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Climate Risk Assessment Collaboration

We are pleased to present this letter of collaboration with Ausgrid on their climate risk assessment.

This letter has been prepared for Ausgrid to evidence the extensive collaboration with KPMG and Risk Frontiers which demonstrates the robustness of the modelling framework employed to deliver Ausgrid's climate risk assessment.

We have set out the following items and discussion points in this letter :

- Background and Scope
- Methodology, Limitations, and Uncertainty, which are covered in in Appendix I of this letter
- Climate Forecasts and Key Assumptions, which are covered in in Appendix II of this letter
- Personnel Involved

This letter should be read in conjunction with the full climate risk assessment report titled "Ausgrid Climate Risk Assessment Report - 4 November 2022.pdf.

Yours sincerely

Richard Yee
Executive

Joseph Hoang-Luu
Associate Director

Background and Scope

KPMG were engaged by Ausgrid to deliver climate risk impact assessment using a stochastic Monte Carlo simulation model. The results of this modelling would be used to support Ausgrid's business case for resilience expenditure to the Australian Energy Regulator ("**AER**") for climate risk.

A business case to the AER needed to be supported by:

- scientifically accurate climate models
- asset and network impact logic that was representative of the assets and network
- clear documentation of limitations and uncertainty with the model
- how uncertainty has been quantified and validated

These elements have been addressed in the information contained in Appendix I.

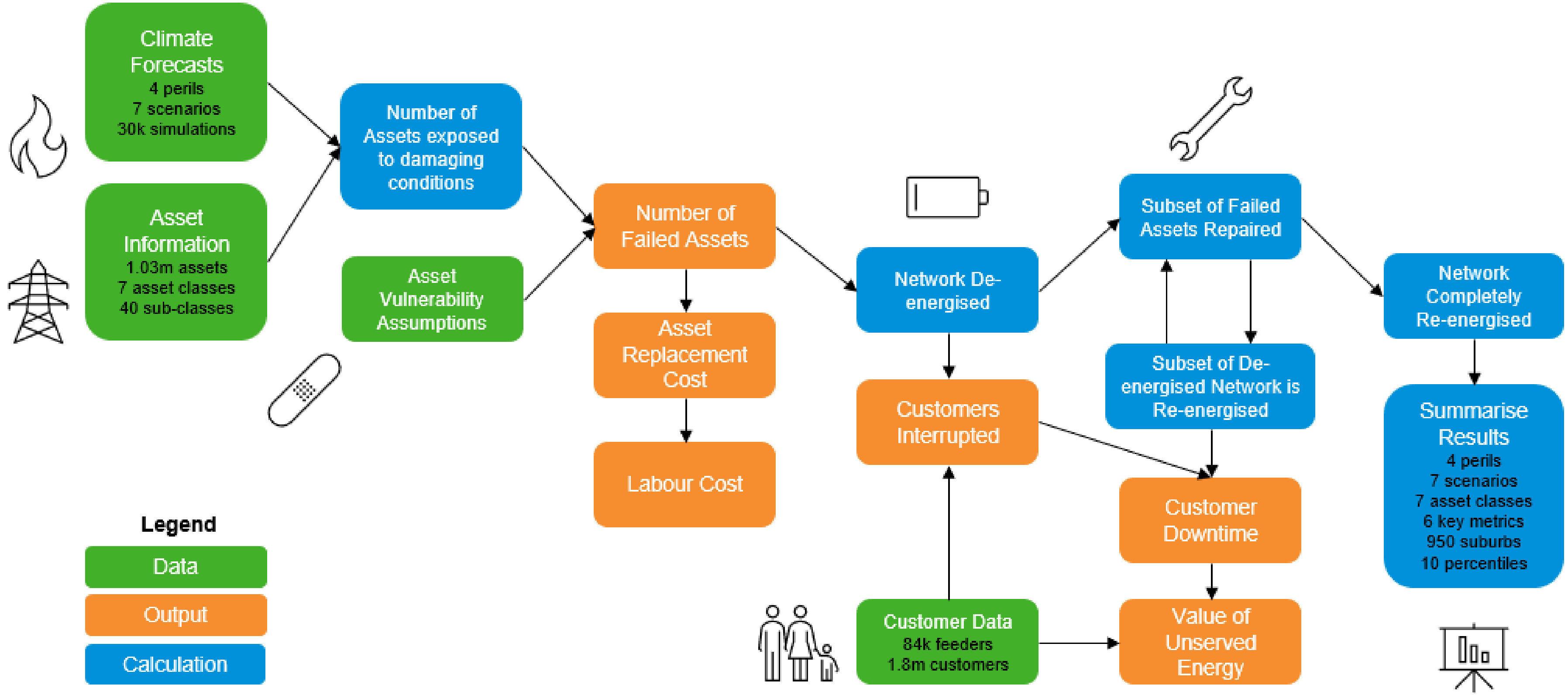
- appropriately granular asset impact modelling
- robust model assumption setting

These elements have been addressed in the information contained in Appendix II.

KPMG have collaborated with Ausgrid on the approach to quantifying climate risk assessment.

Methodology

The physical climate impact assessment executed a series of calculations stochastically up to 30,000 times. This emulated the variability of potential results, which allowed Ausgrid to assess the potential range of impacts and likelihoods. The flow of data, calculations, and outputs has been illustrated by a flow chart below. Details of the methodology have been included in Appendix I and as a separate document "Ausgrid – Physical Vulnerability Playbook - January 2023.pdf". Details of the climate data and assumptions have been included in Appendix II and as a separate document "Ausgrid – Physical Vulnerability Assumptions – January 2023.pdf".



Personnel

Key experts involved in the delivery of this analysis have been summarised in the table below:

KPMG	
Richard Yee Bachelor of Economics Fellow of the Institute of Actuaries of Australia (FIAA) Fellow of the Society Actuaries (FSNZ)	Richard was the KPMG engagement Partner responsible for overall quality assurance of the climate risk assessment. He provided strategic direction and consultation to a comprehensive and multi-disciplinary analysis.
Joseph Hoang-Luu Bachelor of Commerce (Actuarial Studies, Finance) Fellow of the Institute of Actuaries of Australia (FIAA) Certified Enterprise Risk Actuary (CERA)	Joseph is KPMG's head of climate risk modelling and was responsible for the design and delivery of the climate risk assessment. He provided second line analytical assessment and ran multiple workshops for Ausgrid on the methodology.
Matthew Timms Bachelor of Actuarial Studies, Macquarie University Bachelor of Science (Mathematics), Macquarie University Fellow of the Institute of Actuaries of Australia (FIAA) Certified Enterprise Risk Actuary (CERA)	Matthew was responsible for data preparation, algorithm development, execution of the analysis, and construction of visualisations. He provided preliminary analytical observations and challenge to design decisions.
Nicholas Moffatt B.Eng Chemical Engineering PhD Chemical Engineering Fellow of the Institution of Chemical Engineers Chartered Chemical Engineer Registered (Category 1 technical) Greenhouse and Energy Auditor, Australian Clean Energy Regulator	Nick was responsible for the overall execution of the engagement, providing strategic input to scenario development and lead development of public disclosures.
Cameron Reid Bachelor of Business (Accounting) Masters of Environment	Cameron managed the day-to-day interaction between KPMG, Risk Frontiers and Ausgrid.
Andrew O'Connor PhD - Reliability Engineering, University of Maryland Master of Science University of Maryland Bachelor of Engineering Electrical, UNSW Certified Asset Management Assessor Certified Practicing Engineer (CPEng), Eng. Exec and Fellow of Engineers Australia	Andrew is a KPMG Partner and SME for asset management. He was responsible for strategic direction and consultation for the implementation of any climate risk assessment into development of business cases for resilience.

KPMG	
Deepak Sambhi Master Business Administration (Digitisation of the Energy Retail Market) B.Eng. (Hons) Mechanical Engineering IAM Certificate ChMC MSP Practitioner	Deepak was responsible for quality assurance on the interpretation and implementation of modelling of DNSP assets. He provided review for any analysis delivered by Parth.
Parth Dave CPEng (Mech & Electrical) NER CIGRE NGN Master of Professional Engineering (Mechanical), University of Western Australia Bachelor of Science (Engineering Science and Finance), University of Western Australia, 2013	Parth was responsible for the interpretation of Ausgrid's asset data structure and input into the decision logic on the climate risk assessment model.

Risk Frontiers	
Ryan Crompton PhD (Natural Hazards), Macquarie University Postgraduate Diploma in Accounting, Macquarie University Bachelor of Science (Advanced Mathematics), Macquarie University	Ryan is Risk Frontiers' managing director. He was responsible for strategic decisions regarding the delivery of climate and catastrophe data to KPMG for input into the climate risk assessment framework.
Stuart Browning PhD Climate Science, Macquarie University Bachelor of Science (Hons), Climate Science, Newcastle University	Stuart provided subject matter expertise on East Coast Low storms and extreme heat. He ran multiple workshops on climate forecasts for Ausgrid's areas of service.
Tahiry Rabehaja PhD (Computer Science), The University of Sheffield & Macquarie University PgDS Mathematical Sciences, Stellenbosch University Bachelor of Science (Mathematics), University of Antananarivo	Tahiry ran Ausgrid's portfolio through Risk Frontiers' Multi-Peril Workbench and provided technical loss modelling expertise.

Appendix I

PHYSICAL VULNERABILITY ASSESSMENT

PLAYBOOK – STEP BY STEP INSTRUCTIONS

JANUARY 2023

1. Data Specification

The physical vulnerability assessment ("**PVA**") requires exposure and natural peril data, along with a range of assumptions. The exposure data is comprised of "Feeder Asset Data", "Junction Asset Data" and "Asset Risk Factor Data", while the natural peril data is comprised of "Natural Peril Simulation Data" and "Climate Parameter Outputs".

The assumptions include asset impact, probability of impact, customer information, asset restoration time, flood persistence, and natural peril correlations.

1.1 Exposure Table

The Feeder Asset Data has been sourced from Ausgrid's Geographic Information System ("**GIS**"). The database identifies each feeder according to the voltage level. There are 2 types of feeders, being low-voltage ("**LV**") and high-voltage ("**HV**").

The data fields within the Feeder Asset Data table that are required for PVA modelling are:

1.1.1 Feeder Asset Data Table

Data Field	Purpose
GIS ID	This field uniquely identifies each subsection of the feeder assets.
Asset Class	This field will be "Feeder".
Voltage	This field captures the voltage of the feeder. It will either be "LV", "5kV", "11kV", "22kV", "33kV", "66kV", or "132kV".
Identifier	This field identifies the substation that supplies the feeder.
Criticality	This field is derived according to the importance of having the given feeder restored. The importance is measured according to an agreed simple set of Ausgrid operational rules, e.g. high voltage feeders have priority over low voltage feeders during the asset restoration process.

The Junction Asset Data has been sourced from Ausgrid's GIS. Junction Asset Data is comprised of data tables for assets located in a single longitude / latitude that can be directly damaged by events.

The data fields within the Junction Asset Data table that are required for PVA modelling are:

1.1.2 Junction Asset Data Table

Data Field	Purpose
Asset ID	This field uniquely identifies each junction asset.
Asset Class	This field describes the class of asset, e.g. "pole" or "substation". For a breakdown see section 10.1.

Data Field	Purpose
Asset Sub-Class	This field describes the sub-class of asset. For a breakdown see section 10.1.
Identifier	This field is used specifically for mapping substation impacts to the feeders that they supply.
Longitude	This field provides a longitude of the junction asset.
Latitude	This field provides a latitude of the junction asset.
Feeder GIS ID	This data field is an indicator of a segment of assets. We use this field to inform the dependency of assets with respect to energy supply.

The Asset Risk Factor Data has been sourced from Ausgrid's GIS. Asset Risk Factor Data is comprised of asset details that inform vulnerability to natural perils.

The data fields within the Asset Risk Factor Data Table that are required for PVA modelling are:

1.1.3 Asset Risk Factor Data Table

Data Field	Purpose
Asset ID	This field uniquely identifies each junction asset.
Construction Material	This field identifies the construction material of the asset. It informs the vulnerability of the asset to BF and WS.
Installation Date	This field identifies the date the asset was installed. It informs the vulnerability of the asset to WS.

1.2 Natural Peril Table (Event Loss Models)

The Natural Peril Simulation Data has been sourced from Risk Frontiers ("**RF**"), who are a natural peril specialist in Australia. Natural Peril Simulation Data are sourced from RF proprietary "Event Loss Models", which is comprised of tables for Bushfire ("**BF**"), and Flood ("**FL**") natural perils under different climate scenarios and time horizons.

The data fields within the Natural Peril Simulation Data Tables that are required for PVA modelling are:

1.2.1 Natural Peril Simulation Data Table

Data Field	Purpose
Future Climate	This will be RCP2.6, RCP4.5, or RCP8.5
Year	This is a unique identifier for a simulation year.
Event ID	This is a unique identifier for an event. There can be multiple events within a simulation year.
Asset ID	This field uniquely identifies the asset impacted by the natural peril.
Peril Type	This is BF or FL
Natural Peril Metric	For BF, this field captures a burnt location indicator. For FL, this field captures the flood depth.

1.3 Climate Parameter Outputs (Windstorms & Coastal Inundation)

Windstorms ("**WS**") and Coastal Inundation ("**CI**") data have been sourced from the Electricity Sector Climate Information ("**ESCI**") project. The data is comprised of outputs under different climate scenarios and time horizons.

This dataset differs from the Natural Peril Simulation Data as it is not sourced from an Event Loss Model and hence data is produced deterministically. The forecasted results are produced per future forecast year and future climate scenario. To determine return periods using this data, extreme value theory is used (Appendix 10.3).

The data fields within the Windstorms and Coastal Inundation Data Tables that are required for PVA modelling are:

1.3.1 Windstorms and Coastal Inundation Data Table

Data Field	Purpose
Future Climate	This will be RCP2.6, RCP4.5, or RCP8.5
Forecast Year	This is a unique identifier for a forecast year.
Event ID	This is a unique identifier for an event. There can be multiple events within a simulation year.
Asset ID	This field uniquely identifies the asset impacted by the natural peril.
Peril Type	This is WS or CI
Natural Peril Metric	For WS, this field captures the maximum windspeed. For CI, this field captures the flood depth.

1.4 Climate Parameter Outputs (Extreme Heat)

Extreme Heat ("**EH**") data have been sourced from the Electricity Sector Climate Information ("**ESCI**") project. The data is comprised of outputs under different climate scenarios and time horizons.

This dataset differs from the Natural Peril Simulation Data as it is not sourced from an Event Loss Model and hence data is produced deterministically. The forecasted results are produced per future forecast year and future climate scenario.

EH does not cause an immediate impact on Ausgrid's assets, so the financial and non-financial impacts are considered to represent a chronic risk. There may be impacts to Ausgrid's assets due to EH, such as asset deterioration or impacts to network reliability.

The data fields within the Extreme Heat Data Table that are required for PVA modelling are:

1.4.1 Extreme Heat Data Table

Data Field	Purpose
Future Climate	This will be RCP2.6, RCP4.5, or RCP8.5
Forecast Year	This is a unique identifier for a forecast year.
Longitude	This field provides the longitude at which the natural peril metric (see below) value is provided.
Latitude	This field provides the latitude at which the natural peril metric (see below) value is provided.
Natural Peril Metric	This field captures the total number of consecutive days above 35 degrees Celsius at the given longitude-latitude location.

1.5 Assumption Tables

The assumptions that drive the PVA have been developed with the input of Ausgrid, particularly where the data to parameterise such assumptions are limited. Ausgrid's asset managers' expertise is relied upon to validate the quantum of these assumptions. In this section, the assumptions underlying the PVA are described.

The assumption for the cost to replace a junction asset is captured in the Asset Impact Data Table. This table maps an asset replacement cost to each junction asset by impact type, while the assumption for the cost to replace a feeder asset is a flat dollar assumption per metre.

Assumption fields for the Asset Impact Data Table include:

1.5.1 Asset Impact Data Table

Assumption Field	Purpose
Asset Class	This field describes the class of asset.
Asst Sub-Class	This field describes the sub-class of asset.
Region	This field will be South, Central, or North.
Natural Peril	This field describes the natural perils that are modelled for a given asset class/sub-class, i.e., which of "Windstorm", "Bushfire", "Flood", and "Coastal Inundation" are modelled.
Impact Value	This field provides the financial cost to restore or replace the asset. Some of this information was provided by Ausgrid's unit rates team.

The assumption for probability of impact for a junction asset is captured in the Probability of Impact Data table. This table assigns a probability associated with an asset class/sub-class, given it is exposed to a severity of a natural peril. Assumption fields for Probability of Impact Data Table include:

1.5.2 Probability of Impact Data Table

Assumption Field	Purpose
Asset Class	This field describes the class of asset.
Asset Sub-Class	This field describes the sub-class of asset.
Natural Peril Metric	For WS, this field captures the maximum windspeed. For BF, this field captures a burnt location indicator. For FL, this field captures the flood depth. For CI, this field captures the flood depth.
Probability	This field assigns a probability that the asset is impacted, given the natural peril metric.

With respect to FL and CI, the Probability of Impact Data Table assigns a probability that a junction asset is de-energised, given that the asset is exposed to a flood depth above a specified threshold. These thresholds are provided in the Flood Depth Threshold Data Table:

1.5.3 Flood Depth Threshold Data Table

Assumption Field	Purpose
Asset Class	This field describes the class of asset.
Asset Sub-Class	This field describes the sub-class of asset.
Threshold	This field describes the flood depth, in metres, above which the asset class/sub-class is susceptible to de-energisation due to flood.

1.5.4 NDVI Data Table

Assumption Field	Purpose
Longitude	The longitude at which the NDVI (see below) value is provided.
Latitude	The latitude at which the NDVI (see below) value is provided.
NDVI	The Normalized Difference Vegetation Index (NDVI) measures the level of vegetation at a given longitude-latitude location. Higher NDVI values correspond to land areas with greater green vegetation.

A customer information table is needed to determine the number of customers for an impacted feeder. Assumption fields for the Customer Information Data Table include:

1.5.5 Customer Information Data Table

Assumption Field	Purpose
Feeder GIS ID	This data field is an indicator a segment of assets. This field is used to inform the dependency of assets with respect to energy supply.
Customers	This field provides the number of customers for the given Feeder GIS ID.
Energy at Risk	This field captures the average hourly consumption (kWh) for the Feeder GIS ID.
VCR	This field captures the Value of Customer Reliability. It is dependent on the type of customers within the Feeder GIS ID.

An asset restoration time table is needed to determine the duration to restore an impacted asset. Assumption fields for the Asset Restoration Time Data Table include:

1.5.6 Asset Restoration Time Data Table

Assumption Field	Purpose
Impact ID	This is a unique identifier for the combination of asset class and impact type.
Asset Class	This field describes the class of asset.
Asst Sub-Class	This field describes the sub-class of asset.
Impact Type	This field describes the types of asset impact that is modelled.
Impact Restoration Time	This field describes the hours required to restore the impacted asset by one service team.

A natural peril correlation matrix is needed to allow for natural peril correlation. This is a three-by-three matrix, corresponding to the three natural perils WS, BF and FL, for which correlated metrics are calculated. Assumption fields for the Natural Peril Correlation Matrix include:

1.5.7 Natural Peril Correlation Matrix

Peril	WS	BF	FL
WS	1	σ_{ab}	σ_{ac}
BF	σ_{ab}	1	σ_{bc}
FL	σ_{ac}	σ_{bc}	1

2. Data cleansing

The feeder asset and junction asset data need to be cleansed. This is to account for missing values in the raw data. The steps to clean the feeder asset and junction asset data are described in this section.

2.1 Junction Asset Data Cleansing

It is required that every junction asset has a designated feeder. This is so that the impact on a given junction asset can be properly translated to the de-energisation of its corresponding feeder.

Where a junction asset has no assigned feeder, the feeder of the closest junction asset (as measured by straight-line physical distance) is assigned.

3. Data Mapping

Certain variables need to be mapped to each asset before proceeding with the calculations. In this section of the playbook, this data mapping process is described.

3.1 Windstorm Asset Impact (WS)

What impacts are modelled for a fallen pole?
A fallen pole would result in de-energisation of the parent and there is a cost to replace the pole.
What impacts are modelled for a leaning pole?
A leaning pole does result in de-energisation of the pole but there is no cost to restore the pole.
What impacts are modelled for a pole mounted asset?
A pole mounted asset may be damaged due to wind.
All impacts are summarised in the Asset Specification Table.

An Asset Specification Table is used to identify whether an WS can cause damage to a junction asset.

For junction assets that are susceptible to WS, vulnerability curves are used to determine if such assets would be damaged due to an WS, given the maximum windspeeds that have been modelled at their locations. There may be different curves depending on the junction asset sub-class, the age and construction material of the junction asset, and whether the surrounding vegetation is assumed to be the cause of asset failure.

The vulnerability curves translate the natural peril metric field, maximum windspeed, into a probability of impact ("**POI"**) for a given junction asset. There is a POI for fall and a POI for lean.

The vulnerability curves are derived from a combination of:

1. Research papers;
2. Historical event analysis; and
3. Expert judgment provided by KPMG engineers.

Furthermore, for the purpose of modelling WS asset impact, the NDVI must be mapped to each junction asset. For each junction asset, an adjustment factor is calculated as the ratio of the NDVI to the maximum NDVI in the NDVI Data Table. This adjustment factor can be applied to the POI as part of the asset impact calculation described in section 5.1.

3.2 Flood Asset Impact (FL and CI)

Does the analysis allow for damage caused to assets during a flood due to moving debris?
No allowance has been made for asset impacts due to moving debris.
What impacts are modelled for a ground mounted asset?
Ground mounted assets may be impacted by flood.
All impacts are summarised in the Asset Specification Table.

An Asset Specification Table is used to identify whether a flood can cause damage to a junction asset.

In addition, for junction assets that can be impacted, a Probability of Impact Data Table and a supplementary Flood Depth Threshold Table are used to determine whether asset replacement is required due to flood damage.

3.3 Bushfire Asset Impact (BF)

What impacts are modelled for a burnt asset? *A burnt asset may require replacement.*

An Asset Specification Table is used to identify whether a bushfire can cause damage to a junction asset.

In addition, for junction assets that can be impacted, a Probability of Impact Data Table provides a likelihood for the junction asset burning, given it is in a burnt location. These burn probabilities, in turn, depend on asset class and asset density.

3.4 Customer Information

Customer information needs to be assigned to each feeder asset. This is important for performing the service disruption calculation in section 6.

3.5 Restoration Time

The restoration times for different types of damage (i.e., different natural perils) need to be assigned to each junction asset. This is important for performing the service disruption calculation in section 6.

3.6 Junction Asset Replacement Value

The Asset Impact Data Table is used to map replacement value to each junction asset in the junction asset data tables. This produces a replacement value column in each junction asset table.

4. Calculation Flow Chart

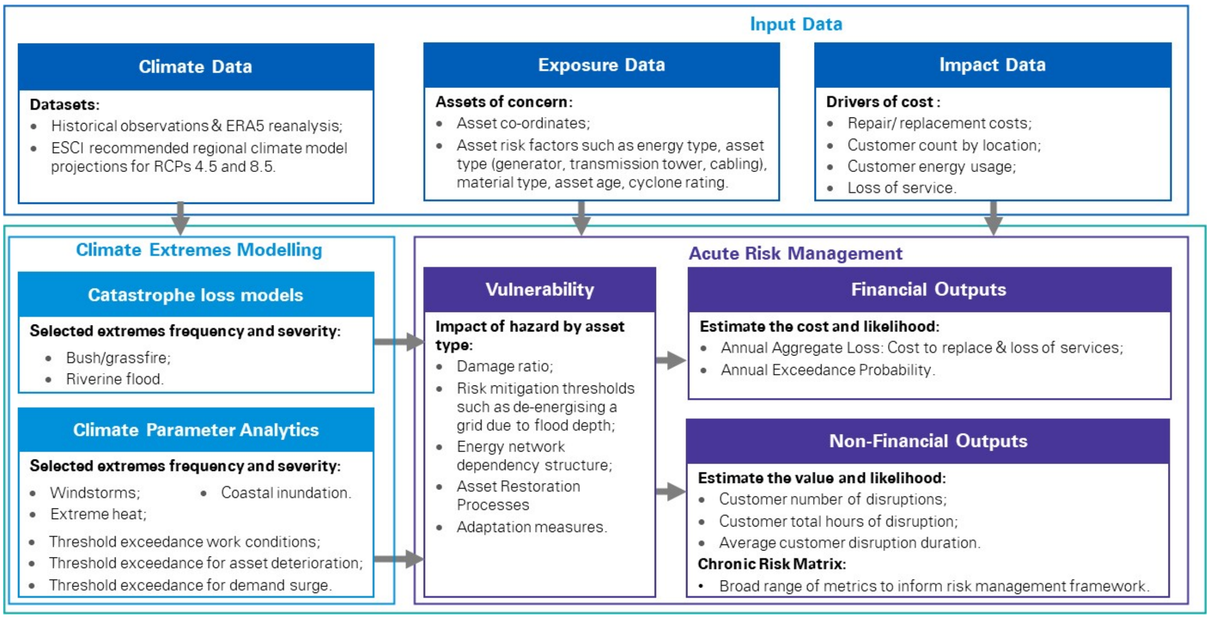
In this section of the playbook, a description of how the modules of the modelling framework link together is provided. A flowchart is used to depict key sections of the methodology, where each element of the flowchart corresponds to one of the sections of this playbook.

4.1 Physical Climate Risk Assessment

The physical climate risk assessment incorporates asset information provided by Ausgrid and overlays stochastically generated natural peril metrics. The impact of the natural peril metrics is informed by probability of impact assumptions. These datasets have been described in detail in section 1.

The flow chart below depicts how each of these datasets link together to produce the financial and non-financial outputs of the physical climate risk assessment.

4.1.1 Physical Climate Risk Assessment Flow Chart



The climate data is used as an input into the climate extremes modelling. The climate extremes modelling produces the metrics for WS, BF, FL, CI, and EH. To identify the impacts of these metrics on Ausgrid's network, the vulnerability and value of the assets at risk are identified.

The methodology executes a series of calculations to determine:

1. Assets that have been impacted and are therefore de-energised;
2. The downstream impacts of de-energisation on the Ausgrid network;
3. The sequential and prioritised restoration of impacted assets; and
4. The time and financial cost to restore assets.

4.2 Linkage of the Data Components

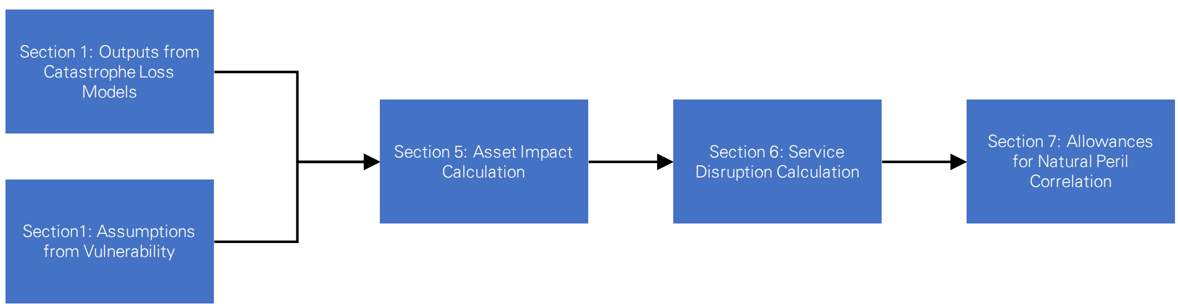
The table below maps the data specification to components of the flow chart:

Data Specification	Flow Chart Element
1.1.1 Feeder Asset Data	Corresponds to the assets of concern in "Exposure Data".
1.1.2 Junction Asset Data	Corresponds to the assets of concern in "Exposure Data".
1.1.3 Asset Risk Factor Data	Corresponds to the assets of concern in "Exposure Data".
1.2.1 Natural Peril Simulation Data	Corresponds to the selected frequency and severity in "Catastrophe Loss Models" for BF and FL.
1.3.1 Windstorms and Coastal Inundation Data	Corresponds to the selected frequency and severity in "Climate Parameter Analytics" for WS and CI.
1.4.1 Extreme Heat Data	Corresponds to the selected frequency and severity in "Climate Parameter Analytics" for EH.
1.5.1 Asset Impact Data	Corresponds to a component of "Impact Data".
1.5.2 Probability of Impact Data	Corresponds to a component of "Vulnerability".
1.5.3 Flood Depth Threshold Data	Corresponds to a component of "Vulnerability".
1.5.4 NDVI Data	Corresponds to a component of "Vulnerability".
1.5.5 Customer Information Data	Corresponds to a component of "Impact Data".
1.5.6 Asset Restoration Time Data	Corresponds to a component of "Impact Data".
1.5.7 Natural Peril Correlation	Corresponds to a component of "Vulnerability".

4.3 Climate Data

The Climate Data is collected by Risk Frontiers and this data is used as inputs to its proprietary models to produce the data for "Catastrophe Loss Models" and "Climate Parameter Analytics".

4.4 Financial and Non-financial Outputs Flow Chart



The asset impact calculation is described in section 5 and the service disruption calculation is described in section 6 of this playbook.

In section 7, a description of how to combine each of the calculations across the various perils is provided. This is to determine the aggregate impact across perils.

5. Asset Impact Calculation

The asset impact calculation quantifies the cost to replace assets due to a **direct** natural peril impact. This section describes the calculation for each natural peril type.

5.1 Calculation of replacement value for WS

The WS simulation data forecasts the maximum windspeed that each junction asset is exposed to in a year. This metric needs to be grossed up to an equivalent 3-second wind gust speed using a wind-gust conversion factor. The wind-gust conversion factor is a random number that follows a Gumbel distribution. The following section describes the mechanics modelled for WS.

The model simulates two random uniform numbers (between 0 and 1), for each junction asset, for each WS event. A "damage due to falling vegetation probability" is assumed, which represents the proportion of WS asset failures that are assumed to be caused by impact damage of vegetation, as opposed to a failure purely caused by wind loads, which would be dependent on the asset age and construction material.

Following the simulation of the two random uniform numbers, the model tests if the 1st random uniform number is less than the vegetation probability. If it is less than the vegetation probability, the model determines that the cause of asset failure is due to the impact of falling vegetation. The model then looks up the relevant vulnerability curve for each junction asset, which is assumed to be that of the most vulnerable sub-class. i.e. if vegetation is the cause of failure, the vulnerability is equal to the most vulnerable asset class. If instead the 1st random uniform number is greater than the vegetation probability, then the relevant vulnerability curve for each junction asset is that which corresponds to its sub-class, age and construction material.

Using the relevant vulnerability curve, the 3-second wind gust speed is converted to both fall and lean POIs for each junction asset. If the surrounding vegetation is assumed to be the cause of asset failure (i.e. the 1st random uniform number is less than the vegetation probability), then the POIs for each junction asset are multiplied by the NDVI adjustment factor described in section 3.1 before proceeding to the step below.

If the 2nd random uniform number is:

- Less than the POI associated with a fall, then the junction asset is modelled as a fallen asset. The junction asset loss is equal to the restoration or replacement value of that junction asset.
- Greater than the POI associated with a fall but less than the POI associated with a lean, then the junction asset is modelled as a leaning asset. There is no junction asset loss for leaning assets but there is assumed to be a service disruption.
- Greater than the POI associated with a lean, then the junction asset is not impacted and there is no junction asset loss incurred.

In addition, for each fallen junction asset associated with an overhead (OH) feeder, the feeder asset loss is equal to an assumed average feeder length multiplied by the per-kilometre feeder asset replacement cost.

5.2 Calculation of replacement value for FL and CI

The FL and CI simulation forecasts the flood depth at each junction asset by event.

The model requires two criteria that must be met for a junction asset to require replacement due to FL or CI. Firstly, the flood depth at the location of a given junction asset must be greater than the threshold indicated in the flood depth threshold table. Secondly, a randomly generated uniform number (between 0 and 1) must be less than the probability of de-energisation indicated in the probability of impact table.

If these two criteria are met for a given junction asset, then the junction asset loss is equal to the replacement value of that junction asset.

It is assumed that feeders cannot directly fail due to flood or require replacement, which means there is no feeder asset loss associated with FL or CI.

5.3 Calculation of replacement value for BF

The BF simulation forecasts whether each junction asset is in a burnt location by event.

If the junction asset is in a burnt location, the model produces a randomly generated uniform number (between 0 and 1), and tests if it is less than the burn probability. If it is less than the burn probability, then the junction asset is modelled as a burnt asset. The burn probability for each junction asset depends on its sub-class.

For a burnt asset, the junction asset loss is equal to the replacement value of that junction asset.

In addition, for each impacted junction asset, the feeder asset loss is equal to an assumed average feeder length multiplied by the per-kilometre feeder asset replacement cost.

5.4 Inflation and Discounting

For the purpose of forecasting, outputs can be inflated using a Consumer Price Index ("**CPI**") forecast or held constant in real terms.

For the purpose of forecasting, outputs can be discounted using a Risk-Free Discount Rate ("$\mathbf{R_f}$") or produced undiscounted.

6. Service Disruption Calculation

The service disruption calculation quantifies the Value of Unserved Energy by allowing for the **indirect** impact of the natural perils. This section describes the calculations sitting behind the disruption of service to Ausgrid's customers, resulting in a Loss of Supply of Energy to Ausgrid customers.

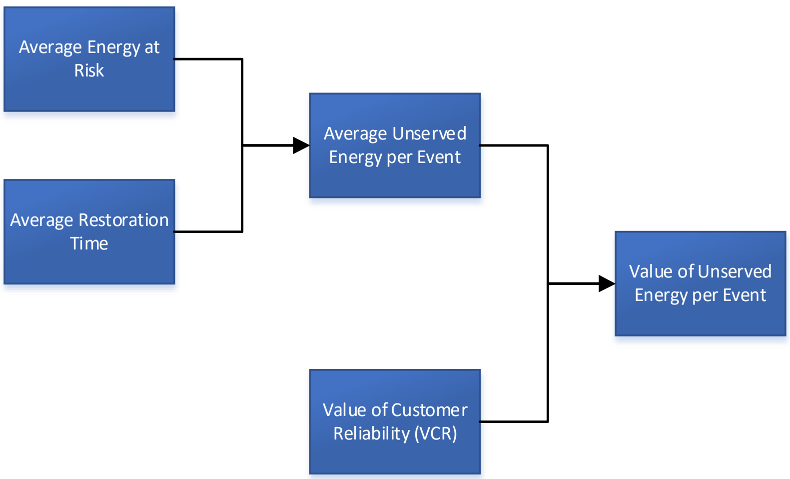
6.1 Determining the feeders with loss of power for each event

- For each event, model maps the impacted junction assets to a Feeder GIS ID. This gives the subset of **directly failed feeders**, i.e., feeders that have lost power due to direct impact.
- The model then determines all the failed substations, which is summarised as:
  - Filter the directly failed feeders for feeders with voltage equal to 5kV, 11kV or 22kV. Look up all the substations supplied by these feeders. This gives the *first* subset of failed substations.
  - Determine all the substations that have been directly impacted. Look up all these substations in the Ausgrid file called "00 – DC Lists by Protection Device and Feeder". This identifies all downstream substations with loss of power (the *second* subset of failed substations).
- Once all the failed substations have been determined, use the "Identifier" field in the Feeder Asset Data Table to determine all the feeders that are normally supplied by these substations. This gives the subset of **indirectly failed feeders**.
- The directly and indirectly failed feeders together represent the feeders with loss of power for a given event.

6.2 Value of Unserved Energy

Unserved energy is valued using the 'Value of Customer Reliability' ("**VCR**") approach.

6.2.1 Value of Loss of Supply of Energy (Value of Unserved Energy) Flow Chart



Unserved energy for a given event is valued according to the following equation:

$$Value\ of\ Unserved\ Energy = \sum_{f=1}^{F} \left(Restoration\ Time_f \times Energy\ at\ Risk_f\ \times\ VCR_f\right)$$

Where F is the number of feeders that have been impacted for a given event. The restoration time is measured in hours and reflects the duration of the outage for the affected customers at a given feeder.

6.3 Calculation of the restoration time

How is the time to replace assets modelled? *Assets are replaced one at a time in order of criticality. The number of assets that can be replaced in a day will be constrained by workforce limitations, i.e. the number of available service teams.*

For each event, extract the impacted junction assets and order the junction assets according to criticality. The Asset Restoration-Time Table determines the time required to restore the respective junction assets. As each feeder (which is usually associated with multiple junction assets) is restored, the time since event initiation needs to be recorded for this feeder (i.e. $Restoration\ Time_f$).

The aggregate time taken to restore the assets will depend on the restoration times of the individual junction assets as well as the number of available service teams for a given event.

it is noted that a limitation of the model is the allowance for flood persistence. There are complexities with calculating flood persistence that cannot be incorporated into the modelling framework.

6.4 Labour Cost

The labour cost is calculated by multiplying the restoration time by the labour rate per hour for overhead and underground feeders.

6.5 Energy at Risk

Energy at risk is calculated using network billing data where each customer's consumption is obtained from their Network Metering Identifier ("**NMI"**). For simplicity, the average daily consumption (measured in kW) per NMI is determined over a full year and converted into an average per hour figure (kWh).

6.6 Criticality

Criticality is calculated at the feeder level.

It is calculated as a score, which is expressed as:

$$Criticality = a * Indicator_{HV} + b * Count\_Life\_nmi + c * Count\_Key\_nmi + d * Count\_nmi$$

Where $a > b \geq c > d$ and $Indicator_{HV}$ takes a value of 1 if the feeder is HV and 0 if the feeder is LV.

6.7 Value of Customer Reliability

VCR values are published by the AER and are available here: https://www.aer.gov.au/networks-pipelines/guidelines-schemes-models-reviews/values-of-customer-reliability

In the spreadsheet of appendices available at the above webpage, VCR values are available for a range of customer types.

- Residential loads: refer to the NSW value in Table 1-1. If the specific climate zone for the customer is known the more detailed values in Table 1-2 may be used instead.
- Business loads: refer to the values in Tables 1-3 and 1-4.

All the VCR values are measured in $/kWh.

6.8 Inflation and Discounting

For the purpose of forecasting, outputs can be inflated using a Consumer Price Index ("**CPI**") forecast or held constant in real terms.

For the purpose of forecasting, outputs can be discounted using a Risk-Free Discount Rate or produced undiscounted.

6.9 Value of Unserved Energy Table

This table summarises the value of unserved energy by year, event, and feeder.

For each event, identify the impacted feeders. The impacted feeders are determined in section 6.1.

A single table is compiled with columns for year, event, and feeder. Then bring in the restoration time results, as calculated in section 6.3. Also bring in the energy at risk and VCR values for each feeder.

Finally, compute the value of unserved energy as the product of restoration time, energy at risk and VCR. This produces the required value of unserved energy table.

An illustrative table is shown below.

Year	Event	Feeder	Natural Peril	Restoration Time (hrs)	Energy at Risk (kWh)	VCR ($/kWh)	Value of Unserved Energy ($)
5	1	Feeder_1	Flood	14	20	0.5	140
5	1	Feeder_5	Flood	7	30	0.5	105
5	1	Feeder_6	Flood	10	22	0.5	110
…	…	…	…	…	…	…	…
28971	4300	Feeder_72	WS	24	40	0.5	480
28971	4300	Feeder_73	WS	12	43	0.5	258
28971	4300	Feeder_74	WS	5	22	0.5	55
28971	4300	Feeder_75	WS	24	61	0.5	732
28971	4300	Feeder_76	WS	24	25	0.5	300
28971	4300	Feeder_77	WS	48	57	0.5	1368

7. Allowances for Natural Peril Correlation

Does the analysis allow for interaction effects between the perils? *The methodology allows for an assumed correlation between the perils. However, it does not directly allow for interaction effects such as extreme heat heightening the impact of BF.*

This section combines the asset impact and service disruption calculations in sections 5 and 6 across natural perils, by allowing for an assumed correlation between the natural perils.

For a given climate scenario, a by-year loss summary table is created for each natural peril. The by-year loss summary tables show the overall loss (sum of direct and indirect loss) for each simulation year 1 to 30,000. These tables can be derived by aggregating the losses calculated in sections 5 and 6.

Then the following steps are performed.

7.1 Import natural peril correlation matrix

Ingest the correlation matrix as depicted in section 1.5.6.

7.2 Generate percentile simulations by natural peril

Generate 30,000 (1 for each year) sets of three (1 for each of WS, BF and FL) correlated standard normal random numbers using the natural peril correlation matrix and a Cholesky transform. Then apply the standard normal cumulative distribution function to the random numbers, which converts them to percentile values.

This produces a 30,000 x 3 percentile simulation table.

7.3 Convert percentile simulation table to year mapping table

Rank the percentiles in each of the three natural peril columns.

Look up the losses in the by-year loss summary tables according to the ranks, and then return the corresponding year. For instance, for an WS rank of 10, look up the 10th highest loss in the by-year loss summary table for WS and retrieve the year corresponding to that loss.

This produces a table that maps each of 30,000 combined impact years to a unique (WS year, BF year, FL year) triplet.

7.4 Combine the stand-alone natural peril metrics using the year mapping table

For each combined impact year, use its corresponding year triplet to subset the WS, BF and FL results calculated in sections 5 and 6. Then sum the stand-alone natural peril metrics across the three subsets.

This produces metrics for all perils combined rather than on a stand-alone natural peril basis. Any given combined metric can be ranked to determine a specified return period for this metric.

8. Physical Vulnerability Outputs

In this section of the playbook, the types of output produced by the PVA are described. There are two distinct parts to the outputs. The first part is related to perils that cause immediate asset impacts such as WS, BF, FL, and CI and the second part is related to EH.

8.1 Outputs for WS, BF, FL, and CI

The table below lists the outputs produced in the PVA for WS, BF, FL, and CI:

Metric	Description
Reactive replacement premium	The reactive replacement premium should be based on the additional costs incurred to replace failed assets reactively. A 20% value in addition to the asset is used as a placeholder by several of Ausgrid's peers.
Asset replacement cost	Replacement costs should be based on current unit rates for replacement of assets. If unit rates are not available, the rate should be calculated from a sample of recent historic replacements.
Asset repair cost	Repair costs should be based on current unit rates for repairs of assets. Repair costs will differ depending on the type of failure that has occurred so should be calculated on a failure mode basis rather than a single value per asset. Repairs will only be applicable for a sub-set of failure modes. If unit rates are not available, the rate should be calculated from a sample of recent historic repairs.
Customer disruptions	A customer is disrupted when an event is simulated that results in the de-energisation of the feeder that the customer was assigned to.
Restoration time	The restoration time represents the time taken to restore energy supply to customers.
Value of unserved energy	The value of unserved energy has been described in section 6.2.

Each output is produced on a forecast for a one-year timeframe. The metrics are presented at different time horizons and future climate scenarios.

8.2 Outputs for EH

The table below lists the outputs produced in the PVA for EH:

Metric	Description
Total number of consecutive days above heat threshold	This output captures the forecast total number of consecutive days above 35 degrees Celsius.
Maximum number of consecutive days above heat threshold	This output captures the forecast maximum number of consecutive days above 35 degrees Celsius.
Customer disruptions	A customer is disrupted when an event is simulated that results in the de-energisation of the feeder that the customer was assigned to.
Restoration time	The restoration time represents the time taken to restore energy supply to customers.
Value of unserved energy	The value of unserved energy has been described in section 6.2.

Each output is produced on a forecast for a one-year timeframe. The metrics are presented at different time horizons and future climate scenarios.

9. Risks and Limitations

9.1 Limitations

The modelling has inherent uncertainty and there are limitations in the approach and assumptions in building and utilising the model. In any modelling types of uncertainty include but are not limited to:

1. Not having the ability to capture every scenario or possible outcomes for many years into the future, and

2. Calibration of the model, while accurate as possible for each assumption contains limitations of historical data availability and applicability.

The modelling did not include the following:

- The model did explicitly consider damage to the energy distribution network due to falling debris onto cables. However, there was limited historical data or literature review on the vulnerability of assets impacted by debris. An assumption was made that the vulnerability of vegetation would be at most as resilient as a 50yo wood pole, so vegetation was modelled to be equivalent to wooden poles older than 50 years.
- There were two forms of asset failure modelled due to windstorms. This included damage and network failure when an asset was damaged and required replacement, and network failure when an asset was not damaged – this has been captured by leaning poles. The vulnerability of leaning poles was aligned to pole failure adjusted for lower windspeeds. This was parameterised by judgement.
- The model did not consider the difference in windspeed vulnerability for soil conditions.
- The simulated results for windstorm were fitted with a log-normal distribution, as the stochastically simulated results for the most extreme wind conditions over-extrapolated asset failures. This is a limitation of wind vulnerability curves applied where windgusts were modelled at a suburb level.
- For windstorm, only 1 extreme event per year per location was modelled.
- The model did not consider damage to the energy distribution network due to physical damage due to debris occurring during a flood or flash flooding. This is potentially a material non-modelled cost.
- Although modelled, heatwave impact modelling was high level, assuming a 0.25% chance that substations would "trip" for a 2-hour duration in these events. This rate was held constant and assumed based on expert assessment.
- The model did not consider the time for flood water to recede. It assumed that service crews could work on failed assets immediately.
- The model results are a point in time estimate based on today's current portfolio of assets. The only exception is the model assumed that poles were to be replaced by a new pole of the same material once they reach 75 years of age.

9.2 Inclusions and exclusions

The scope of the physical risk modelling included modelling of the following natural perils:

Inclusions / Exclusions		
Windstorm	Acute	**Inclusions:** • The windstorm peril model sourced maximum sustained windspeed on annual basis from ESCI data. • The model then simulated a windgust conversion factor from a Gumbel Distribution to produce the maximum 3s windgust on an annual basis per location. • The 3s windgust captured wind generated from any windstorm events. • The 3s windgust is modelled to cause poles to fail. • The 3s windgust is modelled to cause network failures where a pole did not fail, such as conductor clashes. • The 3s windgust is modelled to damage vegetation, causing vegetation impact to poles. **Exclusions:** • The model does not account for the correlation of windgust conversion factors across regions. • The model does not account for soil conditions such as wet / dry soil or soil type. • The model does not account for vegetation type or height. • The model does not account for the impact of heavy precipitation. • The model does not account for the impact of thunderstorms / 'Microcells'. • The model does not account for lightning.
Bushfire / Grassfire	Acute	**Inclusions:** • The bushfire / grassfire peril model simulated fire footprints, where bushfire ignitions / starts captured all possible sources. **Exclusions:** • The model does not account for the total duration that a bushfire would occur over. It assumes the asset repair would occur immediately. • The model does not account for different characteristics of a bushfire / grassfire such as intensity, height, or duration. • The model does not account for costs associated with bushfire liability. This is the liability to Ausgrid for starting a bushfire, which would result in additional costs such as residential, commercial, and industrial property damage, business interruption, personal injury, and loss of life.

Inclusions / Exclusions		
Flood	Acute	**Inclusions:** • The flood peril models damage due to assets exposed to flood depths from water levels rising within a river system. **Exclusions:** • The model does not account for moving debris within flood waters. • The model does not account for flash flooding. • The model does not account for impacts to asset life due to exposure to flood waters. • The model does not consider the time for flood water to recede. It assumes that service crews could work on failed assets immediately. • The model applied a simplified approach to incorporating future climate into the simulation of flood. Flood depths are modelled to change, but the locations and frequency of flood does not.
Heatwave	Chronic	**Inclusions:** • The heatwave peril is modelled, which was defined as 3 consecutive days with maximum daily temperature above 35°C. • The model accounts for trips of substations exposed to heatwave conditions. **Exclusions:** • The approach does not explicitly model increased network load. • The model does not account for asset ratings or the impairment to asset ratings under heatwave conditions. • The model does not account for other asset classes impacted by heatwave. • The model does not account for impacts to asset life due to heatwave.
Sea-level Rise	Chronic	**Inclusions:** • Sea-level rise is only modelled as the expected sea-level rise with tidal surge. • The impact is modelled the same as flood.

9.3 Uncertainty

There was uncertainty within the projection of climate metrics and the resulting climate impacts and financial results.

There was uncertainty related to the damage / failure that would result to an asset class as it was placed under the damaging forces of either bushfires, floods, or storms. The failure curves, burn rates, and flood depth thresholds were informed by literature review, historical Ausgrid events and discussions with Ausgrid asset experts. The windstorm assumptions were formed by external parties and Ausgrid experts who relied on literature review, historical Ausgrid data, and historical data sourced from energy distribution organisations in other countries.

While the analysis performed assessment at an individual asset level, there were uncertainties within these asset level assessments which, when analysed in aggregate overcome the individual asset level uncertainty to present a more robust result when assessing the whole portfolio.

9.4 Validation Testing

Validation testing provided Ausgrid with confidence that the climate risk assessment was producing results in line with expectations and a quantified understanding of the uncertainty inherent within modelling real world phenomena such as climate risk.

Sensitivity Testing

Sensitivity testing involved changing individual model assumptions to assess the impact on the overall results. This allowed Ausgrid to identify the assumptions that the analysis was most sensitive to. This analysis informed where the most scrutiny should be applied on the assumption selections and hence improve the robustness of the assumption setting process.

Convergence Testing

Convergence testing determined the impact of simulation variability on the results informing the conclusions of the analysis. Convergence testing for Ausgrid's analysis was performed by re-running the stochastic simulation for each peril 5 times, to essentially produce 150,000 simulations per peril. The simulations that informed conclusions needed to be representative of the 150,000 simulations.

10. Specification and Adjustments

10.1 Asset Specification Table

Does the analysis include non-Ausgrid / customer assets which support system security?
The inclusion of any asset would be specified by the Asset Specification Table.

10.1.1 Asset Specification Table by Peril

In the Asset Specification Table below, there is a field indicating whether the asset sub-class is modelled to be impacted by each of the natural perils for WS, BF, FL, CI, and EH. This information is captured at a high level (i.e. on an asset class basis) in the table below.

Asset Class	WS	BF	FL	CI	EH
Pole	✓	✓	✗	✗	✗
Pillar	✓	✓	✓	✓	✗
Joint	✗	✓	✓	✓	✗
HV Termination	✗	✓	✓	✓	✗
LV Termination	✗	✓	✓	✓	✗
Substation	✗	✓	✓	✓	✓
Switching Station	✗	✓	✓	✓	✗
Tower	✓	✓	✗	✗	✗

10.2 Summary of Modelling Assumptions

In the table below, the assumptions implied by the applied methodology have been summarised. These assumptions are made to either simplify the modelling or to limit the scenarios that need to be considered when modelling the physical climate risks:

Assumption Reference	Assumption Module	Assumption Description
1.1	Ausgrid Reliance	The data provided by Ausgrid in respect of the Ausgrid exposure information is complete, accurate and current.
1.2	Ausgrid Reliance	The refinements provided by Ausgrid to inform the vulnerability of Ausgrid's assets are appropriate.
2.1	Natural Perils	BF, FL, WS and CI may cause damage to Ausgrid's assets, resulting in the need for asset restoration or replacement.
2.2	Natural Perils	For the purposes of modelling WS, the underlying distribution of each portfolio metric has a finite upper bound.

Assumption Reference	Assumption Module	Assumption Description
2.3	Natural Perils	EH causes long-term strains on the Ausgrid network. Further, while there is no asset replacement cost assumed, there are assumed to be indirect costs (i.e., customer disruptions and losses due to unserved energy).
2.4	Natural Perils	BF, FL, WS and CI may be positively or negatively correlated, such that, respectively, the frequency and severity of one natural peril correlates with the frequency and severity of another natural peril in a year.
3.1	Asset Impact	The vulnerability functions implicitly allow for all sources of failure that coincide with the natural catastrophe event. These sources may include moving debris. This assumption does not apply to FL and CI.
3.2	Asset Impact	The most significant differentiators of the vulnerability of a junction asset are asset class, asset age, asset density and surrounding vegetation.
3.3	Asset Impact	Assets are either "impacted", or they are not. I.e., an asset may be damaged to require replacement, but partial replacement is not modelled. However, multiple types of impact are allowed for, including leaning poles.
3.4	Asset Impact	Asset impact for a given peril is dependent upon a singular metric of the peril such as flood depth.
3.5	Asset Impact	The cost to restore an asset is dependent upon high level regions such as South, Central and North.
3.6	Asset Impact	There is a specific threshold depth above which a FL or CI impacts a junction asset. This could be driven by risk management thresholds or assumed depth to expose energised components. Feeder assets are assumed to be immune to FL and CI.
3.7	Asset Impact	The cost to replace a feeder asset depends on the estimated impacted length.
3.8	Asset Impact	The cost to replace an asset is higher in the aftermath of a natural peril event compared to normal circumstances when replacement is required (i.e. there is a reactive replacement premium).
4.1	Service Disruption	Assets further away from a power source are dependent on assets closer to the power source for energy distribution.
4.2	Service Disruption	All feeder assets identified as downstream of a directly impacted feeder asset are de-energised.
4.3	Service Disruption	Where an asset has not been assigned a feeder, the feeder of the closest asset is assigned.

Assumption Reference	Assumption Module	Assumption Description
4.4	Service Disruption	The number of restoration teams to respond to a catastrophe event are limited to a finite number.
4.5	Service Disruption	The time to restore an asset is dependent upon its asset class, criticality, available service teams and the impact type.
4.6	Service Disruption	The VCR values published by the AER are appropriate to use for the Ausgrid network.

10.3 Extreme Value Theory

In this section, a description is provided of the use of Extreme Value Theory ("**EVT**") to model the impact of WS. EVT is used to model extreme values with respect to a given metric, such as asset replacement cost.

The metrics are modelled for a set of future years. The maximum windspeed underlying these forecast metrics are derived with reference to the ESCI project's national climate projection data.

A suitable distribution for each metric is estimated based on the modelled metrics. This distribution is an extreme value distribution. It can take one of three forms depending on the assumed nature of the underlying distribution of each metric in a given year:

- If the underlying distribution is assumed to have a finite upper bound, then the Weibull form of the extreme value distribution is most appropriate.
- If the underlying distribution is assumed to have a light tail, then the Gumbel form of the extreme value distribution is most appropriate.
- If the underlying distribution is assumed to have a heavy tail, then the Fréchet form of the extreme value distribution is most appropriate.

Based on the possible physical limits of WS in Australia, along with a finitely defined asset portfolio, it has been assumed that in practice the underlying distribution of each metric has a finite upper bound, which implies the use of the Weibull extreme value distribution.

Once the Weibull extreme value distribution has been parameterised based on the modelled metrics, it can be used to simulate further observations for each metric for the portfolio in a given future year.

Percentiles (or return periods) of each metric can be obtained directly from the estimated extreme value distribution.

The advantage of EVT is that the extreme value distribution can be derived with limited data, in this case the metrics modelled for a set of future years. The disadvantage of EVT is the reliance on an appropriate assumption of the nature of the underlying distribution of each metric.

Appendix II

PHYSICAL VULNERABILITY ASSESSMENT

CLIMATE DATA & ASSUMPTIONS

JANUARY 2023

1. Climate Forecasts

Climate projections were based on the climate datasets recommended in the Electricity Sector Climate Information ("**ESCI**") report. The ESCI report evaluated a range of climate model simulations for their representation of temperature and rainfall under Representative Concentration Pathway ("**RCP**") 4.5 and RCP 8.5 scenarios and recommended a 3-model ensemble. The data produced in the ESCI project was limited to bias corrected daily maximum and minimum temperature, daily rainfall, and Forest Fire Danger Index ("**FFDI**"). For variables and scenarios outside the ESCI data, alternative simulations were sourced, and bias corrected.

The datasets used in Climate Risk Assessment were:

- ERA-5 reanalysis: historical weather data from the European Centre for Medium Range Weather Forecasting ("**ECMWF**") ERA5 and ERA5-Land reanalysis. ERA5-Land provided a comprehensive range of hourly weather variables on a 0.1x0.1 degree grid, approximately 9km spatial resolution.
- AWAP: The Australian Bureau of Meteorology ("**BOM**") Australian Water Availability Project ("**AWAP**") provided gridded hydrological and temperature data on a 0.05-degree grid (approximately 5km) for all of Australia.
- ESCI: Energy Sector Climate Information ("**ESCI**") Project evaluated a wide range of simulations from different RCM-GCM combinations. Simulations were bias corrected using Quantile Mapping for Extremes ("**QME**") and evaluated for suitability at representing rainfall and temperature for two scenarios: RCP 4.5 and RCP 8.5.
- NARCliM1.5: The NSW and ACT Regional Climate Model ("**NARCliM**") climate model simulations version 1.5. NARCliM1.5 data were produced as part of a NSW government-led project providing high resolution climate change projections across NSW for two scenarios: RCP 4.5 and RCP 8.5. NARCliM1.5 outputs have been bias corrected using Quantile Mapping.
- CORDEX-GERICS: Data for the RCP 2.6 scenario was sourced from RCM-GCM simulations developed by the Climate Service Center Germany ("**GERICS**") as part of the Coordinated Regional Downscaling Project ("**CORDEX**") and bias corrected using Quantile Mapping.

For all RCP 2.6 scenarios, data has been sourced from the CORDEX GERICS AUS-22 simulations. CORDEX data has been bias corrected to the AWAP temperature and rainfall and Bureau of Meteorology Forest Fire Danger Index ("**BOM FFDI**") for consistency with the ESCI data. Winds have been bias corrected to ERA5 Land.

For RCP 4.5 and RCP 8.5 scenarios, variables which are not part of ESCI climate projections have been sourced from the NARCliM1.5 ensemble; this includes east coast lows, winds, extreme heat, and a suite of variables required for Bushfire modelling. NARCliM1.5 winds have been bias corrected to ERA5 Land.

Climate model data interpretation should only be carried out with full consideration of data limitations, for example as outlined in the CMSI (2020) report. Three important considerations are: bias correction; the use of ensembles; and time averaging to account for natural climate variability. Bias correction accounts for systematic differences between model simulations and observations and has been applied to all climate model data used in this study. To account for possible errors in model accuracy the mean output from a minimum of 3 models is used, with the standard deviation providing an estimate of uncertainty. Projections are also based on a minimum 20-year average to account for natural (stochastic) variability inherent in the climate system and as simulated by climate models. Actual future climate experience would exhibit greater variability, i.e. some years would be worse than the 20 year-average, and some less.

Additional data transformations and models were required to produce the acute climate risk data. A brief description of the models is summarised below:

1.1 Bushfire

For bushfire data, Risk Frontier's ("**RF**") model "**FireAUS**" was used.

FireAUS is Risk Frontiers' probabilistic model for bushfire and grassfire losses in Australia. A key component of the model is to predict fire ignitions for stochastic events using machine learning models. These models are trained on historical fire ignitions derived from the Moderate Resolution Imaging Spectroradiometer ("**MODIS**") Burned Area product, MCD64A1 Version 6 (2001-2018) using fire tracking algorithms. Firstly, these fire ignitions are classified into five categories based on the quantiles of burned area sizes in each state. Two-step supervised machine learning models are then defined on 1° by 1° grid cells. The first model is used to predict if fires occur in a grid for each calendar month and, if so, the second model is used to predict the number of fire ignitions for each burnt area category within that grid. The predictor variables used in these models include grid locations and climate classifications as well as population-based, environmental and climate variables. The climate variables for the training data are derived from the NCEP Climate Forecast System Reanalysis ("**CFSR**") (1979-2010) and Climate Forecast System Version 2 ("**CFSv2**") (2011-2018) data.

To project changes in fire hazard, we use the fire prediction models from FireAUS to estimate the ignition parameter changes for different future climate scenarios. All predictors used in the models, except the climate variables, remain unchanged across historical baseline and future scenarios. Therefore, the changes in fire ignitions are exclusively caused by changes in climate variables for each climate change scenario. We use the CORDEX-GERICS and NARCliM projects to derive climate variables for the ignition projection pertaining to the emission scenarios RCP2.6, RCP4.5 and RCP8.5, as outlined previously.

CORDEX-GERICS and NARCliM climate date are resampled to 1° resolution and bias corrected against the reanalysis data used for the training dataset. Using these derived climate variables as new input predictors, the trained fire prediction models are used to estimate the number of fire ignitions for each 1° by 1° grid for each month. Since the CORDEX-GERICS and NARCliM dataset are multi-member outputs, the predicted fire ignition counts are averaged from the models in the RCMs' ensemble per 1° grid, then averaged again per future time horizon definition (i.e., 2041-2060 for 2050s and 2081-2099 for 2090s). Ignition changes for each 20-year period are then calculated as the ratio of the number of fire ignitions for the reference (1979-2018) to the ignition number for the future periods. These ratios are then used to sample the events for future climate scenarios from the event catalogue of the current FireAUS model.

FireAUS comprised 50,000 years of fire footprints, aggregated into individual events based on the ignition dates and a 7-day time window, under the current climate. The baseline event set for this project was a 10,000-year sample of the full FireAUS catalogue of events.

1.2 Flood

For flood data, RF's "FloodAUS" was used.

FloodAUS is based on the National Flood Information Database ("**NFID**") and generates residential, commercial, and industrial loss estimates for regions covered by these data sources. The scope of the model is further extended by using Risk Frontiers Flood Exclusion Zone ("**FEZ**") methodology to filter out address which do not generate losses. FloodAUS covers a majority of the most flood-prone addresses in Australia.

In this analysis, we use the synthetic event set in FloodAUS to assess the flood risk for current and future climate. This event set has 50,000 simulation years and synthetic events are defined for basins and depths are derived from NFID. Since depth information from NFID are attached to the Geocoded National Address File (G-NAF) dataset, we estimate the depths at an asset based on the G-NAF points within 100m of that asset.

1.3 Windstorm

For windstorm data, maximum sustained windspeeds were extracted from the climate datasets. This metric was grossed up to an equivalent 3-second wind gust speed using a wind-gust conversion factor. The wind-gust conversion factor was stochastically generated from a Gumbel distribution[1].

[1] Comparison of Wind Averaging Conversions between Gust Factor and Statistical Approaches, Tin Nilar Tun, Aye Aye Thant, International Journal of Scientific Engineering and Technology Research, Vol. 3, Issue 10, 2014.

2. Key Assumptions

This section summarises the key assumptions that drive the results of the climate impact analysis. Unless otherwise indicated information and data used and utilised for assumptions was prepared by appropriate Ausgrid staff.

2.1 Unit Rates

The unit rates are used to determine the cost to replace failed assets due to acute perils. The rates were sourced from Ausgrid's unit rates team. The most material assumption within this category is the unit rate for wooden poles, given that Ausgrid has over 445,000 modelled wood poles out of a total of just over a million modelled assets.

The unit rate for wood poles is:

Asset	South	Central	North
Low Voltage Wood	$11,619.98	$12,549.08	$10,666.21
High Voltage Wood	$11,006.98	$11,826.12	$12,705.19
Transmission Wood	$58,566.59	$58,566.59	$33,589.33

2.2 Burn Rates

The burn rates are used to determine whether an asset has failed due to a bushfire. The burn rates were formulated based on the judgement of external and Ausgrid engineers, as well as an estimate of the expected number of assets failed due to bushfire in any one year. The most material assumption within this category is the burn rate for wooden poles, given that Ausgrid has over 445,000 modelled wood poles out of a total of just over a million modelled assets.

The burn rates assumptions are summarised in the table below:

Asset Class	Burn Rate
Joint	50%
Pillar	50%
Pole Wood	80%
Pole Concrete	1%
Pole Metal	1%
Substation	10%
Substation - Kiosk	50%
Substation - Pole	80%
Switching Station	10%
Termination	50%
Tower	1%

2.3 Burn Rate Scaling

The burn rate scaling assumption is used to adjust the burn rates based on the density of the number of poles within a 1km^2 grid cell. This assumption assumes that the density of number of locations is a proxy for population and hence bushfire response effectiveness. The burn rate scaling assumptions were selected based on discussions with Ausgrid engineers.

The burn rate scaling factors are:

Low # Poles / 1km²	High # Poles / 1km²	Burn Rate Scaling
1	5	100.00%
6	10	97.50%
11	15	92.50%
16	20	87.50%
21	30	82.50%
31	40	77.50%
41	50	70.00%
51	75	60.00%
76	100	45.00%
101	150	30.00%
151	200	20.00%
201	250	12.50%
251	300	7.50%
301	350	5.00%
351	400	2.50%
401	9999	1.25%

2.4 Flood Failure Thresholds

The flood failure thresholds are used to determine the flood depth that an asset can fail due to a flood. The flood failure thresholds were sourced from Ausgrid engineers. The most material assumption within this category is the flood failure threshold for pillars, which is due to a combination of a high failure rate, low flood depth risk threshold, and number of assets.

Asset Class	**Asset-Subclass**	Flood Depth Threshold
Joint	LV-Joint	Any flood
Joint	HV-Joint	Any flood
HV Termination	Other	Any flood
HV Termination	Overhead/underground	8.0m
LV Termination	Other	Any flood
LV Termination	Overhead/underground	6.5m
Substation	Ground	0.3m
Substation	Single pole	6.5m
Substation	Zone	0.5m
Substation	Kiosk	0.3m
Substation	Transmission	2.5m
Substation	Chamber	0.3m
Substation	Subtrans metering station	N/A
Substation	Unknown	0.3m
Substation	Bulk supply point	2.5m
Substation	Regulating	8.5m
Substation	Metering station	N/A
Substation	Pole - unknown mounting	6.5m
Substation	Subtransmission pole	9.0m
Substation	Two pole	6.5m
Substation	Subtransmission kiosk	0.5m
Substation	Subtransmission ground	0.5m
Substation	Distribution generator	0.3m
Switching Station	Subtrans switching	0.5m
Switching Station	Isolating/earthing	0.8m
Switching Station	Ring main unit	0.8m
Switching Station	Recloser	5.0m
Switching Station	Subtrans transition pt	Any flood
Switching Station	Transmission recloser	9.0m
Switching Station	Pole top capacitor	8.0m
Switching Station	Sectionalizer	8.0m
Switching Station	Other - oh	8.0m
Switching Station	Autolink	8.0m
Switching Station	Unknown	N/A
Pillar	SL	0.5m
Pillar	Other	0.3m

2.5 Flood Failure Rates

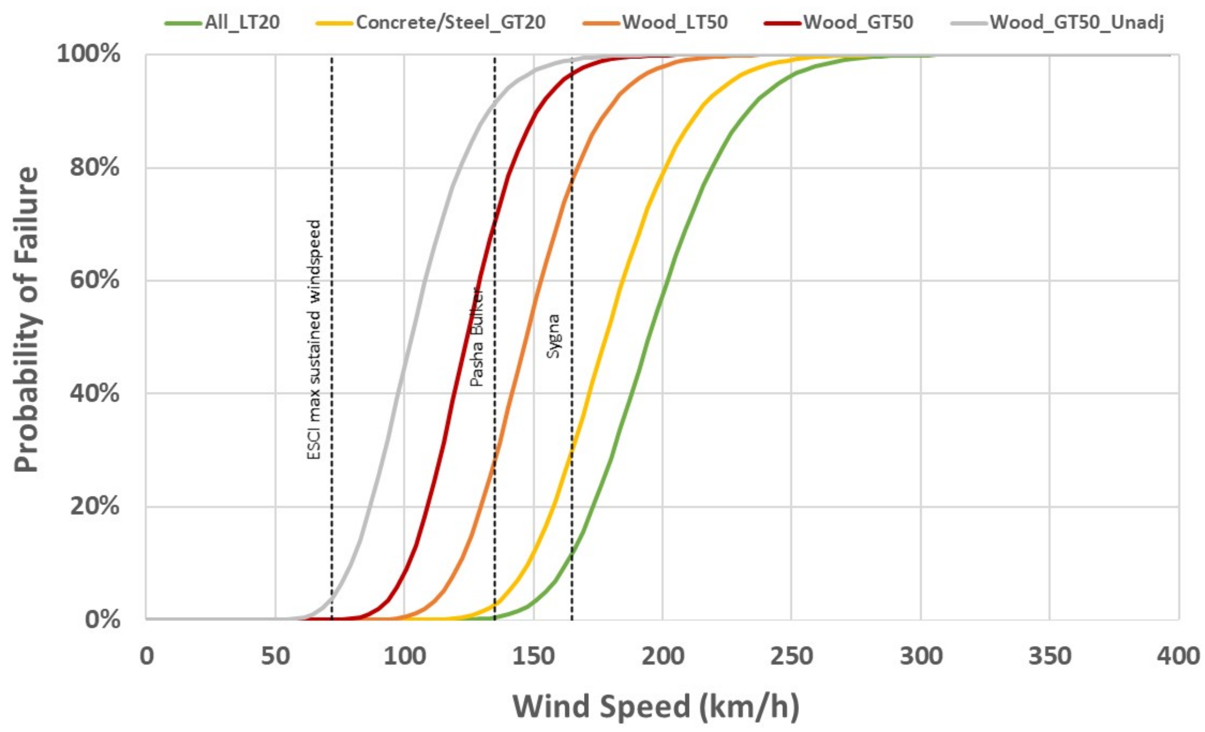
The flood failure rates are used to determine whether an asset has failed due to a flood. The flood failure rates were sourced from Ausgrid engineers. The most material assumption within this category is the flood failure rate for pillars, which is due to a combination of a high failure rate, low flood depth risk threshold, and number of assets.

Asset Class	Asset-Subclass	Flood Failure Rate
Joint	LV-Joint	0.1%
Joint	HV-Joint	0.1%
HV Termination	Other	0.1%
HV Termination	Overhead/underground	49.5%
LV Termination	Other	0.1%
LV Termination	Overhead/underground	94.1%
Substation	Ground	49.5%
Substation	Single pole	49.5%
Substation	Zone	0.5%
Substation	Kiosk	25.0%
Substation	Transmission	0.5%
Substation	Chamber	25.0%
Substation	Subtrans metering station	N/A
Substation	Unknown	25.0%
Substation	Bulk supply point	0.5%
Substation	Regulating	49.5%
Substation	Metering station	N/A
Substation	Pole - unknown mounting	49.5%
Substation	Subtransmission pole	1.0%
Substation	Two pole	49.5%
Substation	Subtransmission kiosk	25.0%
Substation	Subtransmission ground	0.5%
Substation	Distribution generator	25.0%
Switching Station	Subtrans switching	1.0%
Switching Station	Isolating/earthing	25.0%
Switching Station	Ring main unit	25.0%
Switching Station	Recloser	49.5%
Switching Station	Subtrans transition pt	0.0%
Switching Station	Transmission recloser	49.5%
Switching Station	Pole top capacitor	49.5%
Switching Station	Sectionalizer	49.5%
Switching Station	Other - oh	49.5%
Switching Station	Autolink	49.5%
Switching Station	Unknown	N/A
Pillar	SL	94.1%
Pillar	Other	94.1%

2.6 Wind Failure Rates

The windstorm failure rates are used to determine whether an asset has failed due to a windstorm. The windstorm failure rates were sourced from literature review . The most material assumption within this category is the windstorm failure rate for wood poles, given that Ausgrid has over 445,000 modelled wood poles out of a total of just over a million modelled assets.

Due to the granularity of the wind failure datapoints, a graph has been provided to showcase the wind failure rates. Each line represents the wind vulnerability classifications used in the modelling, with an additional reference point "wood_GT50_Unadj", showing the unadjusted failure curve from literature with respect to a wood pole greater than 50 years old.



2.7 Wind Vegetation Adjustment Factor

For the windstorm asset failure calculations, the model first determines whether asset failure is caused by wind loads or vegetation impacts. The model assumed a vegetation rate, which determines how often a wind related asset failure involves vegetation.

Where the model determined vegetation impacts to be the cause of failure, a vulnerability curve for vegetation is assumed to be equal to a 50yo wood pole. This vulnerability is multiplied by a Normalised Difference Vegetation Index ("NDVI") to approximate the likelihood of vegetation impact within a suburb. The NDVI represents the density of vegetation within the suburb, which can range between 0 and 1.

2.8 Vegetation Rate

The model assumes that vegetation is the cause of failure for 87% of asset failures related to windstorm. This assumption was chosen to align with Ausgrid's historical causes of asset failure due to windstorm between FY18-21.

2.9 Heatwave Susceptible Assets

The model assumes that heatwave has a chance to cause certain assets to shut down. The assets that were assumed to be susceptible to heatwave are:

Kiosk substations, pole mounted substation, regulating substation, single pole substation, sub transmission kiosk, sub transmission pole, and two pole substations. The susceptible assets were selected based on discussions with Ausgrid engineers.

2.10 Heatwave Trip Rate

The model assumes that substations will trip during a heatwave with a likelihood of 0.25%. This was chosen as a very low trip rate to provide indicative impacts for future climate scenarios. There was limited data to make the selection on.

2.11 Pole Replacement Age

The model assumes that a pole is replaced for a new pole immediately on the day that it is 75 years old. This assumes that age is a proxy for asset condition. The assumption was chosen based on discussions with Ausgrid engineers.

2.12 Conductor / Cable Replacement Length

The model assumes that each failed pole requires a replacement of conductor / cable in the restoration process. The assumed length of conductor / cable replaced per failed pole is 60 metres. This assumption was provided by Ausgrid.

2.13 Reactive Replacement Premium

The model assumes that assets that are replaced reactively to natural perils incur an additional reactive replacement premium. This is aligned with Ausgrid's Value Framework. The assumed reactive replacement premium is 20%.

2.14 Customer Energy at Risk

The model calculates the value of unserved energy, which requires customer information at each feeder location. This information was sourced from Ausgrid operations, and includes the following fields: Feeder GIS ID, Customer Count, Energy at Risk, and Value of Customer Reliability.

2.15 Asset Restoration Time

The asset restoration assumptions determine how long an individual service crew requires to restore an asset that was modelled to fail. The assumptions were sourced from Ausgrid operations. The complete set of assumptions is broken down by asset type and peril below:

Asset	Peril	Restoration Time (hours)
Pole	Windstorm	20
Pole	Windstorm vegetation	20
Pole	Bushfire	20
Pillar	Flood	16
Pillar	Windstorm	16
Pillar	Windstorm vegetation	16
Pillar	Bushfire	24
Joint	Flood	16
Joint	Bushfire	16
LV Termination	Flood	12
HV Termination	Flood	8
LV Termination	Bushfire	8
HV Termination	Bushfire	12
Substation	Flood	30
Substation	Bushfire	30
Tower	Windstorm	30
Tower	Windstorm vegetation	30
Tower	Bushfire	30

Asset	Peril	Restoration Time (hours)
Switching Station	Flood	30
Switching Station	Bushfire	30
Substation	Heatwave	2

2.16 Service Teams Deployed

The model assumes Ausgrid will deploy service teams depending on the total amount of asset damage caused by an event. The model assumes that the "total" number of effective service teams accounts to the ability to call on other DNSPs and the military if the damage is significant and widespread. These assumptions were determined by Ausgrid to achieve a maximum customer downtime of 7 days. The assumed deployed service teams for the number of failed assets are:

Assets Failed Low Range	Assets Failed High Range	Service Teams
1	100	30
101	200	60
201	300	90
301	400	120
401	500	150
501	600	200
601	700	250
701	800	300
801	900	400
901	1,000	500
1,001	1,200	600
1,201	1,500	700
1,501	2,000	800
2,000	2,500	900
2,501	3,000	1000
3,001	3,500	1100
3,501	4,000	1200
4,001	4,500	1300
4,501	5,000	1400
5,001	99,999,999	1500

2.17 Daily Working Hours

The model assigns services crews to failed assets to restore in order of restoration priority. The model assumes that each service crew will only work a limited set of hours each 24 hours. This is assumed to be 12 hours.

2.18 Asset Restoration Priority

The model executes an order of restoration for failed assets based on a prioritisation logic as follows:

1. Are any HV feeders de-energised?
2. If Yes, Identify feeders with life support and key NMI.
   - Fix substations in these feeders first, then
   - Fix other assets in these feeders.
3. Where there is no life support or key NMI, identify the HV feeder with the most customers.
   - Proceed to restore HV feeders in order of customer count.
4. Are any LV feeders de-energised?
   - If yes, identify the LV feeder with the most customers.

- Proceed to restore LV feeders in order of customer count.