for more than 24 hours	Element off for: MTTR - 24 provided MTTR > 24 or 0.		AEMO administering the NER 5.2.1.1 operational guidelines - AEMO Power System Guidelines – may direct AusNet to switch the primary element off if remaining protection is insufficient or repair exceeds 24 hours in the event of an unplanned outage of a single protection system. Given remaining protection is a primary scheme, this translates to an outage if repair time exceeds 24 hours.

The Reliability Block Diagrams (RBDs) represent a two-component redundant system, typical of protection or communications systems — e.g., X/Y or A/B configurations. In the diagrams, the system is divided into X and Y protection groups, where:

- **X system** consists of relays **R1 and R2**
- **Y system** consists of relays **R3 and R4**

Two failure modes are modelled:

1. Spurious Trip

- **Definition**: A relay operates without a valid trigger.
- **Initiating Event**: A spurious trip signal from any one of the four relays — i.e., **R1 OR R2 OR R3 OR R4**.
- **System Impact**: A single relay malfunction can cause an unintended trip.

2. Failure to Operate

- **Definition**: A relay fails to operate when a valid trigger is present.

- **Initiating Event**: This applies to **Scenarios 2, 3, and 4**.
- **System Impact**:
    - **Scenario 2 & 3**: The protection system is considered unavailable when **(R1 OR R2) AND (R3 OR R4)** are both unavailable — i.e., both X and Y systems fail.
    - **Scenario 4**: This is not a true failure but a contingency management situation. If R1 or R2 fails a 24-hour timer starts, **24h.** The whole system will then fail if 24h runs out, R3 fails, or R4 fails. The entire system could also fail if R3 or R4 were first to fail, then 24h, R1 or R2 fail.

For enabling assets such as **communications** and **auxiliary supplies** the applicable scenarios are based on scenarios 2 and 4.

5.5.5.4. System vs Target Risk

As noted in Section 5.5.5.1 and shown in Table 10, unavailability-based risk differs between the system level and the asset level. System unavailability depends on the probability of failure (PoF) and mean time to repair (MTTR) of all assets within that system.

Because multiple components contribute to system unavailability, the **inclusion-exclusion** principle is used to account for overlapping failure scenarios. This ensures the overall system risk isn't overstated by double-counting shared failure events.

When evaluating the risk of replacing an entire system—such as both the X and Y protection systems—system-level unavailability risk is appropriate. Simply summing the individual asset risks would overestimate the total system risk due to overlapping contributions from different components.

Methodology to seamlessly scale of quantified risks at different system levels has yet to be developed at AusNet, therefore risk aggregation and disaggregation has to be undertaken manually. The simplified method used to allow assets to be scaled up and down is to create target risk as a weighted proportion of system risk based on the relative levels of unavailability. Consider unavailability of one asset A and another asset B:

$$Risk_{A\_target} = \frac{U_A}{(U_A + U_B)} \cdot Risk_{System}$$

Equation 17 - Target Risk of A

Where:

U_A = unavailability of asset A

U_B = unavailability of asset B

This can be visualised by the Venn diagram in Figure 12, where the green shading shows portion of risk based on U_A and the yellow shading the portion of risk based on U_B. The summation green and yellow is equal to the union of U_A and U_B – ie U_A U U_B.

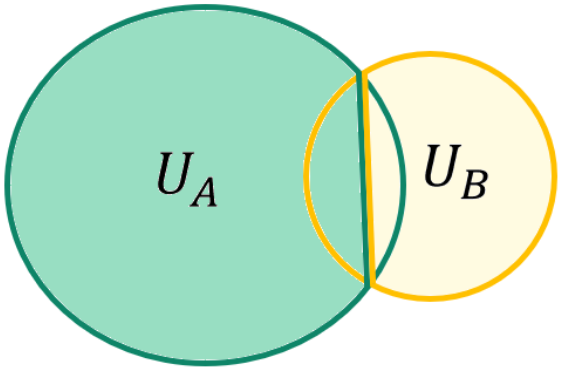


Figure 12 - Target Risk as a Portion of Component Unavailability

In a general form:

$$Risk_{C_i} = \frac{U_{C_i}}{\sum_{j=1}^{n} U_{C_j}} \cdot Risk_{System}$$

Where:

C_i = is an asset within a system of n assets

$Risk_{Ci}$ = Unavailability of asset i

U_{Cj} = Unavailability of j^{th} asset within a system of n assets

5.5.6. Gas

Cost of consequence for gas assets has not been quantified a part of issue 4 of this document.

6. Risk Evaluation

6.1. Quantified Risk

The consequence of failure (CoF) and probability of failure (PoF) determined in section 4. and section 4. respectively are used to determine the risk ranking of assets and in the calculations of economic assessment.

Figure 13 shows the general form of the quantification of risk using PoF and CoF.

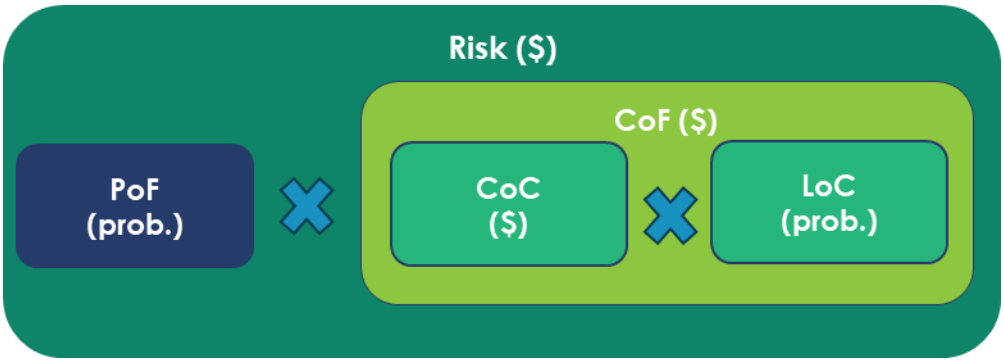


Figure 13 - Risk Components

6.2. Risk Matrix

6.2.1. Likelihood/Consequence

The CoF and PoF results are scaled into Likelihood and Consequence levels and ranked as shown in Table 13. The values could be displayed in a risk matrix.

Table 13: Risk Ranking

Rank	Likelihood	Consequence
25	5	5
24	4	5
23	5	4
22	3	5
21	4	4
20	5	3
19	2	5
18	3	4
17	4	3
16	5	2
15	1	5
14	2	4
13	3	3
12	4	2
11	5	1
10	1	4
9	2	3
8	3	2
7	4	1
6	1	3
5	2	2
4	3	1
3	1	2
2	2	1
1	1	1

6.2.2. Presenting Likelihood on a Risk Matrix

Likelihood is a term used on a risk matrix to describe the chance of an asset failure occurring. At AusNet, likelihood is a 1 to 5 scale, where the 1 'bucket' depicts the lowest chance, where bucket 5 depicts the highest chance

The score reflects the relative probability of failure (PoF) for each failure mode model, depending on the analysis context. For asset replacement decisions, wear-out failure modes are used. In contrast, wear-in failure modes inform initial inspection strategies or help assess the risk associated with different asset interventions.

The likelihood score is derived from two reliability-based indicators that reflect both time-to-risk threshold (how soon failure becomes likely) and longevity (how long the asset is expected to continue performing reliably):

Time to Risk Threshold (TTR)

The estimated number of years until an asset reaches a 10% conditional probability of failure, given survival to its current age. This metric, derived from the Weibull distribution quantile, identifies how soon an asset is likely to reach a risk threshold.

Mean Residual Life (MRL)

The expected remaining life of an asset, conditioned on its current age. This metric reflects how long the asset is expected to continue performing reliably.

TTR can be used to determine a likelihood bucket alone. A more refined value can be obtained by the combination of TTR and MRL. The combination provides a quantitative method for assigning likelihood ratings on the risk matrix.

6.2.2.1. Estimating Time to Risk Threshold (TTR)

The Time to Risk Threshold (TTR) represents the number of years until an asset's cumulative probability of failure reaches 10% (p10), conditional on survival to the current age. Mathematically, this is determined by using the quantile function of the fitted survival distribution. For a Weibull distribution Equation 18 applies.

$$t_{remaining} = \eta * \left(-\ln\left(1 - \left(p + (1-p) * F_{age}\right)\right)\right)^{\frac{1}{\beta}} - t$$

Equation 18: Remaining Life to p-quantile

Where:

F = Cumulative density function (cdf) = $F_{age} = 1 - e^{-\left(\frac{age}{\eta}\right)^{\beta}}$
$t_{remaining}$ = number of years from current age
p = quantile (0.1)
age = current service age of asset
β = shape parameter
η = characteristic life
t = effective age for ML or HS, or age for all others

Time-to-risk threshold levels

The number of years to p10 are divided into five urgency levels

Level	Years remaining to Risk Threshold (TTR)	Interpretation
T5	<= 1 year	Asset expected to reach risk threshold within a year
T4	> 1 year but <= 2 years	Asset nearing risk threshold
T3	> 2 years but <=3	Condition stable but threshold approaching
T2	> 3 years but <= 4 years	Early signs of degradation
T1	> 4 years	Comfortable margin before reaching threshold

Table 14: Conversion of Remaining Life to Likelihood Scale

6.2.2.2. Estimating Asset Longevity (Mean Residual Life MRL)

The time to risk threshold method can be refined by incorporating the Mean Residual Life (MRL). MRL represents the expected remaining life of an asset, given it has survived to its current age.

Equation 19 applied for a Weibull distribution:

$$MRL(t) = \eta * \left[\frac{\Gamma\left(1 + \frac{1}{\beta}, \left(\frac{t}{\eta}\right)^{\beta}\right)}{e^{-\left(\frac{t}{\eta}\right)^{\beta}}}\right] - t$$

Equation 19 - Mean Residual Life Calculation

The MRL is divided into four longevity levels:

Table 15: Longevity

Level	Years Remaining	Description
M4	<= 5 years	Short remaining life
M3	> 5 years but <= 10 years	Moderate remaining life
M2	> 10 years but <=20	Long remaining life
M1	> 20 years	Very long remaining life

By intersecting Time-to-Risk threshold (TTR-level) and Longevity Category (MRL-level), an overall Likelihood Rating (L-score) is determined. This provides a link between reliability modelling outputs and risk assessments used in the risk matrix.

Table 16 – Integrating TTR and MRL

	M4	M3	M2	M1
T5	5	4	3	2
T4	4	3	2	1
T3	3	2	1	1
T2	2	1	1	1
T1	2	1	1	1

6.2.2.3. Likelihood Scale Definitions

The T-level reflects how soon the asset is expected to reach a threshold probability of failure. Assets with high age or rapidly deteriorating condition exhibit higher cumulative failure probability, resulting in smaller TTR values (shorter time to 10% failure). These assets fall into high TTR categories (T5–T4), signaling an imminent need for risk-based intervention, increased inspection frequency, or proactive replacement planning. Conversely, younger assets or those with stable condition indicators have larger TTR values, indicating lower near-term failure probability and lower TTR categories (T1–T2).

The M-level captures the expected remaining life. Assets with poor health, severe degradation, or repeated failures tend to have short MRL values, placing them in lower longevity classes (M4–M3). Assets in good condition or with strong environmental and operational resilience have longer expected remaining life, corresponding to higher longevity classes (M2–M1).

The likelihood level reflects the combined effect of degradation (condition) and time-dependent reliability (age). The intersection of TTR (short-term failure risk) and longevity (expected durability) forms a two-dimensional reliability surface. Assets with both high TTR level and short longevity (T5 × M4) are classified as "Very Likely" failures within 12 months, while assets with low TTR level and long longevity (T1 × M1) are "Very Unlikely" to fail in the foreseeable horizon. This combined approach ensures that risk prioritization reflects both immediate reliability threats and long-term sustainability.

Table 17: Likelihood Scale Definitions

Level	Likelihood Descriptor	Indicative Timeframe for Action
5	Very Likely	<= 1 year
4	Likely	> 2 years but <= 5 years
3	Possible	> 5 years but <=10
2	Unlikely	> 10 years but <= 20 years
1	Very Unlikely	> 20 years

6.2.2.4. Health Score Normalisation Method

The normalised method is a simplified analysis where a suitable statistical distribution cannot be produced from the available historical failure data. The health scores are normalised to 100 and a likelihood level is assigned based on Table 18.

Table 18: Converting Normalised Health Score to Likelihood Level

LEVEL	Likelihood Scale	Health Score
5	Very Likely	90-100
4	Likely	60-89
3	Possible	40-59
2	Unlikely	20-39
1	Very Unlikely	0-19

6.2.3. Presenting Consequence on Risk Matrix

The methodology remains under development at the time of publishing.

6.2.4. Interpretation

A risk matrix is one tool used to visualize asset risk and support broad comparisons across a fleet. High-level strategies can be applied in line with Section 7 to determine actions.

In this context, the matrix reflects the results of a quantified risk assessment, with numerical values mapped into qualitative categories.

As calibration of a consistent asset-level consequence model across all asset classes is ongoing, a risk matrix consistent across all asset classes cannot be developed. However, the combination of likelihood bucket, risk score, and relative asset class consequence can guide indicative actions:

Table 19 - High Level Guidance on Potential Risk Mitigation Actions

Likelihood Bucket	Relative CoF	Indicative Risk Interpretation	Potential Action
Low	Low	Broadly acceptable	No action
Low	High	Potentially unacceptable due to consequence	Consider mitigating consequence
High	Low	Broadly acceptable	May warrant monitoring or low-cost mitigation
High	High	Unacceptable	Action required to reduce likelihood, consequence, or both

7. Risk Treatment

7.1. Risk Ranking

Risk treatment involves selecting and implementing measures to modify risk based on its assessed likelihood and consequence. The approach is guided by a structured Risk Ranking Framework using a 5×5 matrix to prioritise assets from Rank 1 (lowest) to Rank 25 (highest). For example:

High-risk: Transformer with Likelihood 5 and Consequence 5 - risk rank 25

Low-risk: Streetlight with Likelihood 2 and Consequence 1 - risk rank 2

The model used in this methodology is shown in Figure 14 as an overlay on the risk matrix.

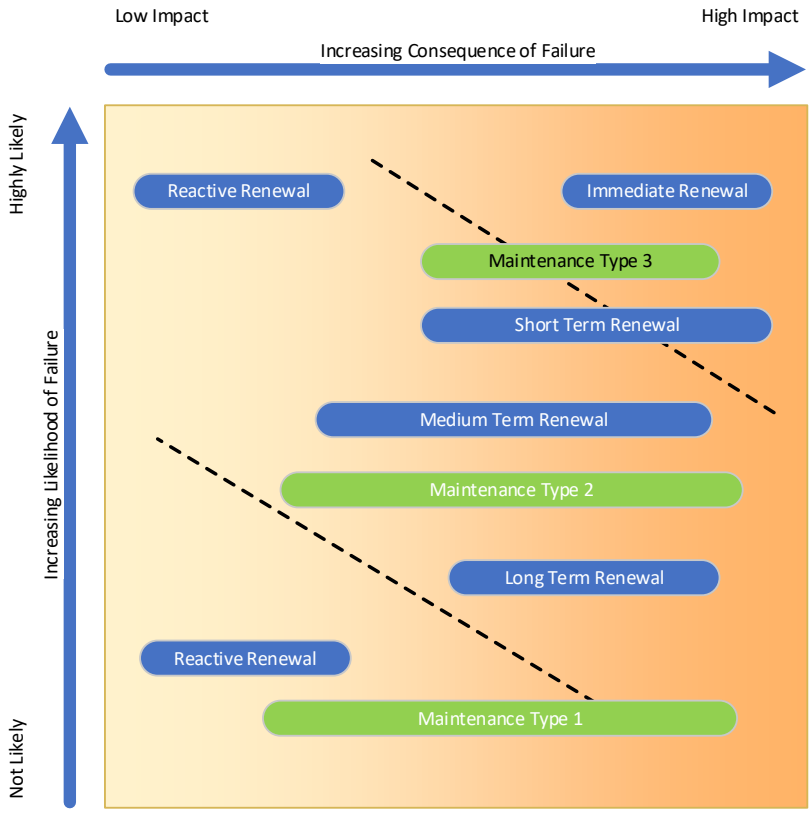


Figure 14: Risk Treatment Model

7.2. Risk Treatment Strategies

Assets are treated through two primary mechanisms:

- Maintenance (OPEX): Aims to reduce PoF by extending asset life and detecting early signs of failure (e.g., inspections, condition monitoring, refurbishment, etc).
- Renewal (CAPEX): Aims to reduce CoF or eliminate risk by replacing or redesigning assets.

Treatment decisions depend on Risk Rank and are classified as:

- Reduce Likelihood (e.g., increased monitoring, preventive maintenance),
- Reduce Consequence (e.g., containment, modify asset design),

- Retain Risk (with documented justification, for low-risk cases)

Maintenance types vary by intensity:

- Type 3 (High Frequency) for high-risk assets,
- Type 2 (Moderate) for medium-risk,
- Type 1 (Low Frequency) for low-risk or run-to-failure assets.

7.3. Planning Horizons for Renewal

CAPEX planning is based on risk-driven urgency:

- Immediate (0–2 years): High-risk assets requiring urgent intervention
- Short-term (2–5 years): Assets with rising deterioration; planned renewal
- Medium-Term (5–10 years): Stable assets; monitored for future renewal
- Long-Term (10+ years): Stable assets; monitored for future renewal
- Reactive: Low-risk assets; replaced on failure.

Example: A transformer showing imminent failure risk triggers immediate CAPEX; a performing transmission line may only require long-term planning.

7.4. Economic Justification

Every treatment decision is backed by economic analysis to ensure optimal allocation of resources. Asset replacement justification is based on comparing monetised Risk – as per **Equation 20** – and the replacement cost - $C_{replace}$.

$$Risk\ Cost\ \$ = PoF \times CoF_{total}$$

Equation 20 - Risk Cost

Where:

PoF: Probability of Asset Failure

CoF_{total}: Combined Consequence of Failure

CoF is the product of Cost of Consequence (CoC) and Likelihood of Consequence, respectively, worst case credible outcome and probability of CoC given an asset failure. **Figure 13** illustrates how risk is produced from its components – where PoF and LoC are probability values, and CoC is a monetisation of the output:

Three questions can be addressed by comparing quantified expected risk and replacement costs:

- Optimal Replacement Time Analysis (ORTA): Identifies when to replace an asset to minimize total cost over time.
- Lifecycle Cost Analysis (LCCA): Quantifies total cost of ownership (acquisition, operation, failure, disposal) to support long-term decisions.
- Cost Benefit Analysis (CBA): Evaluates whether a project, investment or decision is worthwhile by comparing its total expected costs against its total expected benefits.

7.4.1. Optimised Replacement Timing Analysis

This method determines the optimal timing for asset replacement by comparing the annual cost of risk with the annualised cost of replacement. Replacement is considered optimal when the risk cost exceeds the annualised cost of replacement, indicating the cost of continuing to operate the assets outweighs the cost of renewal.

This approach optimizes replacement timing for risk exposure over a short to medium term planning horizon. It is suitable for assets in the latter part of their useful lives, where the consequences of failure are high and risk exposure is no longer acceptable. It is appropriate where replacement is a valid means of reducing risks – ie where risk is driven by PoF rather than CoF.

Mathematically, optimal replacement occurs for the value of t when the risk cost exceeds the annualised replacement cost:

$$t_{optimal} = min\left\{t \in \mathbb{N} \middle| \left[\left(\frac{F_{(age+t)} - F_{(age+t-1)}}{R_{(age+t-1)}}\right) \cdot CoF > \left(\frac{r}{(1+r)^{-n}}\right) \cdot C_{replace}\right]\right\}$$

Equation 21: Optimal Replacement Timing t

Where:

$t_{optimal}$ = t where risk exceeds annualised replacement cost
CoF = consequence of failure
$C_{replace}$ = total asset replacement cost
r = discount rate
F(t) = Cumulative density function (CDF)
R(t) = Reliability Function [1-F(t)]
age = conditional age of asset at present time
n = Accounting Life of asset

Note:

- $t \in \mathbb{N}$ means t is part of the set of integers from t to ∞.
- Risk is the product of CoF and conditional probability of failure - probability of failure given an asset survives to age + t:

$$\text{PoF} = \frac{F_{(age+t)} - F_{(age+t-1)}}{R_{(age+t-1)}}$$

Equation 22 - Conditional Probability of Failure

Where:

$R(t) = 1 - F(t)$

7.4.2. Lifecycle Cost Comparison

The following method compares total risk costs of an existing asset, and the risk cost of a replacement asset and the replacement cost to replace a given year 't_r'. It does so by summating the discounted risk and replacement costs over a specific time horizon T.

$$\text{NPRC} = \sum_{i=1}^{t_r}\left(\frac{F_{(age+i)} - F_{(age+i-1)}}{R_{(age+i-1)}}\right) \cdot \frac{CoF_{total}}{(1+r)^i} + \sum_{i=1}^{T-t_r}\left(\frac{F_{(t_r+i)} - F_{(t_r+i-1)}}{R_{(t_r+i-1)}}\right) \cdot \frac{CoF_{total}}{(1+r)^{t_r+i}} - \frac{C_{replace}}{(1+r)^{t_r}}$$

Equation 23: Lifecycle Cost NPRC

Where:

NPRC = net present risk cost
r = discount factor,
T = analysis time horizon
t_r = replacement year,
F = Cumulative distribution function (CDF)
age = current age of asset or effective age of asset

Typically, 20 years is a sufficient time horizon to produce meaningful results.

The replacement time optimised for cost is the year 't_r' with the lowest NPRC. In this respect t_r values greater than 1 represent different replacement options, while no replacement – inherent risk – represents the business-as-usual option, or counterfactual.

This approach optimises replacement timing for cost rather than risk exposure.

8. Recording and Reporting

Results of the quantification can be presented in a risk matrix.

The matrix helps to visualize the type of action AusNet may take to address the risk in conjunction with the economic analysis. Figure 15 shows an example of an asset in the 'likely' likelihood and 'high' consequence. This shows that, left to deteriorate, the asset may result in an unacceptable risk. It also shows that proactive replacement in conjunction with preventive maintenance are actions that may be considered.

Figure 15: Risk Matrix Dashboard Example

9. Legislative references

STATE	REGULATOR	REFERENCE
VIC	WorkSafe Victoria	Occupational Health and Safety Act 2004
	EPA Vic	Environment Protection Act 2017

10. Resource references

DOCUMENT ID	DOCUMENT TITLE
AMS 01-09-02	Consequence Analysis - Addendum

11. Appendices

A. Asset Classes

Table 20:List of Asset Classes

Station type	Asset Class
DS, TS	AIR SYSTEMS
DL, TL	ANTENNA
DL	AUTOMATICSWITCH
DL	BATTERY
DL	BUS
DS, TS	BUS SYSTEMS
DL	CABLE
DL, TL	CABLE
TL	CABLEJOINT
TL	CABLELINKBOX
DS, TS	CABLES
DL	CABLESEGMENT
TL	CATHODICPROTECTUNT
DL, DS, TS	CIRCUIT BREAKERS
DL, TL, DS, TS	COMMUNICATION TECHNOLOGIES
DL	CONDUCTOR
DL	CONTROLBOX
DS, TS	COOLING SYSTEMS
DL, TL	CROSSARM
DL	CURRENTTRANSFORMER
DS, TS	DCAC SUPPLY SYSTEMS
DL	DISTCABINET
DL	DISTTRANSFORMER
DL	EARTHINGSWITCH
DS, TS	ENERGY STORAGE SYSTEMS
TL	ENVIRONMENTALSYS
DS, TS	FAULT LIMITERS
DL	FAULTINDICATOR
DL	FAULTLOCATOR
DS, TS	FIRE EQUIPMENT

Station type	Asset Class
DL	FUSEDISCONNECTOR
DL, TL	GROUNDWIRE
DS, TS	INSTRUMENT TRANSFORMERS
DL, TL, DS, TS	INSULATOR
DL	LINECAPACITOR
DL	MANUALSWITCH
DS, TS	NON SYSTEM EQUIPMENT
DL	ONLOADTAPCHGR
DL	ONLOADTAPCHGRME
DS, TS	PHYSICAL PLANT PROPERTY
DL, TL	POLE
DL	PRIVELECTRICLINE
DS, TS	PROTECTION AND CONTROL
DS, TS	REACTIVE SUPPORT
DS	REFCL
DL	RELAY
DS, TS	SECURITY
DL	SECURITYCAMERA
TL	SHEATH
DL	SHELF
DL	STATICVARGEN
DL, TL, DS, TS	STRUCTURES
DL	SUBSTATION
DL, DS, TS	SURGE DIVERTERS
DL	SWITCH
DS, TS	SWITCHGEAR
DS, TS	TRANSFORMERS
DL	VOLTAGEREGULATOR
DL	VOLTAGETRANSFORMER
DL, TL	WIRESEGMENT

B. Disproportion Factor

Safety legislation requires investment 'as far as reasonably practicable' – that is, invest until the costs are grossly disproportionate to the benefits or risk reduced. Disproportion factors (DF) are used to provide guidance on when this point has been reached.

According to the UK's Health and Safety Executive (HSE), DFs that may be considered gross vary from upwards of 1 depending on several factors including the magnitude of the consequences and the frequency of realising those consequences, i.e. the greater the risk, the greater the DF. A DF of greater than 10 is unlikely. HSE submission to the1987 Sizewell B Inquiry[12] suggesting that a factor of up to 3 (i.e. costs three times larger than benefits) would apply for risks to workers; for low risks to members of the public a factor of 2, for high risks a factor of 10. HSE has not formulated an algorithm which can be used to determine when the degree of disproportion can be judged as 'gross'; the judgement must be made on a case-by-case basis. It is generally understood that the greater the risk, the more that should be spent in reducing it, and the greater the bias on the side of safety. Additionally, the choice of DF may be higher when there is a low level of trust between the duty-holder and the community they operate in. In these circumstances, when trust levels are low, there may be an expectation to spend more to reduce risks.

The DFs given in Table 21 are to be applied to fatalities caused by electrical infrastructure, excluding fatalities caused by a bushfire started by electrical infrastructure. These values have been selected following a high-level review of values used across the electricity industry within Australia and by other industries across Australia and internationally.

Table 21 - Disproportion Factors – Fatality caused by Electrical Infrastructure (excluding bushfire start)

Scenario	Disproportionality Factor
Public Trespass	1
Single Fatality (public or worker)	3
Multiple Fatality (public or worker)	6

Table 22 gives the disproportion factors to be used when assessing the risk of a fatality cause by a bushfire started by electrical infrastructure.

Table 22 - Disproportion Factors – Fatalities due to bushfires started by electricity assets

Scenario	Disproportionality Factor
Asset in LBRA	1
Asset in HBRA	3
Asset in REFCL Area	6
Asset In Codified Area	10

The disproportion factors for fatalities due to bushfires started by electrical infrastructure have been selected considering the weighting scale for the geographic dimension of the Ignition Risk Unit (IRU) calculation () as a guide of the community's expectation around preventing bushfires and the resulting fatalities.

These values have been applied at AusNet since 2019.

[12] **Sizewell B Inquiry.** (1987). *Report of the public inquiry into the proposed construction of a Pressurised Water Reactor at Sizewell, Suffolk*. EG 2/2800–2808. The National Archives, Kew. Available at: https://discovery.nationalarchives.gov.uk/details/record?catid=5747&catln=3

C. Values of Customer Reliability

Table 23 and Table 24 show the average value of customer reliability (VCR) per ZSS and Terminal Station as per the updated VCR values from 2024.

Zone Substations

Table 23 shows the average value of customer reliability by zone substation. The value reflects the make-up of the station output by type of customer – commercial, residential, industrial, agricultural.

Table 23 - Average VCR by zone substation

[C-I-C]	[C-I-C]
[C-I-C]	[C-I-C]
[C-I-C]	[C-I-C]
[C-I-C]	[C-I-C]
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Terminal Stations

Table 24 – Average VCR by Terminal Station

Terminal Station	VCR ($/MWh)
ATS	39,788
BATS	40,481
BETS	40,877
BLTS	36,232
BTS	38,323
CBTS	41,612
DPTS	39,890
ERTS	38,777
FBTS	36,444
FTS	41,568
GNTS	38,003
GTS	39,632
HOTS	40,394
HTS	41,171
KGTS	38,695
KTS	40,996
MBTS	39,663
MTS	42,583
MWTS	38,662
RCTS	38,527
RTS	39,574
RWTS	41,009
SHTS	38,468
SMTS	40,733
SVTS	39,797
TBTS	44,886
TGTS	38,403
TSTS	43,845
TTS	36,732
WETS	33,109
WMTS	35,442
WOTS	37,955

D. PoF Models and Parameters

Table 25 and Table 26 captures a summary of the current methods used to produce the initial PoF, the method used to extrapolate the PoF over time, as well as the parameters used in the extrapolation.

Table 25 - Summary of PoF methods and parameters by Transmission asset type

Network	Asset Class	Initial PoF	PoF Extrapolation	Parameters
TS	Transmission Line Insulators	Health Score - simple	Weibull - SME Parameters	Corrosivity 1: η = 70, β = 3.5 Corrosivity 2: η = 45, β = 3.5 Corrosivity 3: η =30, β = 3.5
TS	Circuit Breakers	Hybrid (ML/HS)	Weibull - SME Parameters	MV: η = 65, β = 3.6 HV: η = 55, β = 3.6 EHV: η = 45, β = 3.5
TS	Transmission Lines Conductors (Ph Cond)	Health Score - simple	Weibull - SME Parameters	Corrosivity 1: η = 100, β = 5 Corrosivity 2: η = 70, β = 5 Corrosivity 3: η = 40, β = 5
TS	Transmission Lines Conductors (GW)	Health Score - simple	Weibull - SME Parameters	Corrosivity 1: η = 90, β = 6 Corrosivity 2: η = 60, β = 6 Corrosivity 3: η = 35 β = 6
TS	Secondary Systems	Weibull	Weibull	η = 29, β = 3.5
TS	Power Transformers and Oil Filled Reactors	Health Score	Weibull - Health Score at Failure [Linear regression of HS/age to extrapolated health score]	η(HS) = 65, β = 3.5. [65 HS = 50y, HS = 0.8192t - 26.228]
TS	Power Transformer Bushings	Health Score	Weibull - Health Score at Failure [Linear regression of HS/age to extrapolated health score]	η = 39y, β = 2.4
TS	Communication Systems	Weibull	Weibull	η = 20.9, β = 5.8
TS	Transmission Line Structures	Health Score - simple	Weibull - SME Parameters	Corrosivity 1: η = 138, β = 6.5 Corrosivity 2: η = 71, β = 6.5 Corrosivity 3: η =49, β = 6.5
TS	Disconnectors and Earth Switches	Machine Learning	Weibull- SME Parameters	Not extrapolated[13]
TS	Auxiliary Power Supplies (Batteries)	Weibull	Weibull	η = 18, β = 2.88
TS	Power Cables	Weibull	Weibull - CIGRE Data	η = 32, β = 2.9
TS	Current Transformers	Health Score	Weibull - SME Parameters	η = 45, β = 3.5
TS	Civil Infrastructure	Likelihood	Health Score Simple	Qualitative
TS	Surge Diverters	Weibull	Weibull - SME Parameters	η = 45, β = 3.5
TS	Voltage Transformers	Health Score	Weibull - Failed assets using health score	η (HI) =136, β =2.29

[13] Year 1 ML PoF outputs used

Table 26 - Summary of PoF methods and parameters by Distribution asset type

Network	Asset Class	Initial PoF	PoF Method	Parameters
DS	Power Transformers – 20MVA	Weibull	Weibull – MLE Analysis	η = 74.44, β = 9.30
DS	Power Transformers – 10MVA	Weibull	Weibull – MLE Analysis	η = 84.34, β = 7.09
DS	Power Transformers – 5MVA	Weibull	Weibull – MLE Analysis	η = 91.02, β = 14.25
DS	PT Bushings	Weibull	Weibull – MLE Analysis	η = 83.39, β = 3.79
DS	Circuit Breakers – oil indoor	Weibull	Weibull – MLE Analysis	η = 73.32, β = 10.71
DS	Circuit Breakers – oil outdoor	Weibull	Weibull – MLE Analysis	η = 66.75, β = 8.87
DS	Current Transformers – oil	Weibull	Weibull – MLE Analysis	η = 62.41, β = 3.35
DS	Current Transformers – non oil	Weibull	Weibull – MLE Analysis	η = 81.79, β = 1.75
DS	Voltage Transformers – oil	Weibull	Weibull – MLE Analysis	η = 58.21, β = 4.47
DS	Voltage Transformers – non oil	Weibull	Weibull – MLE Analysis	η = 83.01, β = 1.34
DS	Station Surge Arrestors	Weibull	Weibull – MLE Analysis	η = 45.08, β = 1.71
DS	Neutral Earth Resistors	Weibull	Weibull – MLE Analysis	η = 52.58, β = 2.96
DS	Insulators	Weibull	SME estimate	η = 80, β = 3.5
DS	Distribution Transformers - Pole	Weibull	SME estimate	η = 100, β = 3.5
DS	Distribution Transformers - Ground	Weibull	SME estimate	η = 80, β = 3.5
DS	Conductors	Weibull	SME estimate	η = 70, β = 7.0
DS	Control Boxes	Weibull	Weibull – MLE Analysis	η = 23.15, β = 1.59
DS	Automatic Circuit Reclosers	Weibull	Weibull – MLE Analysis	η = 46.55, β = 1.29
DS	Manual Gas Switches	Weibull	Weibull – MLE Analysis	η = 31.49, β = 1.45
DS	Air Break Switches	Weibull	Weibull – MLE Analysis	η = 39.05, β = 1.59
DS	Indoor / Ground Switches	Weibull	Weibull – MLE Analysis	η = 25.61, β = 1.29
DS	Fuses	Weibull	Weibull – MLE Analysis	η = 43.57, β = 2.11
DS	Pole Top Capacitors – MV	Weibull	Weibull – MLE Analysis	η = 17.64, β = 1.40
DS	Pole Top Capacitors – LV	Weibull	Weibull – MLE Analysis	η = 169.34, β = 1.12
DS	Protection and Control	Weibull	Weibull – MLE Analysis	η = 48.62, β = 1.42
DS	Remote Telemetry Units	Weibull	SME estimate	η = 45, β = 3.5
DS	Auxiliary Supplies	Weibull	Weibull – MLE Analysis	η = 22.58, β = 2.76
DS	Line Voltage Regulators – Cooper	Weibull	Weibull – MLE Analysis	η = 28.95, β = 5.62
DS	Live Voltage Regulators - Other	Weibull	Weibull – MLE Analysis	η = 76,95, β = 1.72

E. Health Score Calculation

As an example of developing a health score for assets using four categories and subcategories in Table 27. The assessment uses a five-level condition scoring system (Table 28) and the category assessment method is shown in Table 29

Table 27: Example Categories and Subcategories

Category	Subcategory
CAT01	CAT01-01
CAT02	CAT02-01
CAT03	CAT03-01
	CAT03-02
	CAT03-03
CAT04	CAT04-01
	CAT04-02

Table 28: Example Condition Levels

Condition Levels
5
4
3
2
1

For a given asset, Equipment ID 300000, the condition scores, category score and category count per condition level is shown in Figure 16

Health score calculation using Equation 24

$$Health\ Score = \sum_{n=0}^{k-1} x_n i^n$$

Equation 24: Formula to Calculate HS

K = number of condition levels = 5

i = number of categories = 4

x = count of categories in each condition level

Example:

For the following x values: CL1 = 0, CL2 = 1, CL3 = 1, CL4 = 2, CL5 = 0

$HS = 0 \times 4^0 + 1 \times 4^1 + 1 \times 4^2 + 2 \times 4^3 + 0 \times 4^4 = 148$

Table 29: Condition Scoring System and Category Assessment

Category	Subcategory	Condition Description	Condition Score	Category Assessment
CAT01	CAT01-01		5	CS = Condition Score
			4	
			3	
			2	
			1	
CAT02	CAT02-01		5	CS = Condition Score
			4	
			3	
			2	
			1	
CAT03	CAT03-01		5	CS = Average Condition Score of sub-categories (Roundup)
			4	
			3	
			2	
			1	
	CAT03-02		5	
			4	
			3	
			2	
			1	
	CAT03-03		5	
			4	
			3	
			2	
			1	
CAT04	CAT04-01		5	CS = Max Condition Score of sub-categories
			4	
			3	
			2	
			1	
	CAT04-02		5	
			4	
			3	
			2	
			1	

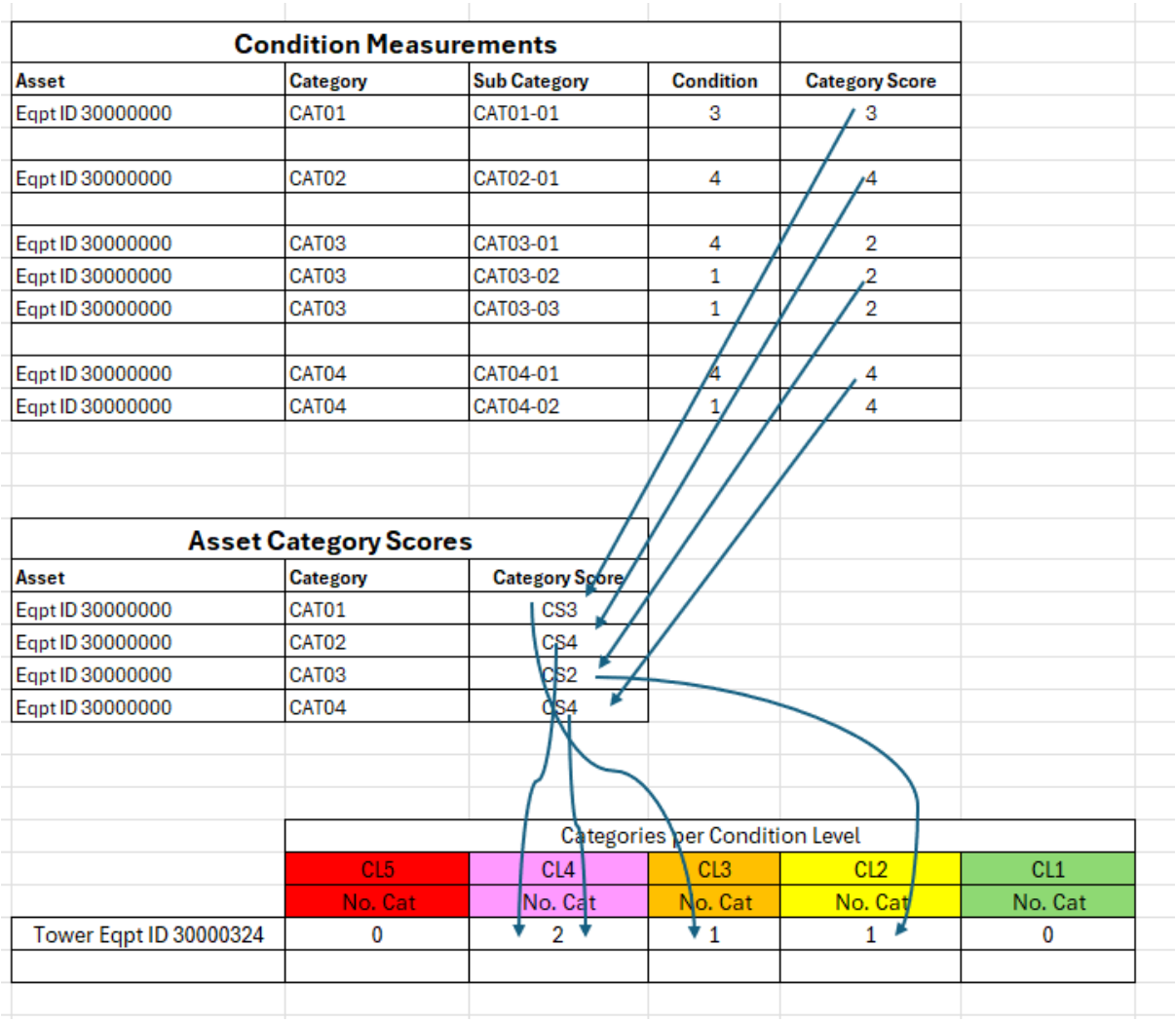

Figure 16: Example Asset Condition Score and Categories per Condition Level

12. Schedule of revisions

ISSUE	DATE	AUTHOR	DETAILS OF CHANGE
1	03/10/2019	A Dickinson	Original issue
2	06/10/2020	A Dickinson A Payne-Billard	▪ Updated with feedback from organisation. ▪ Fix minor typing errors. ▪ Clarified AusNet Services uses FMECA rather than FMEA. ▪ Section 3.3 added further details on the derivation of the asset replacement risk matrix, including the addition of Appendix C. Consequence scale on asset replacement matrix changed. ▪ Section 3.6.3 added emphasis on criticality being combination of consequence and frequency of occurrence. ▪ Section 5.1 clarified that deterioration in condition leads in an increase in likelihood of failure and a subsequent increase in risk. ▪ Section 5.3 added new subsection on how condition-based probabilities are determined and deleted subsection on small population assets. ▪ Section 6.1 clarified proactive preventative maintenance. ▪ Section 6.2 included proactive preventative maintenance and refurbishment in addition to replacement. ▪ Appendix Schedule of Revisions. ▪ Appendix Acronyms added. ▪ Appendix added for Weibull Rates ▪ Appendix added for Obsolescence Model ▪ Appendix added Transformer Market Impact ▪ Appendix added Road/Rail crossing effects costs ▪ Appendix added Easement Type effects costs ▪ Section 4.7 added for Asset Obsolescence ▪ Section 4.8 added for Asset Criticality for Transformers and Transmission Lines
3	13/12/2024	A Nainhabo C Yates	▪ Updated document template ▪ Updated to align with asset risk modelling methods ▪ Incorporated learnings from 2026-31 EDPR submission modelling
4	22/10/2025	A Nainhabo C Yates	▪ Added transmission customer and market CoF description ▪ Expanded PoF and CoF methodologies ▪ Expanded and refined the descriptions of PoF and CoF methodologies ▪ Refined Scope section ▪ Improved flow – PoF first, CoF second
4.1	24/11/2025	C Yates	▪ Added Distribution Weibull values in Appendix D, corrected a typographical error in Equation 23, and improved flow in section 4.5.
4.2 & 4.3	27/11/2025	C Yates	▪ Corrected an error in heading numbering – section 3.1 in the body has been corrected to section 4. ▪ Fixed paragraphs to make sure all tables are on the one page.
4.4	27/08/2026	A Nainhabo	▪ Added more explanations in the Finance Consequences category section 5.4.

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