A Resilience-based Maintenance Optimisation Framework Using Multiple Criteria and Knapsack Methods*

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Abstract

Business fluctuations and pandemics such as COVID 19 have revealed the need for more resilient approaches and processes in the asset management domain. This research aims to design a resilience-based maintenance optimisation (RbMO) framework that absorbs the fluctuations in the operating context and sustains asset performance at optimum maintenance cost and acceptable risk. The paper proposes a framework that employs the analytical hierarchy process (AHP) to translate the different operating context parameters into risk aspects with relative weights that differ from one operating scenario to another. Then, the Knapsack method uses these relative weights to define the risk reduction of each maintenance task and pick the optimum ones within the allocated maintenance budget. Additionally, the approach introduces the nested criticality grid (NCG), which graphically demonstrates the inherent, Knapsack and residual risk profile from the failure mode level up to the unit level enabling an informative decision-making process, where the asset owner can wisely distribute the maintenance budget or achieve efficient cost savings.

Keywords: Analytical Hierarchy Process, Knapsack method, maintenance optimisation, data-driven decision making

1. Introduction

The current challenging business environment forces organisations to accept more risk, which increases the probability of significant failures; hence, there is a need for resilient-based frameworks that react to the forces pushing to conditions of more risk [5, p. 95]. Also, the unexpected changes in the market and operating conditions caused by global events such as climate-change-related disasters and pandemics like the recent Covid-19 scenario demand more efforts from organisations to survive and be sufficiently agile to maintain their growth and vitality in volatile environments.

One of the main characteristics organisations need to adapt in order to survive is resilience; the word resilience has been originally originated from the Latin word "resiliere", which means to "bounce back", and the common use of this word implies the ability of an entity or system to return to a normal condition after the occurrence of an event that disrupts its state (Hosseini, Barker and Ramirez-Marquez, 2016, p. 47). Resilience modelling has been proposed in the aftermath of the pandemic, where it was suggested that there is a need for a paradigm shift towards prioritisation of resilience over efficiency (Labib, 2021). As the assets represent the primary building block of any systems; hence, the organisation's resilience starts from the resilience of its assets which is defined as the asset's ability to predict, counter, digest, react to, adapt to, and recover from a disturbance (Tan, Wu and Che, 2023, p. 4) from both natural or artificial circumstances (Goerger, Madni and Eslinger, 2014, p. 866).

An asset resilience is highly influenced by its management, which is the organisation's coordinated activities to realise value from assets (ISO 55000, 2014, p. 14); therefore, incorporating the resilience concepts with the asset management practice can form a comprehensive risk management method that enhances asset management decision-making, such as repair, maintenance, and modifications (Liu and Mcneil, 2020, p. 190).

2. Literature Review

Recently, there has been an increase in the number of research works and practices that consider resilience as a maintenance optimisation criteria that is becoming more critical and need to be considered by asset owners (Pinciroli, Baraldi and Zio, 2023, p. 7). The standard definition of resilience concentrates on the reactive aspects of resilience and the ability to recover 'bounce back' after an upset, or disturbance; however, there is a proactive aspect of resilience, preventing disturbances; thus, resilience can be defined as "the ability of systems to prevent or adapt to changing conditions in order to maintain (control over) a system property" (Leveson *et al.*, 2012, p. 95). Maintenance is one of the key elements of the proactive aspect of resilience, as it contributes to organisational resilience; hence, the improvement of the resilience properties of maintenance work processes, including maintenance planning, improves organisational resilience (Okoh and Haugen, 2015, p. 225), increases systems reliability (Asadzadeh, Maleki and Tanhaeean, 2020, p. 919), and enhances the safety of the critical systems (Azadeh, Asadzadeh and Tanhaeean, 2017, p. 157) resilience promotes the development of new means of dealing with different uncertain disturbances to ensure system safety (Sun, Yang and Wang, 2022a, p. 10). In other words, preserving the safety and reliability of critical systems is crucial for resilience improvement (Magoua and Li, 2023, p. 1); however, organisations cannot properly conduct resilience management without considering risk (Aven, 2021, p. 2073) through a comprehensive maintenance risk management that helps improve resilience (Kaewunruen, Sresakoolchai and Lin, 2021, p. 4). Also, safety constraints may significantly increase maintenance costs in some situations; therefore, the decision-maker must balance cost control and risk aversion (Xu, Zhao and Liu, 2021, p. 11); thus, there is a need for an approach that combines resilience concepts with risk-based maintenance principles to create a data-driven decision-making process that enables smart maintenance (Bokrantz *et al.*, 2020b) (Bokrantz *et al.*, 2020a) and optimises maintenance.

Maintenance cost and resilience are two crucial system characteristics (Fu and Zhu, 2023, p. 2), and maintenance optimisation can reduce the first and enhance the second (Sun, Yang and Wang, 2022b, p. 996), system resilience describes the capacity to maintain the required functionality under disturbances, which is significant for productivity and safety (Geng *et al.*, 2023, p. 1); however, the use of classical maintenance systems, such as reliability-centred maintenance (RCM) is not sufficient to help organizations achieve the required level of resilience; thus, there is a need for new maintenance frameworks that meet the requirements of resilient operation (Bukowski and Werbińska-Wojciechowska, 2020). Hence, several papers have tried to enhance the maintenance planning and strategy selection based on the resilience concept (Durán and Vergara, 2022, p. 5), or propose a preventive maintenance scheduling approach that improves asset resilience by changing the optimal operation points (Gargari, Hagh and Zadeh, 2021, p. 7). Also, the concept of resilience-based maintenance has been introduced based on the four main resilience potentials to respond, monitor, learn and anticipate (Bukowski and Werbińska-Wojciechowska, 2021, p. 305)(Hollnagel, 2017, p. 27) as the maintenance strategy determines the guide to quickly recover the system performance after a failure event (Zhang *et al.*, 2022, p. 1); additionally, a resilience index has been introduced to highlight the impact of maintenance strategy on the resilience of systems, and the importance of the balance between them (Durán, Aguilar and Capaldo, 2021, p. 10). One more important balance that impacts system resilience and needs to be established based on the overall availability is the balance between maintenance strategy and maintenance resources (Durán *et al.*, 2021, p. 15); maintenance resources are one of the principal factors that affect resilience (Cai *et al.*, 2018, p. 216) as the use of economic cantered maintenance methods helps improving system resilience [19, p. 10].

The literature needs to further explore maintenance planning resilience as a proactive risk management process to improve the safety performance of critical systems (Azadeh *et al.*, 2016, p. 1078). This paper extends previous work (Karar, Labib and Jones, 2022)(Karar, Labib and Jones, 2021), where a conceptual framework is proposed for an agile asset performance management (AAPM) system of eight integrated processes; the work introduced the definition and the expected outcomes of each process without an in-depth discussion of the processes' design and their application. Hence, this paper suggests a detailed design for three of the eight AAPM processes (Shape Packages, Specify Scenarios and Start Analysis) with their application in developing a resilience-based maintenance optimisation (RbMO) approach.

The "shape packages" process application in the post-warranty maintenance strategy selection has been presented through a comprehensive approach that enables asset owners to select the maintenance strategy at the warranty termination time (Karar, Labib and Jones, 2023). The approach depends only on the shape package process and doesn't consider the integration with any of the remaining AAPM seven processes. Hence, a proposed area for future research was expanding the approach to studying a dynamic decision process that checks the maintenance package and retunes it according to the operating context changes. Likewise, the "specify scenarios" and "start analysis" processes were the main pillars of the resilience-based asset management strategy (RAMS) (Karar, Labib and Jones, 2022) approach, which was proposed to absorb business environment fluctuations and sustain asset performance at optimum cost and acceptable risk. Additionally, it has been highlighted that there is a need to develop RAMS further to help asset owners justify their maintenance budget, as the overall organisation resilience is determined by how efficiently and effectively it manages people, processes and systems (Taarup-Esbensen, 2020, p. 2402).

3. The RbMO Approach

3.1. Overview

Figure 1 depicts the three fundamental processes of the RbMO framework, which are "Specify Scenarios", "Start Analysis" and " Shape Packages". Firstly, the "Specify Scenario" process lists the potential operating context scenarios and determines their relative importance; then, it defines the relative weights of risk dimensions within each scenario before generating the combined criticality weights to drive the following processes; this process also responds to the operating context changes via considering new scenarios or amending the relative importance of the existing ones.

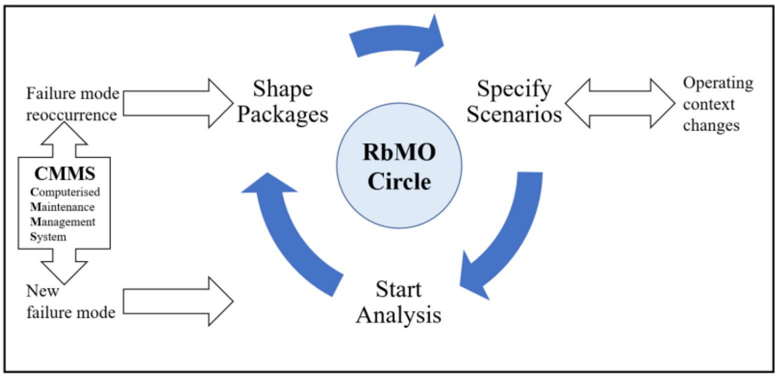

Figure 1: RbMO Circle (Karar, Labib and Jones, 2022)

Secondly, the "Start Analysis" process analyses the reasonably likely failure modes and quantifies their consequences in each potential operating context scenario using the combined criticality weight; then assigns the relevant maintenance task to mitigate failure modes. Integrating this process with the computerised maintenance management system (CMMS) enables the continuous update of the failure modes list and their relevant risk assessment. Lastly, the "Shape packages" process employs the Knapsack method to pick the optimum maintenance tasks and form a maintenance program within the allocated maintenance budget, considering task cost and risk mitigation value; as the prioritization of maintenance actions using the Knapsack method enhances asset resilience (Zou and Chen, 2019, p. 16). This process also introduces the nested criticality grid (NCG) to demonstrate the risk profile from the failure mode level up to the unit level enabling data-informed decisions making by asset owners for better cost/risk balance. The following sections discuss the three processes with relevant illustrative examples.

3.2. "Specify scenarios" process

As defined in SAE JA 1012, "the operating context is the circumstances in which a physical asset or system is expected to operate" (SAE.JA1012, 2002, p. 6). These circumstances include market demand, raw material supply, spares availability, environmental standards, the intensity of operation, safety regulations, asset design and configuration. The "specify scenarios" process defines the operating context parameters with their likely changes, which determines the potential operational scenarios; in other words, the different parameter combinations create different scenarios. For example, the market demand and raw material supply in seasonal industries may differ in summer and winter, which means there are two scenarios where the risk of breakdowns and production loss is not the same.

The RbMO employs AHP to help asset owners determine the importance of potential scenarios and to differentiate between the significance of risk dimensions within each scenario, which then influences the maintenance strategy selection via a proposed risk matrix. Munier and Hontoria have listed several shortcomings of the analytical hierarchy process (AHP), such as the ambiguity of pair-wise comparisons, the incapacity to solve complex problems, the quantifying preferences and considering relationship and dependency as the same thing (Munier and Hontoria, 2021); however, several authors have addressed the maintenance decision-making process via the use of AHP in selecting maintenance strategies to help asset owners choose the best maintenance programs according to relevant selection criteria (Abdul Jawwad and AbuNaffa, 2021) (Alsyouf *et al.*, 2021) (Shafiee *et al.*, 2019) (Labib, no date), as the AHP offers a good trade-off between perfect modelling and usability of the model (Ishizaka and Labib, 2011, p. 14342). As depicted in Figure 2, the "specify scenarios" uses AHP to translate the defined operating context parameters into risk dimensions such as safety of personnel, environmental impact, production availability and cost of material loss (Siddiqui and Ben-Daya, 2009).

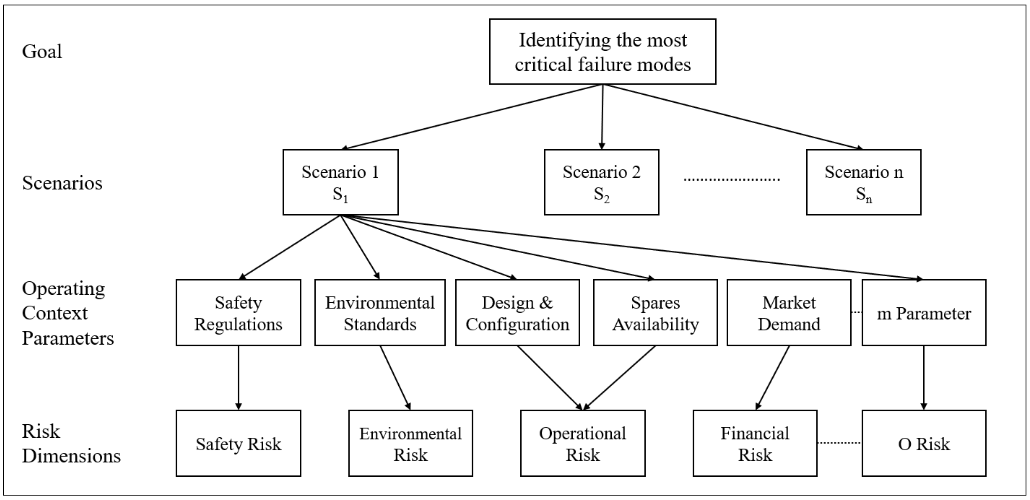

Figure 2: "Specify Scenarios" process hierarchical structure

This mapping ensures the proper representation of the different parameters in the criticality assessment process, enabling the identification of the risk profile associated with each operating context scenario. There are 'n' potential scenarios: $S_1, S_2, \dots, S_n$, and the AHP links each scenario to the applicable risk dimension through an intermediate link with the operating context parameters; the figure depicts a number 'O' of risk aspects: safety, environmental, operational, financial and ‘O’ risks linked to the relevant scenarios through 'm' operating context parameters.

Table 1: Scale of relative importance (Saaty, 2004, p. 6)

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favour one activity over another
5	Strong importance	Experience and judgment strongly favour one activity over another
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
1/3, 1/5, 1/7, 1/9	Values of inverse comparison	

The AHP uses the scale of relative importance in Table 1 to compare the potential scenarios $S_1, S_2, \dots, S_n$ as per the illustrative example in Table 2. As shown in the pair-wise comparison matrix, S_1 is three times important as S_2 and five times as important as S_n; S_2 is five times as dominant as S_n. Then, the initial scenario criticality weight (ISCW) is calculated using AHP calculation software (GGI, 2021).

Then, the AHP determines the initial risk dimension weights (IRDW) for each potential operating context scenario. As presented in Table 2, in S_1 the safety risk is three times as important as the environmental risk and five times as important as the operational and financial risk; while, in S_2 and S_n, these relative weights are not necessarily the same as the IRDW is scenario-dependent; all judgements were consistent as the C.I was less than the recommended limit of 0.1 in all cases.

Table 2: Illustrative example of pair-wise comparison for ISCW and IRDW calculations

Scenarios pair-wise comparison:						
Operating context scenario	S_1	S_2	S_n	Initial scenario criticality weight (ISCW)		
S_1	1.00	3.00	5.00	0.637		
S_2	1/3	1.00	3.00	0.258		
S_n	1/5	1/3	1.00	0.105		
Risk dimensions pair-wise comparison:						
Operating context Scenario	Risk dimension (RD)	Safety	Envir.	Opera.	Finan.	Initial risk dimension weight (IRDW)
S_1	Safety	1.00	3.00	5.00	5.00	0.550
	Envir.	1/3	1.00	3.00	3.00	0.248
	Opera.	1/5	1/3	1.00	1/3	0.074
	Finan.	1/5	1/3	3.00	1.00	0.129
S_2	Safety	1.00	3.00	3.00	5.00	0.506
	Envir.	1/3	1.00	3.00	3.00	0.251
	Opera.	1/3	1/3	1.00	1/5	0.080
	Finan.	1/5	1/3	5.00	1.00	0.163
S_n	Safety	1.00	1.00	3.00	5.00	0.400
	Envir.	1.00	1.00	3.00	3.00	0.360
	Opera.	1/3	1/3	1.00	3.00	0.159
	Finan.	1/5	1/3	1/3	1.00	0.081

In the end, the "specify scenarios" process identifies the relative importance of each operating context scenario ($ISCW$) and the relative weight of every risk dimension ($IRDW$) within each scenario, as depicted in Figure 3; it also determines the initial combined criticality weight ($ICCW$) using the $ISCW$ and the $IRDW$ calculated in Table 2.

Where,

$$ICCW = ISCW \times IRDW \quad (3\text{-}1)$$

For S_1, the combined criticality weight of the safety aspect calculated as;

$$ICCW\ (S_1, safety) = 0.637 \times 0.550 = 0.350$$

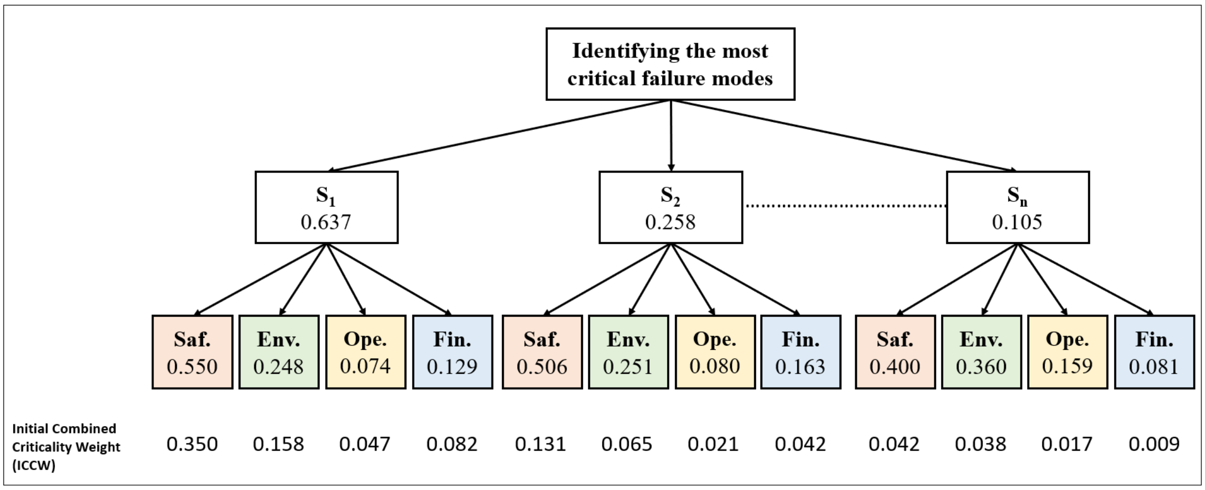

Figure 3: The "specify scenarios" process outcome - illustrative example.

The $ICCW$ enables asset owners to update FMEA priorities and manipulate the risk aspects according to the changes in the operating context scenario, so the maintenance strategy-related risks are updated seamlessly. An excellent example of this need is operating two identical assets in two different countries, wherein country A, the power offtaker applies a significant fine on the forced outages. In contrast, in country B, the offtaker applies a minor penalty. In such a case, there is no need to rework the complete FMEA analysis; only having two scenarios with different relative weights helps update all the risk values at the failure modes level and saves time and effort.

3.3. "Start Analysis" process

The RbMO approach uses the $ICCW$ resulting from the "Specify Scenario" process to intensify the "Start Analysis" process introduced in the agile asset performance management (AAPM) framework (Karar, Labib and Jones, 2021). As depicted in Figure 4, the "Start Analysis" process has eight classical steps, and the RbMO uses the $ICCW$ to enrich the inherent and residual risk assessment in steps five and eight, so the failure mode risk is assessed at different operating context scenarios.

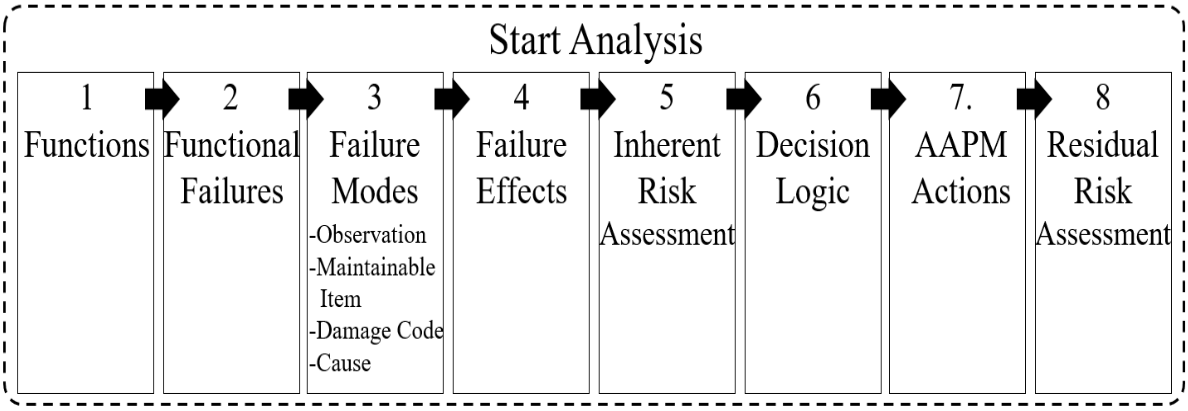

Figure 4: "Start Analysis" process (Karar, Labib and Jones, 2021)

3.3.1. Functions

The functions list indicates stakeholders' expectations of the asset. This includes the primary function or why the asset has been acquired in the first place and secondary functions that reflect the additional expectation, such as environmental and safety compliance.

3.3.2. Functional Failures

The functional failure records show how the asset could fail in delivering the required functions either through a total failure by not delivering at all or through a partial loss via giving less than the required output.

3.3.3. Failure Modes

The failure mode is the "manner in which the inability of an item to perform a required function occurs" (BSI 13306, 2017, p. 26); thus, this step associates each maintainable item with the relevant reasonably likely failure cause. The maintainable item is the "item that constitutes a part or an assembly of parts that is normally the lowest level in the equipment hierarchy during maintenance" (ISO 14224, 2016, p. 10); for instance, bearings, impeller, seal and casing are regarded as pump maintainable items. While the failure cause is "circumstances during specification, design, manufacture, installation, use or maintenance that result in failure" (BSI 13306, 2017, p. 27), such as installation failure, operating error or expected wear and tear.

3.3.4. Failure Effects

The failure effect is "What happens when a failure mode occurs" (SAE.JA1011, 1999, p. 4). The failure effect statement explains the failure impact on the RbMO risk dimensions (safety, environmental, Operational and financial).

3.3.5. Inherent Risk Assessment (Failure Mode Inherent Criticality)

The inherent criticality assessment step evaluates failure mode criticality assuming zero-based maintenance (no maintenance) using a risk matrix which is a commonly used tool for risk assessment (Li, Bao and Wu, 2018, p. 115) it is a "combination of the severity of an effect and the frequency of its occurrence or other attributes of a failure as a measure of the need for addressing and mitigation" (BS EN 60812, 2006, p. 6); usually, the risk matrix is used to practically enable risk-management decision-making because it is simple, easy to understand and does not involve any complex mathematics (Bier, 2020, p. 2214) ; thus, it has been used to determine some essential data to weigh the accident preventive measures' cost against their hypothetical benefits and choose the most cost-efficient actions using the knapsack algorithm (Reniers and Sörensen, 2013, p. 2066).

However, using such scoring methods has its limitations; as listed by Hubbard, it does not consider the issue of risk perception, which leads to inconsistency; also, the deviations in the understanding of the qualitative descriptions of likelihood result in variations in use; besides, the unintended consequences of the scoring schemes structure (Hubbard, 2020, p. 122). Nevertheless, despite these limitations, this paper proposes a hybrid approach that has the strength of reducing subjectivity and streamlining the decision-making process using well-known methods among practitioners.

Similarly, Cox has highlighted four limitations of risk matrices: poor resolution, errors, suboptimal resource allocation and ambiguous inputs and outputs; however, he suggested using risk matrices with caution and careful explanation of embedded judgements (Anthony Cox, 2008, p. 497). Cox has also introduced weak consistency, betweenness, and consistent colouring; as three axioms that risk matrices should satisfy and these three axioms have been considered in the design of the RbMO risk matrix as shown in Figure 5, where the points in the top risk category represent higher quantitative risk than points in the bottom category; there are intermediate cells between the lower left end and the upper right cells; also, each cell quantitative risk is as high as the other cells with the same colour but less than the cells with higher priority colour and greater than the cells with lower priority colour.

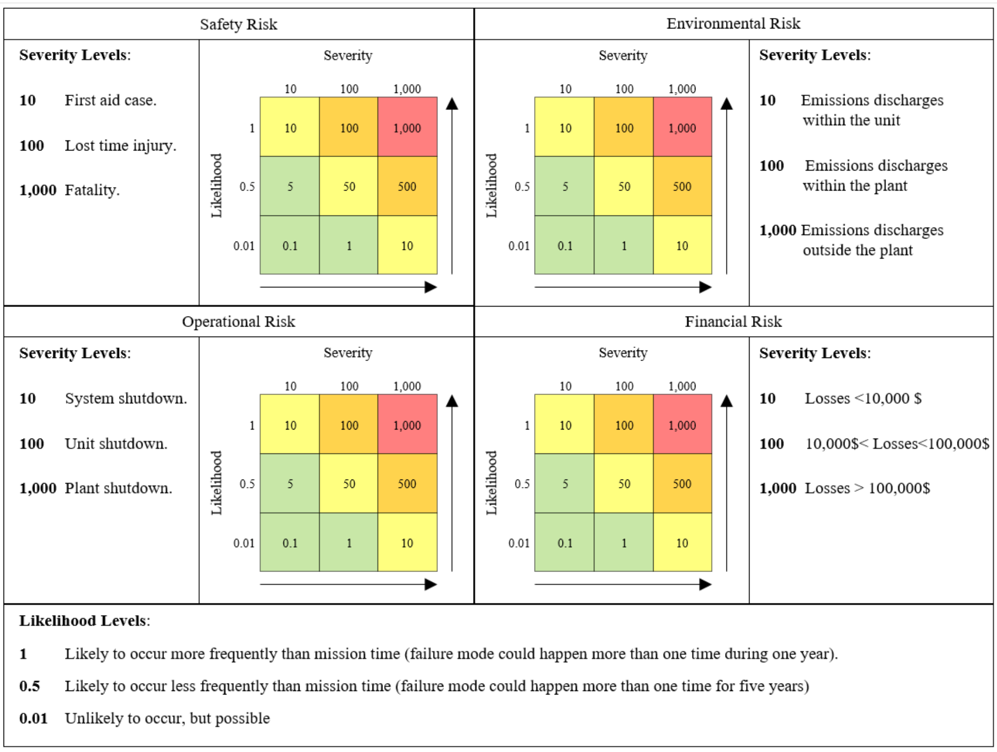

Figure 5: Criticality Assessment

This quantitative risk of each cell is calculated by multiplying the cell severity column level by its likelihood row level; these levels are defined as in Figure 5. As suggested by Sutherland, Recchia, Dryhurst and Freeman (Sutherland *et al.*, 2022, p. 1039), the proposed risk matrices use ordinal, explicitly nonlinear scale labels to represent the nonlinear change from one cell to another by increasing in a suitable geometric progression (10, 100, 1000).

Table 3 gives an illustrative example that considers three different failure modes where the of FM_1 shows 100, which is the product of high likelihood (1) and Moderate severity (100).

Table 3: An illustrative example of normalised failure mode inherent criticality (FMIC)calculations

Failure Mode (FM)	Failure Mode Inherent Risk Rank				Failure Mode Inherent Criticality (FMIC)			
	Saf.	Env.	Ope.	Fin.	S_1	S_2	S_n	Generic FMIC
FM_1	100	50	500	50	71	29	15	115
FM_2	50	500	100	1,000	183	83	32	298
FM_z	100	50	100	500	89	40	12	140

Table 3 also explains the calculations $FMIC$ per scenario which uses the $ICCW$ introduced in Figure 3. For m number of risk dimensions:

$$FMC\ (FM_x, S_y) = \sum_{R=1}^{m} ICCW_{Ry} \times Risk\ Rank_{Rx} \tag{3-2}$$

For example, to calculate the $FMIC$ of FM_2 in the case of S_2:

$$FMC\ (FM_2, S_2) = 0.131 \times 50 + 0.065 \times 500 + 0.021 \times 100 + 0.042 \times 1000 = 83$$

Also, to understand the relative importance of each failure mode, the generic failure mode inherent criticality ($GFMIC$) for a failure mode FM_y can be calculated as:

$$GFMC(FM_y) = \sum_{x=1}^{n} FMC\ (S_x) \tag{3-3}$$

For example, the $GFMIC$ of failure mode 1:

$$GFMIC\ (FM_1) = 71 + 29 + 15 = 115$$

As shown in the table, FM_1 is more critical in S_1 than S_2 and S_3; having this visibility of the failure mode inherent criticality across the different operating scenarios enables better optimisation in the mitigation actions selection step.

3.3.6. Decision Logic

The maintenance strategy decision logic is a series of questions that determine the failure mode consequence category (safety, environmental, operational) and directs the asset owner to select the proper maintenance type to mitigate its risk. RbMO follows the AAPM decision logic which proposed as part of the conceptual framework of agile asset performance management process (Karar, Labib and Jones, 2021).

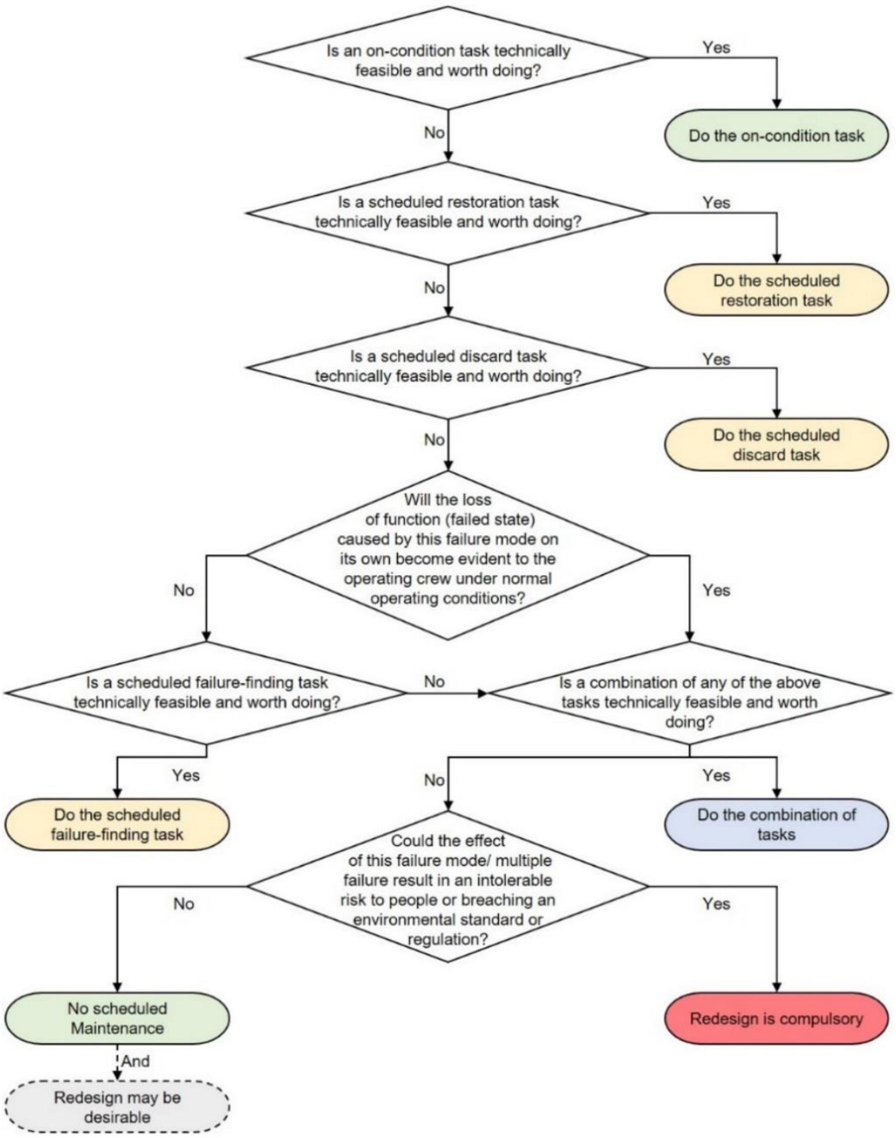

Figure 6: AAPM decision logic (Karar, Labib and Jones, 2021)

3.3.7. AAPM Actions (Mitigation Actions)

This step utilises the FMIC calculations to define a dedicated strategy for each scenario; each strategy consists of a set of maintenance actions to mitigate the scenario critical failure modes. The strategy may contain different types of maintenance actions, such as condition-based maintenance and predetermined maintenance.

3.3.8. Residual Risk Assessment (Failure Mode Residual Criticality)

This step re-evaluates the failure mode criticality, assuming the mitigation actions in place to identify how far these actions effectively reduce FMIC to an acceptable failure mode residual criticality (FMRC). The step employs the criticality assessment tool used to identify FMIC, to assess the FMRC; then, it applies the $ICCW$ introduced in the "Specify Scenarios" process to calculate the FMRC per scenario, using equations 3-2 and 3-3, as explained in the case study in Table 6.

3.4. The "Shape Packages" process

As discussed in the previous section, the "Start Analysis" process identifies a list of maintenance tasks with their cost and risk reduction, which is the difference between inherent and residual risk. Then, the "Shape Packages" process uses the task cost and risk reduction figure, respectively, when applying the Knapsack method to select the optimum maintenance package.

The knapsack method has been used to optimise the budget allocated for the maintenance and rehabilitation of building components (Thohir, Sangadji and As'ad, 2017, p. 236), and in the proposed algorithm for maintenance task assignment by the 0–1 knapsack problem to help fulfil the maintenance optimisation (Sun, Sun and Zhou, 2021, p. 1). However, the RbMO extends this work by introducing the knapsack risk to demonstrate the impact of maintenance optimisation on the asset risk profile using the nested criticality grid (NCG), which represents an extension of the hierarchy failure modes and effects analysis (FMEA) structure (Chen, 2013, p. 5407); that links equipment criticality analysis with FMEA, as suggested by Karar and Labib (Karar and Labib, 2020, p. 12) and gives a line of sight risk management from the failure mode level to the unit level.

For the Knapsack method, The mathematical model:

$$\text{maximise } \sum_i^n pr_i \,.\, T_i \qquad \textit{3-4}$$

$$\text{subject to: } \sum_i^n C_{ij} \,.\, T_i \leq B_j \qquad \textit{3-5}$$

j = 1,...,m

where:

pr_i is priority of i^{th} alternative maintenance task proposed in the start analysis decision sheet Table 6 .

T_i is alternative maintenance task i.

c_{ij} is the cost of executing the i^{th} maintenance task.

B_j is the maintenance budget.

There are n maintenance tasks, which require m resources (cost).

pr_i and $c_{ij} \geq 0$

$i = 1, \dots, n$

$j = 1, \dots, m$

T_i = 1 if maintenance task i is selected,

= 0 otherwise

$i = 1, \dots, n$

The objective is to find the optimal assignment of resources to strategic alternatives so as to maximise the sum of resource utilisation and utility (satisfaction).

Sensitivity Analysis

Figure 7 depicts the sensitivity analysis for an illustrative task with a risk reduction of 500 and a task burden of 500. As shown in the graph, the task priority increases as its risk reduction increases and its burden decreases, while the lowest priority tasks are those with the highest burden and lowest risk reduction. The task risk reduction is the difference between the FMIC and the FMRC, reflecting the capability to reduce the failure mode risk further, while the task burden is the multiplication of task cost, frequency and ISCW. Reducing the task cost and frequency will increase its priority, but at the same time, it will reduce the task risk reduction; hence, the use of the Knapsack method helps in selecting the highest priority tasks within the allocated budget and eliminating the lowest priority tasks.

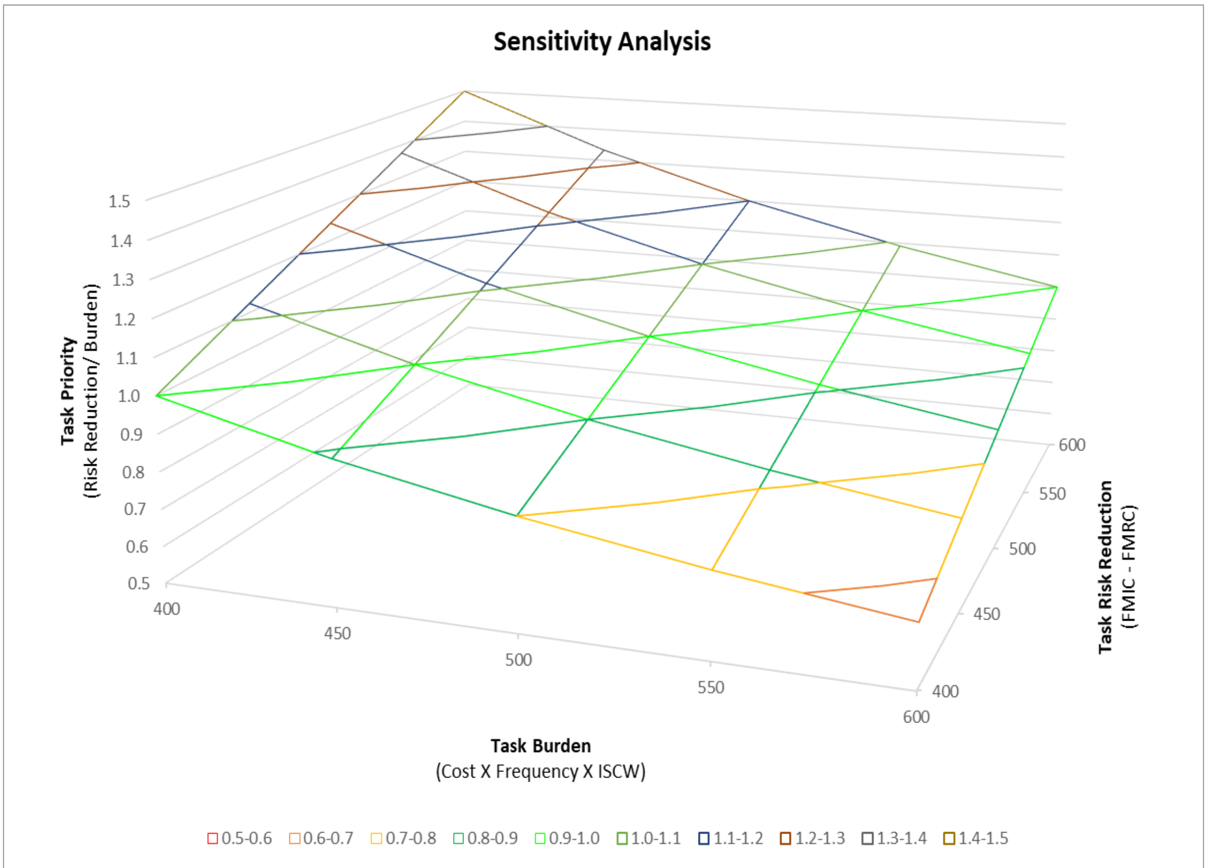

Figure 7: Sensitivity analysis

The Nested Criticality Grid

The "Shape Packages" process expands the hierarchy FMEA structure (Chen, 2013, p. 5407) into a comprehensive NCG to present the inherent risk profile, which assumes zero maintenance, and the residual risk profile, which considers the execution of all maintenance tasks as suggested by the "Start Analysis" process. However, the asset owner may execute only a subset of the proposed maintenance tasks due to budget constraints, so the RbMO employs the Knapsack method to select this subset of tasks; thus, we call the new risk profile the Knapsack risk.

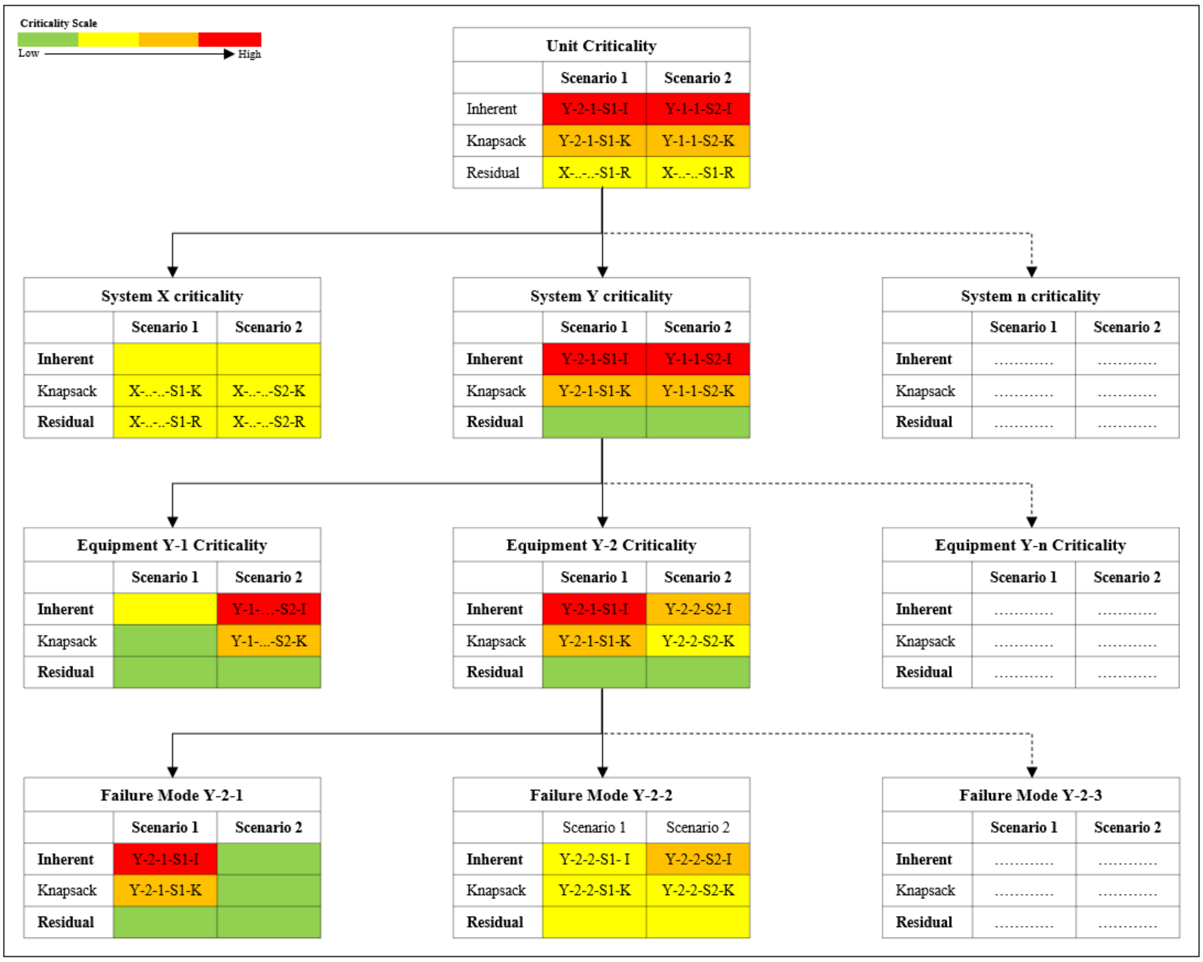

Figure 8: An illustrative example of the nested criticality grid (NCG)

The Knapsack risk could equal the residual risk if there are no budget limitations and the Knapsack method selects all "Start analysis" proposed tasks; on the other hand, if Knapsack does not select any of the proposed tasks (zero budget), its risk will be the same as the inherent risk. Therefore, the NCG enables asset owners to understand the system risk profile and how the maintenance budget has been allocated to mitigate that risk at all levels, facilitating the budget discussion and promoting informative decision-making.

$$Residual\ Risk\ \leq Knapsack\ Risk \leq Inherent\ Risk \qquad \textit{3-6}$$

For instance, as depicted in Figure 8, in Failure Mode Y-2-1 during scenario 1, the Knapsack risk rank falls between the inherent and residual risk, which means that the Knapsack method has selected a subset of the proposed maintenance tasks.

The NCG demonstrates how the criticality is aggregated from the failure mode level up to the unit level for each scenario. For instance, equipment inherent criticality (EIC), equipment Knapsack criticality (EKC) and residual criticality (ERC) can be calculated by equations 3-7, 3-8 and 3-9:

$$EIC_{Y-2} = \max(FMIC_{Y-2-1}, FMIC_{Y-2-2}, \ldots \ldots FMIC_{Y-2-n}) \qquad \textit{3-7}$$

$$EKC_{Y-2} = \max(FMKC_{Y-2-1}, FMKC_{Y-2-2}, \ldots \ldots FMKC_{Y-2-n}) \qquad \textit{3-8}$$

$$ERC_{Y-2} = \max(FMRC_{Y-2-1}, FMRC_{Y-2-2}, \ldots \ldots FMRC_{Y-2-n}) \qquad \textit{3-9}$$

In the illustrative example, failure mode Y-2-1 is the most critical failure mode for equipment Y-2 during scenario 1. Hence, the inherent equipment criticality in scenario 1 is Y-2-1-S1-I. While, during scenario 2, failure mode Y-2-2 is more critical; therefore, Y-2 inherent criticality during scenario 2 is Y-2-2-S2-I. Then, the system inherent criticality (SIC), Knapsack criticality (SKC) and residual criticality SRC can be calculated via equations 3-10, 3-11 and 3-12:

$$SIC_{Y} = \max(EIC_{Y-1}, EIC_{Y-2}, \ldots \ldots EIC_{Y-n}) \qquad \textit{3-10}$$

$$SKC_Y = \max(EKC_{Y-1}, EKC_{Y-2}, \dots \dots . EKC_{Y-n}) \quad 3\text{-}11$$

$$SRC_Y = \max(ERC_{Y-1}, ERC_{Y-2}, \dots \dots . ERC_{Y-n}) \quad 3\text{-}12$$

As depicted in Figure 8, equipment Y-2 has the highest inherent criticality among system Y equipment during scenario 1. Hence, the inherent system criticality in scenario 1 is Y-2-1-S1-I. While, during scenario 2, Equipment Y-1 is more critical; therefore, system Y inherent criticality during scenario 2 is Y-1-..-S2-I. Next, equations 3-13, 3-14, and 3-15 calculate the unit inherent criticality (UIC), Knapsack criticality (UKC) and residual criticality (URC):

$$UIC = \max(SIC_X, SIC_Y, \dots \dots . SIC_n) \quad 3\text{-}13$$

$$UKC = \max(SKC_X, SKC_Y, \dots \dots . SKC_n) \quad 3\text{-}14$$

$$URC = \max(SRC_X, SRC_Y, \dots \dots . SRC_n) \quad 3\text{-}15$$

In the illustrative example, system X has the highest residual criticality among all systems within the unit, so the unit residual criticality for both scenarios is the same as system X; and system Y has the highest inherent criticality for the two scenarios, representing the unit's inherent criticality. Finally, the NCG reveals the Knapsack of each potential operating scenario, which is then fed into the "specify scenario" process with the adjusted scenario criticality weight ($ASCW$) according to the changes in the allocated maintenance budget or the risk of failure modes. The $ASCW$ can be calculated as:

$$ASCW_m = \frac{SKC_m}{\sum_{x=1}^{n} SKC_x} \quad 3\text{-}16$$

Where:

$ASCW_m$: Adjusted Scenario Criticality Weight of scenario m

SKC_m : Scenario Knapsack Criticality of scenario m

n : The total number of potential scenarios

3.5. RbMO as an integrated approach

One of the main shortcomings of the AHP method that it “takes for granted that once the relative importance between criteria is determined they remain constant”(Munier and Hontoria, 2021, p. 67), thus the RbMO introduces the detailed circle Figure 9, which shows how the three fundamental processes integrate to form a dynamic approach.

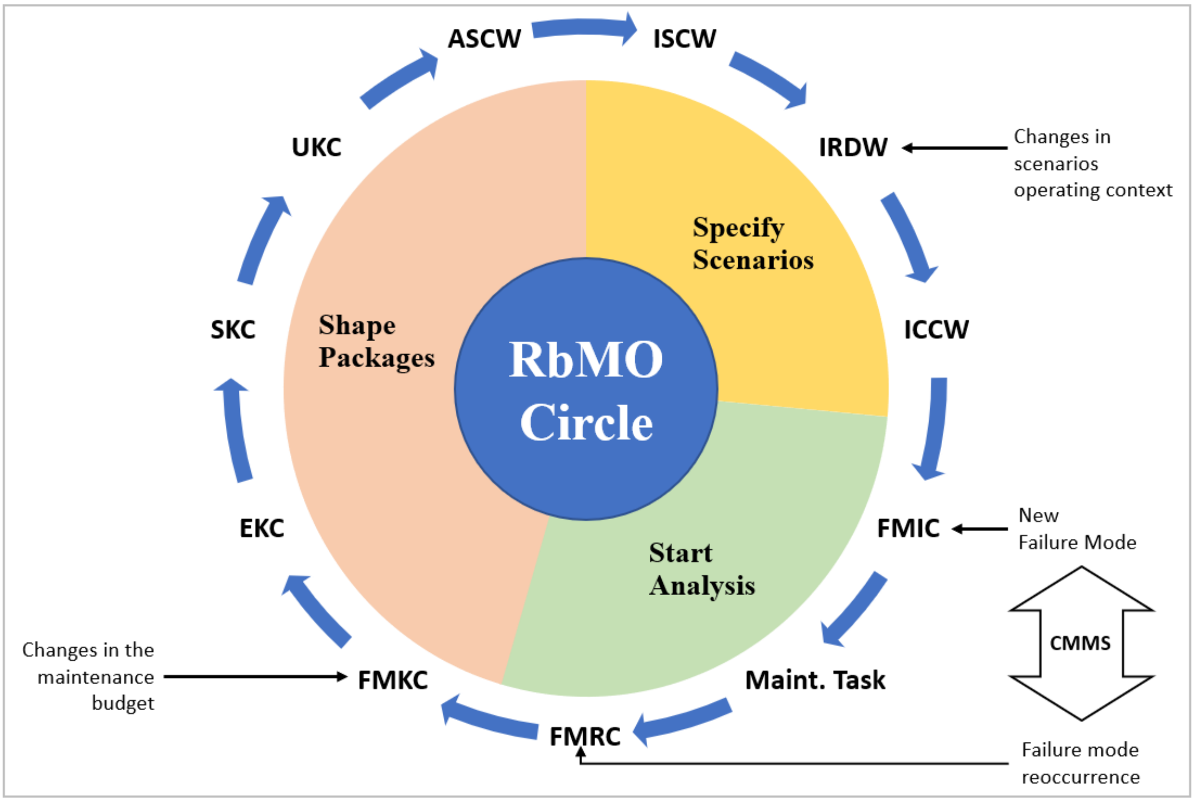

Figure 9: RbMO detailed circle

The procedure starts with the identification of the initial scenario criticality weight (ISCW), which is then multiplied by the initial risk dimension weight (IRDW) to create the initial combined criticality weight (ICCW). As the $ICCW$ considers the differences in the risk dimension weight between scenarios to enable the assessment of the failure mode inherent criticality (FMIC) at each potential scenario; then, the start analysis process helps assign the relevant maintenance mitigation tasks before the failure mode residual criticality (FMRC) assessment step. Finally, the shape packages process facilitates the rational selection of a subset of the proposed maintenance tasks considering budget constraints creating the failure mode knapsack criticality (FMKC); which is then aggregated to form equipment knapsack criticality (EKC), system knapsack criticality (SKC) and unit knapsack criticality (UKC). Then, the UKC helps determines the adjusted scenario criticality weight (ASCW) to readjust the $ISCW$ and retrigger the procedure if the difference between $ISCW$ and $ASCW$ exceeds 10% for any scenario.

$$If\ ISCW_m \approx ASCW_m, then\ no\ adjustement\ is\ needed \qquad 3\text{-}17$$

Maintenance budget changes, operating context deviations, the reoccurrence of a mitigated failure mode and the occurrence of a new failure mode; are additional triggers of the RbMO cycle. When the maintenance budget increases, the knapsack selects more maintenance mitigation tasks which reduce the failure modes and the scenario criticality; on the other hand, maintenance budget reduction increases the failure mode and scenario criticality as it eliminates more maintenance mitigation tasks. Also, changes in the operating context demand amendments in the $IRDW$, so the approach entire risk assessment process is updated up to the failure mode and unit level. Moreover, the occurrence of a new failure mode (not listed in the FMEA tables) triggers the update of the start analysis process to consider it and assign the needed mitigation task; while the reoccurrence of a listed failure mode highlights the need to update its likelihood and FMRC.

4. Case Study

The power generation industry plays a significant role in supplying all other sectors with the essential energy needed to sustain productivity and performance. The demand for this vital energy changes from one season to another; as a result, the vulnerability to failures and downtime changes. Hence, "Maintenance scheduling and asset management practices play an important role in power systems" (Sabouhi, Fotuhi-Firuzabad and Dehghanian, 2016, p. 87).

This case study considers a power plant that comprises two (400 MW) combined-cycle units plus a series of common systems. Combined cycle power plants are those plants that generate electricity through the joint use of gas and steam turbines, where a boiler uses the gas turbines exhaust to produce the feed for the steam turbine operation. The main unit equipment are gas turbines, steam turbine, a heat recovery boiler, natural gas compressing station, a backup fuel storage tank and a distributed control system (DCS).

The selected system for the RbMO study is a turbo-group lube oil system that aims to keep the bearings of the turbo-group lubricated and supply lubrication oil to other systems. The turbo-group includes the gas turbine, the generator, the clutch, and the steam turbine, with a total number of eight bearings, as depicted in Figure 10, which also shows the system boundaries for RbMO implementation. The system has three pumps, two filters, two heat exchangers, a temperature-regulating valve, and a lubrication oil tank, all operated via the plant-distributed control (DCS) system.

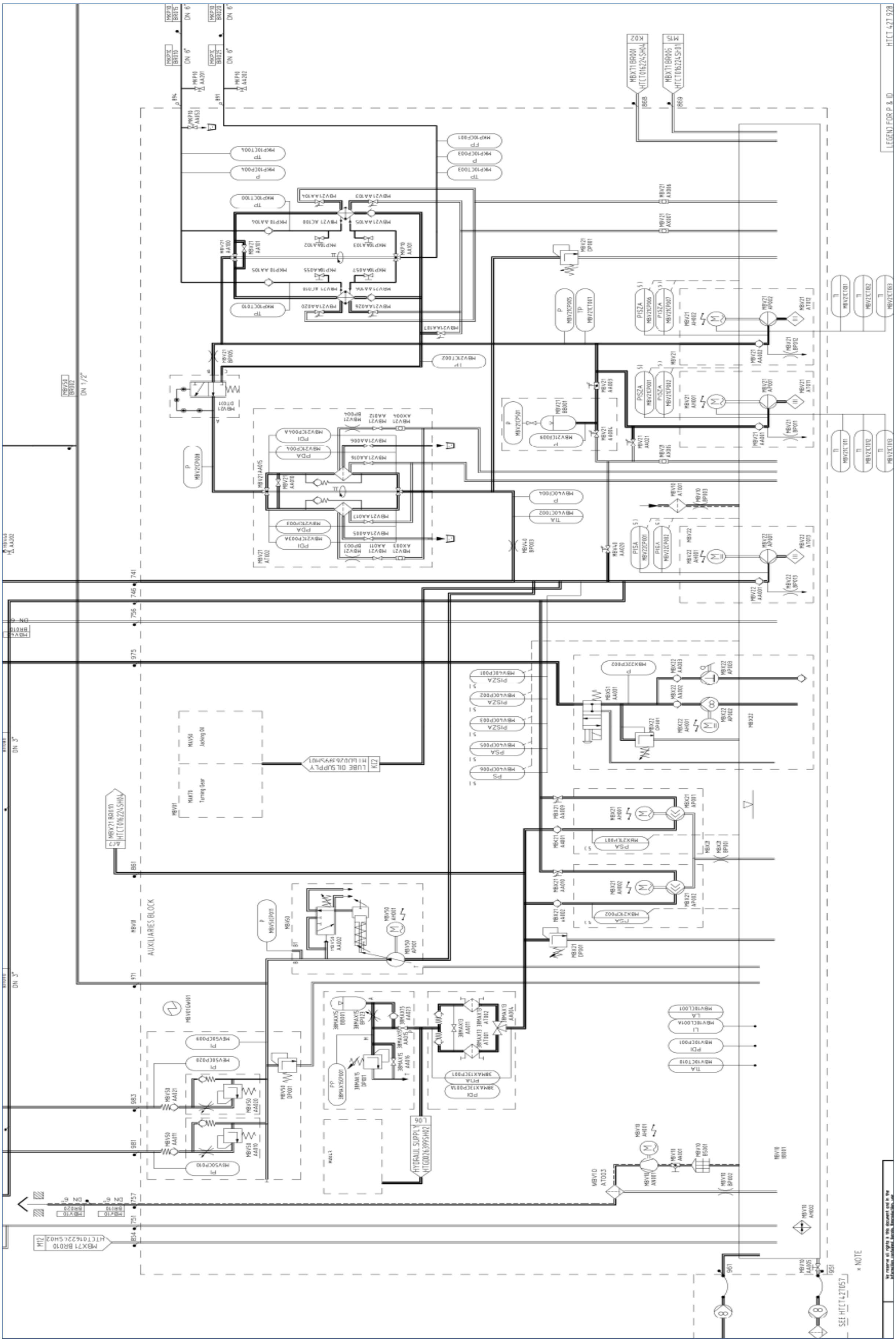

Figure 10: The turbo-group lube oil system

4.1. "Specify scenarios" process for the turbo-group lube oil system

Few parameters influence the plant operating context and determine the potential scenarios, including safety regulations, environmental standards, gas price, electricity demand, spares and resources availability. Safety regulations and environmental standards are reviewed by the regulator every five years to ensure compliance with international standards and regulations; however, safety is always a priority during all operation scenarios. On the gas price side, the government controls the natural gas price for power generation plants; however, as part of the country's economic reform plan, the government is very soon tying the local prices to the global market; this may lead to significant changes in natural gas prices, increasing costs during the high-demand season.

The electricity demand changes during the year as the consumption sharply increase in the summer season when the temperature reaches 30°C, and consumers tend to use air condition systems which is one of the main electricity consumers (Dababneh, Li and Sun, 2016, p. 44) for extended periods, while the demand is less during the winter season as the average temperature is less and could reach 10°C; thus, plant forced-outages during the summer season have more severe consequences than the winter season outages. Similarly, spares and resources availability play a vital role in returning the plant back to operation in case of forced outages; this role becomes more important during the summer season when the demand is high, and the electricity regulatory body does not have backup power plants to accommodate a long forced-outage. Hence, the unavailability of spares, special tools and human resources needed for repair activities increases the plant downtime and the operation risk.

As a result, the operating context parameters show two dominant scenarios, as illustrated in Figure 11, which depicts the overall connection between goals, scenarios, operating parameters and risk dimensions. Firstly, the summer season scenario in which the demand is high and any production interruption will negatively impact customer satisfaction and plant revenue. Secondly, the winter season scenario which has an opportunity to shut down a few assets for maintenance as the demand is less.

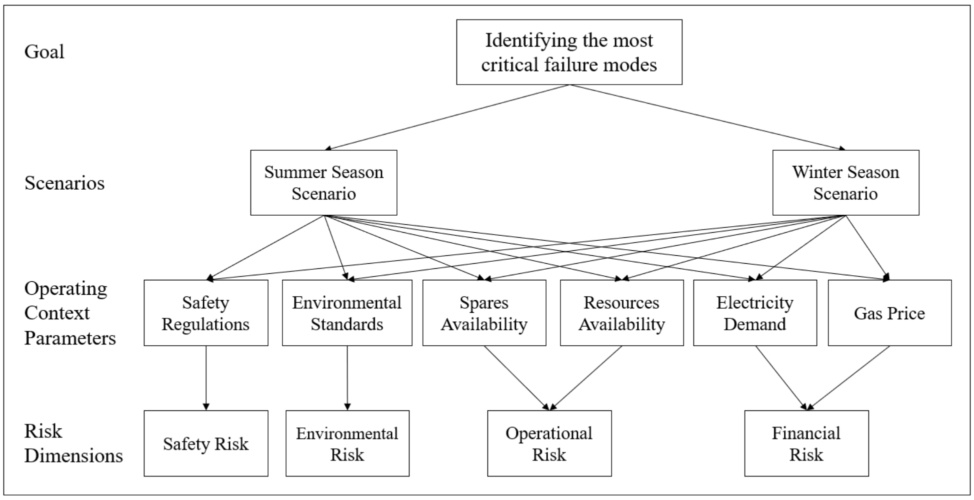

Figure 11: Case study hierarchical structure

The power plant offtaker's community yearly temperature trend shows only four months per year where the temperature drops below 20 degrees which the RbMO views as a winter scenario; on the other side, the process considers the remaining eight months as a summer scenario. Hence, the oil system is exposed to the summer scenario twice the time as the winter, which is demonstrated by the scenarios relative weights, as represented in Table 4, where the CI levels show a good level of consistency for both scenarios and all judgements were consistent as the C.I was less than the recommended limit of 0.1 in all cases.

Table 4: Case study pair-wise comparison for ISCW and IRDW calculations

Scenarios pair-wise comparison:			
Operating context scenario	Summer Season Scenario	Winter Season Scenario	Initial scenario criticality weight (ISCW)
Summer Season Scenario	1.00	2	**0.667**
Winter Season Scenario	0.5	1.00	**0.333**

Risk dimensions pair-wise comparison:						
Operating context Scenario	Risk dimension (RD)	Safety	Envir.	Opera.	Finan.	Initial risk dimension weight (IRDW)
Summer	Safety	1.00	3.00	1.00	2.00	**0.351**
	Envir.	1/3	1.00	1/3	1/2	**0.109**
	Opera.	1.00	3.00	1.00	2.00	**0.351**
	Finan.	1/2	2	1/2	1.00	**0.189**
Winter	Safety	1.00	3.00	3.00	2.00	**0.460**
	Envir.	1/3	1.00	1/2	1/2	**0.119**
	Opera.	1/3	2	1.00	3.00	**0.201**
	Finan.	1/2	2	1/3	1.00	**0.220**

Table 4 also explains the risk dimensions pair-wise comparisons within each scenario. During the summer scenario, the plant forced-outages have the most significant damage and highest cost (Kim and Cho, 2017, p. 244) as firms experience power outages also incurred the high damage (Dormady *et al.*, 2022, p. 8); hence, it is crucial to resume the operation immediately after any outage, regardless of the financial impact of repair activities. Thus, the operation risk dimension is equally important as the safety risk dimension, and both have the same relative weights, while the financial and the environmental risk have lower relative weights.

On the other side, the winter scenario has less power demand, and the offtaker has a buffer capacity to accommodate a few forced outages; still, it is important to return the tripped plants to service quickly as the disruption of some services may result in a substantial destructive effect (Liang and Li, 2023, p. 1), but there is room to extend the downtime if this reduces the overall financial consequence of repair work. Hence, the operation and environmental risk have lower relative weights than the financial risk; however, the safety risk still has the highest relative weight.

At the end the "Specify Scenario" process determines the initial combined criticality weight of each risk dimension within summer and winter scenarios as depicted in Figure 12.

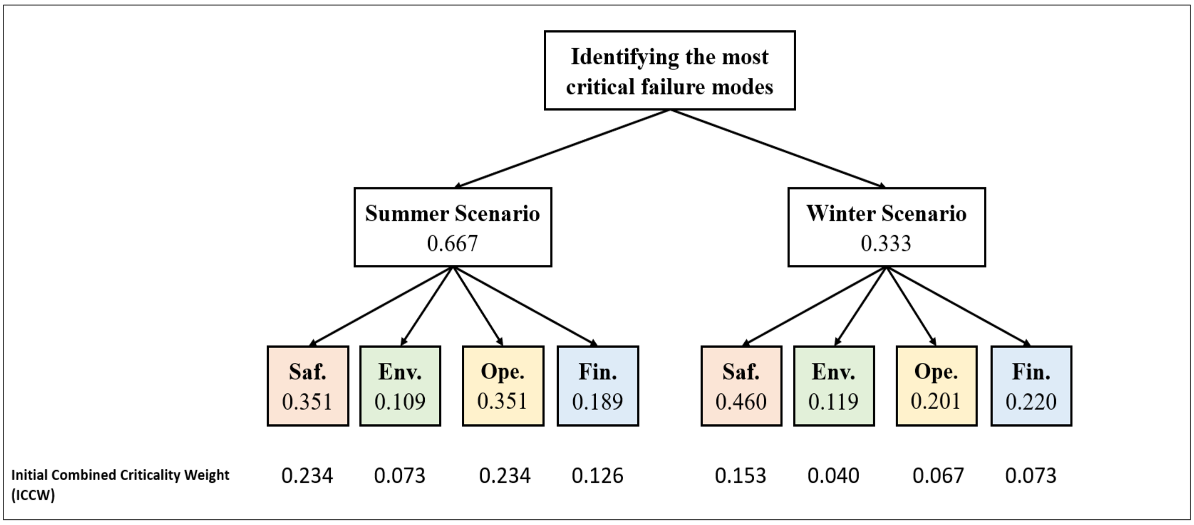

Figure 12: Case study combined criticality weights

4.2. "Start Analysis" process for the turbo-group lube oil system

The implementation of the start analysis process follows the depicted process in Figure 4, through two sheets. Firstly, the information sheet lists the functions, functional failure, failure modes, failure effects, and inherent risk assessment outcomes. Secondly, the decision sheet documents maintenance policy selection steps, the proposed task, the frequency, the resource required, the residual risk assessment and the knapsack calculations.

Table 5 shows samples of the "Start Analysis" information sheet for the turbo-group lube oil system; it documents the first classical steps depicted in Figure 4 besides the inherent criticality assessment section, which is one of the key contributions of the RbMO approach. This section uses the risk matrix introduced in Figure 5 to assess the failure mode inherent risk rank against the four risk dimensions (safety, environmental, operational and financial). Then, the information sheet calculates the inherent criticality for each scenario using the CCW introduced in Figure 12; additionally, the sheet computes the GFMIC via equation 3-3. Moreover, the information sheet highlights and categorises the failure modes based on the inherent criticality assessment results into low critical (<10), medium critical (<100), high critical (<1,000) and very high critical failure modes (>1,000), as highlighted in different colours. The information sheet reveals that the DC lube oil pump has the most critical failure mode, reflecting the vital role of this equipment as the last line of defence to the safe shutdown of the turbo-group in case of AC power outage or the failure of the main lube oil pumps.

Table 5: "Start Analysis" Information Sheet

Sr. No.	Function	Functional Failure	Failure Mode	Failure Effect	Failure Mode Inherent Risk Rank				Failure Mode Inherent Criticality (FMIC)		
					Saf.	Env.	Ope.	Fin.	Summer S_1	Winter S_2	GFMIC
1.A.2	To pump lube oil to the turbo-group at a pressure greater than 5.2 bar in the presence of the standby pump.	Not able to pump any oil at all.	Main lube oil pump bearing failure due to wear-out.	If these bearings fail, the pump locks up and stops pumping. The control starts the standby pump and the emergency DC pump. Once the system is stable, the operator turns off the emergency DC pump. When the fault is detected, it is necessary to wait for the plant to stop and cool down before disassembling the pump and changing the bearings. In total, including cooling down, the pump is replenished in 5 days.	0.1	0.1	100	5	24.06	7.08	31.14
2.A.9	To pump lube oil to the turbo-group at a pressure greater than 5.2 bar in case of main pump failure.	Not able to pump any oil at all.	Standby oil pump motor failure due to grease deterioration.	This fault causes the standby pump to fail. Then, the control triggers the turbo-group when the pressure drops below 5.2 bar, and the pressure gauge starts the emergency DC pump to safely shutdown the turbo-group. In total, this stop would entail a week of downtime.	0.1	5	50	50	18.39	7.22	25.61
2.B.3		Not able to pump oil at pressure greater than 5.2 bar.	Main lube oil pump non-return valve failed open.	In this case, the standby pump pumps, but the discharge pressure drops below 5.2 bar. The control trips the plant and starts the emergency DC pump to start the turbo-group safe shutdown. In total, this stop would entail a week of downtime.	0.1	5	50	5	12.72	3.93	16.65
4.A.7	To pump lube oil to the turbo-group during the cooldown in case of lube oil pumps failure.	Not able to maintain the lube oil supply needed for turbo-group cooldown in the absence of AC power.	Motor winding insulation deterioration of the emergency DC lube oil pump.	When the emergency DC pump fails, the turbo-group stops without lubricating oil. This stop becomes critical at low rotors revolutions, causing severe damage to bearings and even rotors. The replacement time of the machines can be up to months.	0.1	5	10	500	65.73	37.39	103.12
4.A.8		It does not pump oil in the event of a lubrication pump failure, until the turbo-group is cold.	Emergency pump motor fan failure due to environmental conditions.	When the emergency pump fails, the turbo-group stops without lubricating oil. This stop becomes critical at low rotors revolutions, causing severe damage to bearings and even rotors. The replacement time of the machines can be up to months.	0.1	0.1	10	500	65.37	37.19	102.56
4.A.13		Not able to maintain the lube oil supply needed for turbo-group cooldown during the lube oil pumps failure.	Emergency DC lube oil pump failure due to line blockage.	When the emergency DC pump fails, the turbo-group stops without lubricating oil. This stop becomes critical at low rotors revolutions, causing severe damage to bearings and even rotors. The replacement time of the machines can be up to months.	0.1	5	500	500	180.39	70.22	250.61
9.A.3	To keep the oil in the sump at a temperature between 32 and 65ºC in case of failure of the main exchanger.	Not able to maintain the sump oil at a temperature below 65ºC.	Standby heat exchanger fouling.	This failure mode prevents the ability to operate with this exchanger; then the alarm goes on at 65ºC. The temperature increase leads to viscosity loss of the oil, and this can lead to the tripping of the machine due to high temperature in the bearings or low pressure in the manifold. In the worst case, the bearings get damaged and replaced in months.	0.1	5	50	50	18.39	7.22	25.61
11.A.8	To extract condensate from the lube oil system	No able to extract any condensate at all.	Exhaust fan failure due to contamination of the internal filters.	This failure causes the fan to fail and stops extracting condensate from the lubrication oil tank. If we stop extracting these condensates, water accumulates in the oil, and the system can be damaged by corrosion. Failure of the fan also causes a greater quantity of oil vapours to concentrate in the tank with the danger of self-combustion.	500	50	10	1	123.12	79.24	202.36
13.A.1	To keep the system oil supply clean of particles greater than 150 microns in the presence of a standby filter.	Not able to keep the oil clean of particles greater than 150 microns	The filter bypass valve fails open.	If the bypass valve fails open, part of the oil supplied by the system will not be filtered. This unfiltered oil can severely damage bearings. This failure mode can be detected via oil analysis.	0.1	1	100	500	86.50	43.26	129.76
16.A .2	To completely drain the oil from the system when required.	Not able to drain any system oil at all, when required.	System drain-valve fail closed due to lack of grease.	The system cannot be drained, and this prevents its maintenance.	0.1	0.1	50	50	18.03	7.02	25.05
19.A.2	To isolate the system electrically according to applied regulations.	Not able to isolate the system electrically.	Disconnection of grounding.	Disconnecting the grounding causes a risk to the safety and health of people.	500	0.1	50	0.1	128.72	79.86	208.58

Table 6: "Start Analysis" decision sheet

Sr. No.	Evident / Hidden	Decision Logic Recommendation	Proposed task	Freq. (times/year)	Cost/ time $	Responsible	Failure Mode Residual Risk Rank				Failure Mode Residual Criticality (FMRC)		Knapsack calculations: Risk reduction =FMIC - FMRC		Knapsack calculations: Burden =Freq. × Cost× ISCW		Knapsack calculations: Risk reduction / Burden	
							Saf.	Env.	Ope.	Fin.	Summer S_1	Winter S_2	S_1	S_2	S_1	S_2	S_1 [Order]	S_2 [Order]
1.A.2	Evident	On-condition Task	**Vibration Monitoring:** Measure vibrations of the main lube oil pump and save the results at System One expert system (Alarms 5mm / s peak and 8mm / s peak).	12 (monthly)	200	Mechanical Supervisor	0.1	0.1	50	5	12.36	3.73	11.70	*3.35*	1600	800	0.0073 [T_{21}]	0.0042 [T_{22}]
2.A.9	Hidden	Scheduled Restoration	**Greasing:** Grease the standby pump motor.	4 (quarterly)	300	Mechanical Supervisor	0.1	5	1	50	6.92	3.93	11.47	*3.28*	800	400	0.0143 [T_{19}]	0.0082 [T_{20}]
2.B.3	Hidden	Failure-finding task	**Functional Test**: Start the standby pump and check the output pressure is higher than 5.2.	12 (monthly)	50	Operation Supervisor	0.1	5	1	5	1.25	0.65	11.47	*3.28*	400	200	0.0287 [T_{17}]	0.0164 [T_{18}]
4.A.7	Hidden	On-condition Task	**Megger test:** Perform motor megger test and if the measurement value is out of acceptable limits, repair the insulation.	1 (Yearly)	600	Electrical Supervisor	0.1	5	10	10	3.99	1.62	61.74	35.77	400	200	0.1543 [T_{13}]	0.1790 [T_{12}]
4.A.8	Hidden	Scheduled Restoration	**Cleaning:** Remove the cover and clean the fan from the pump motor	1 (Yearly)	200	Mechanical Supervisor	0.1	5	10	10	3.99	1.62	61.38	35.57	133	67	0.4601 [T_5]	0.5341 [T_3]
4.A.13	Hidden	Failure-finding task	**Start/Stop Test:** Start/stop test of emergency DC pump.	12 (monthly)	30	Operation Supervisor	0.1	5	10	10	3.99	1.62	**176.40**	68.60	240	120	0.7346 [T_1]	0.5722 [T_2]
9.A.3	Hidden	Failure-finding task	**Operator Round:** Start up the exchanger and check any signs of fouling.	1 (Yearly)	50	Operation Supervisor	0.1	5	1	1	0.75	0.36	17.64	*6.86*	33	17	0.5289 [T_4]	0.4120 [T_6]
11.A.8	Evident	Scheduled Discard Task	**Filter Replacement:** Replace the fan internal filters.	1 (Yearly)	600	Mechanical Supervisor	10	1	10	1	4.88	2.31	**118.24**	76.93	400	200	0.2954 [T_8]	0.3850 [T_7]
13.A.1	Hidden	On-condition Task	**Oil Analysis:** Take an oil sample from the filter outlet and check that there are no particles larger than 150 microns.	4 (quarterly)	400	Mechanical Supervisor	0.1	1	50	10	13.06	4.14	73.44	39.12	1067	533	0.0688 [T_{16}]	0.0734 [T_{15}]
16.A .2	Hidden	Scheduled Restoration	**Lubrication:** Grease the valves.	1 (Yearly)	75	Mechanical Supervisor	0.1	0.1	1	50	6.56	3.74	11.47	*3.28*	50	25	0.2292 [T_{11}]	0.1315 [T_{14}]
19.A.2	Hidden	On-condition Task	**Inspection:** Perform earth review by step and contact voltage measurement and repair the earthing in case of non-compliance measures.	1 (Yearly)	800	Electrical Supervisor	10	0.1	1	0.1	2.59	1.61	**126.13**	78.25	533	267	0.2364 [T_{10}]	0.2937 [T_9]

Table 6 presents a corresponding sample of the "Start Analysis" decision sheet, it classifies the failure modes into two main categories; evident failure modes, which are apparent to the operator under normal circumstances; and hidden failure modes, which cannot be detected without a functional test or inspection task are considered hidden, such as standby equipment or protection device failures. This classification helps decide the right maintenance task, as failure-finding tasks such as functional testing and start/stop tests apply only to the hidden failure mode.

Also, the sheet document the proposed maintenance type based on the decision logic outcome before the proposed task description is introduced accordingly with its frequency, cost and responsibility. Then, the residual risk is assessed for each dimension using the risk matrix in Figure 5, and the residual criticality is calculated for each scenario via equation 3-2. Additionally, the sheet calculates the risk reduction, which is the risk reduction value achieved by each task as an indicator of task effectiveness, where tasks with risk reduction >100 are the high effectiveness tasks. In contrast, tasks with risk reduction <10 are the low effectiveness tasks, and the rest are medium effectiveness.

The analysis sheets indicate that the failure mode criticality and the proposed task effectiveness are scenario-dependent. In other words, the failure mode consequences are different from one scenario to another, and the maintenance task does not have the same level of effectiveness across all scenarios. Hence, each scenario can have a different maintenance package consisting of the proposed tasks of an acceptable level of effectiveness for that specific scenario, which depends on the organization's risk appetite and maintenance budget limitations.

4.3. "Shape Packages" process for the turbo-group lube oil system

The “Shape Packages” process uses the Knapsack calculations section in Table 6 to select a subset of tasks with the highest risk reduction/burden ratio within the allocated maintenance budget. Assume the maintenance budget limit is \$2,200, then:

$$\sum_{x=1}^{n} Cost\ (T_x) \leq 2{,}200$$

$$\sum Cost\ (T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8, T_9, T_{10}, T_{11}) \leq 2{,}200$$

$$Total\ cost\ of\ Knapsack\ selected\ tasks$$

$$= 240 + 120 + 67 + 33 + 133 + 17 + 200 + 400 + 267 + 533 + 50$$

$$= 2{,}060$$

$$Remaining\ from\ Budget = 2{,}000 - 2060 = 140$$

As $Cost\ (T_{12}) = 200 \geq 140$

Hence, to maximise the utilisation of the allocated budget, Knapsack suggests scheduling T_{12} (megger test) at a lower frequency (2 years); this reduces the task cost to \$99.9, which maintains the overall plan within the budget. In this case, Knapsack risk reassesses the failure mode risk using the risk matrix provided in Figure 5 and Knapsack risk value falls between the inherent and the residual risk. Besides the winter scenario megger test (T_{12}), Knapsack recommends the execution of the following tasks in both scenarios:

- 4.A.8 Cleaning
- 4.A.13 Start/Stop Test
- 9.A.3 Operator Round
- 11.A.8 Filter Replacement

- 19.A.2 Inspection

Also, Knapsack suggests the implementation of task T_{11} Lubrication only during the summer scenario. On the other side, the remaining tasks will not be considered due to the budget limitation and their low RR/B ratio compared to the selected ones.

The "Shape Packages" process uses the information and decision sheets data to graphically represent the inherent, Knapsack and residual risk profile via the NCG, which aggregates the criticality from the failure mode level up to the unit level, where the Knapsack ASCW is identified and feedback to the "Specify Scenario" process.

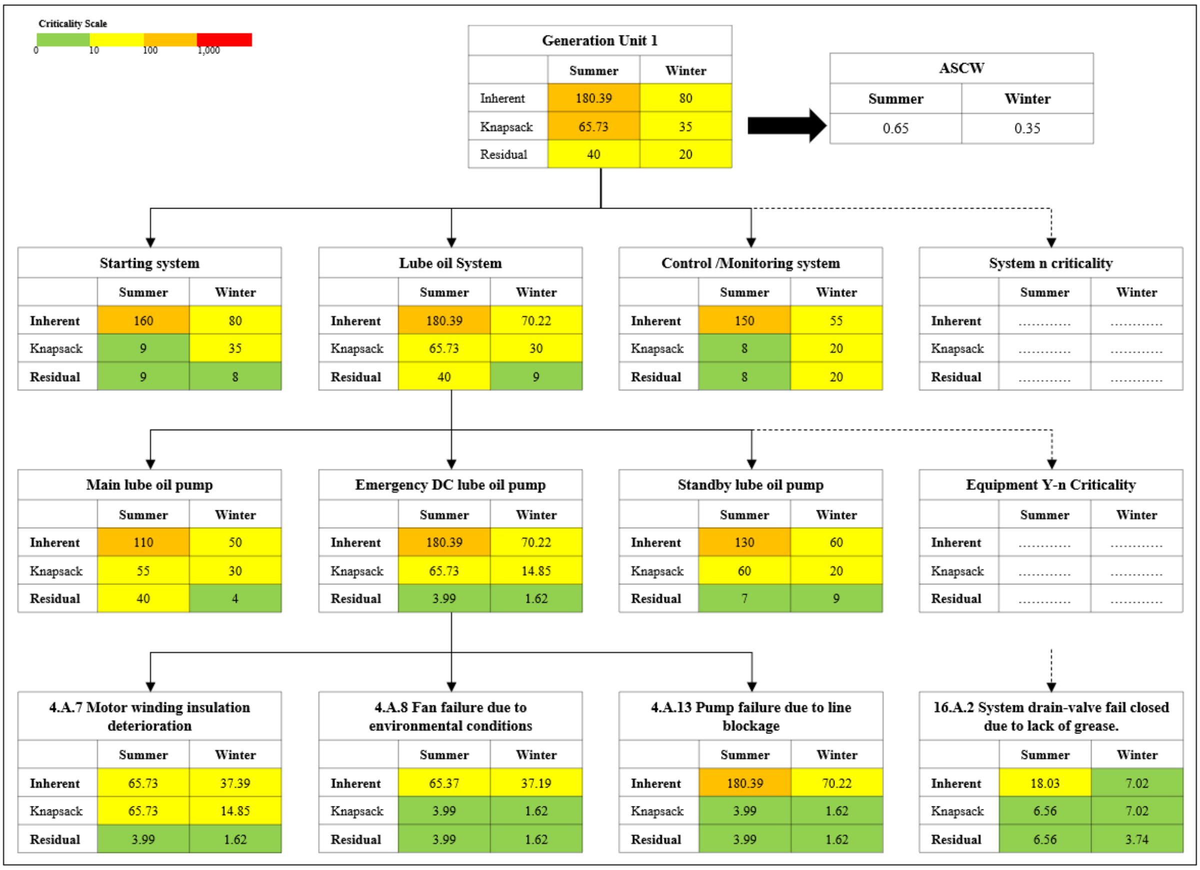

Figure 13: Part of the generation unit nested criticality grid (NCG)

As depicted in Figure 13, the NCG displays the failure modes listed in the "Start analysis" process information sheet with their inherent, Knapsack and residual risk. The Knapsack risk equals the inherent risk if the failure mode is not mitigated by any task, as in failure mode # 4.A.7; in contrast, the Knapsack risk equals the residual risk, if the failure mode is mitigated by all the suggested mitigation actions, as in failure mode # 4.A.8; while if the mitigation tasks are partially implemented, the Knapsack risk value will fall between the inherent and residual risk, as in failure mode # 4.A.7 in the winter scenario.

As shown in the NCG, the pump line blockage has the highest inherent risk; hence, this failure mode represents the DC lube oil pump's inherent criticality and to determine the lube oil system's inherent criticality during the summer scenario, the NCG selects the highest inherent risk among the system's equipment, which is the emergency DC lube oil pump risk. Similarly, the NCG determines the generation unit criticality according to the highest inherent, knapsack and residual risk value within the unit systems for each scenario, which creates the risk line of sight from the failure mode level up to the unit level.

Finally, to determine if a readjustment is needed, the $ASCW$ is calculated for each scenario using equation 3-16 as following:

$$ASCW_{Summer\ scenario} = \frac{65.73}{65.73 + 35} = 0.65$$

$$ASCW_{Winter\ scenario} = \frac{35}{65.73 + 35} = 0.35$$

As,

$$ASCW_{Summer\ scenario} \approx ISCW_{Summer\ Scenario}$$

$$ASCW_{Winter\ scenario} \approx ISCW_{Winter\ Scenario}$$

Then, according to equation 3-17 no adjustment is needed as the allocated budget ($2,200) maintains the same $ISCW$; however, any changes in the allocated budget will change the knapsack selected tasks and failure modes risk; consequently, these changes may trigger the RbMO cycle to react and adapt to the new budget.

5. Conclusion

The RbMO framework proposed in this paper aims to achieve a resilience maintenance strategy that digests, reacts to, adapt to, and recover from business fluctuations and operating context changes, including the instabilities in production demand. The paper demonstrates RbMO as a framework that enriches the asset management informative decision-making process by adopting tools such as the AHP and Knapsack methods and introducing new tools such as the NCG.

As demonstrated in the case study, the application of AHP has streamlined the comparison of scenarios and the mapping of operating context parameters to the correspondent risk dimensions before generating the relative and combined criticality weights. Also, the "Start Analysis" process quickly highlighted the differences in task effectiveness in risk reduction between scenarios, which was then used by the Knapsack method to represent the task benefit and guide the selection of the optimum maintenance strategy within the allocated budget. At the end, the NCG has demonstrated the risk profile from the failure mode level up to the unit level for each scenario enabling asset owners to allocate resources better for risk mitigation and providing the needed feedback to the "specify scenario" process to adjust the ISCW.

Creating an agile integration framework between the NCG and the CMMS could be exciting for future research, where the failure mode reoccurrence on the same asset or any similar assets updates the failure mode likelihood and subsequently modifies the entire NCG. Improving the financial risk assessment is an additional point for further research, where the potential repair cost and production losses are quantified as an economic consequence and used to justify the maintenance budget. Also, introducing a dynamic maintenance deferral protocol to modify the task cycle and determine the date of the subsequent execution when changing between scenarios further facilitates RbMO implementation and represents an interesting area to explore.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article.

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