Multi-stage quantitative risk assessment of a critical system in mining industry

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Abstract. Engineering Asset Management (EAM) is a strategic approach focused on the optimal management of physical assets throughout their lifecycle. By integrating engineering principles with financial and operational strategies, EAM aims to enhance asset performance, reliability, and longevity while minimizing risks and costs. This holistic methodology ensures that machinery, equipment, and infrastructure operate efficiently, thereby reducing failures and maximizing productivity. A critical component of EAM is understanding the criticality of each asset within a system. Criticality analysis evaluates the potential impact of different failure modes, considering factors such as failure likelihood, consequences, system interdependencies, cost implications, and associated risks. This analysis is essential for prioritizing maintenance efforts and allocating resources effectively. Risk assessment plays a pivotal role in this context, involving the systematic identification, analysis, evaluation, and management of potential risks associated with asset failures. However, traditional risk assessment methods often face challenges due to subjectivity and variability in evaluations, which can lead to inconsistencies in maintenance decision-making. To address these challenges, this paper proposes a novel multi-stage quantitative Failure Modes, Effects, and Criticality Analysis (FMECA) framework. This approach systematically analyses failure rates, downtime, and cost implications, providing a comprehensive understanding of each failure mode's impact. By integrating these quantitative parameters, the framework enhances objectivity in risk assessment and supports more informed decision-making. It enables organisations to systematically prioritize maintenance activities and optimize resource allocation. This approach not only mitigates operational risks but also aligns asset management practices with overarching business objectives, leading to improved efficiency and reduced costs. The proposed methodology is particularly beneficial in industries such as mining, manufacturing, and aerospace, where unplanned downtime and maintenance costs can have significant operational and financial repercussions. By adopting this multi-dimensional approach, organizations can improve asset performance, enhance safety, and achieve more sustainable operations.

Keywords: engineering asset management, mining industry, criticality, quantitative risk assessment, failure rate, downtime, maintenance cost.

1. Introduction

Engineering Asset Management (EAM) is a systematic approach towards managing and maintaining physical assets throughout their lifecycle. EAM plays a crucial role in ensuring optimal performance, reliability, and longevity of physical assets. It integrates engineering, financial, and operational strategies to enhance asset reliability and performance while minimizing risks and costs. Proper asset management ensures that machinery, equipment, and infrastructure operate at peak efficiency, minimizing failures and maximizing productivity. A study by Amadi-Echendu, et al. [1] highlights that asset management plays a vital role in mitigating operational risks and ensuring compliance with safety and environmental laws. According to ISO 55000 standards [2], sustainable asset management supports efficient resource utilization, waste reduction, and compliance with environmental policies. Asset Management (AM) has traditionally been regarded as a routine discipline. However, it should now be seen as a strategic philosophy that must be integrated across all levels of an industry. By fostering awareness throughout the industry, AM can enhance the understanding of the importance of optimizing engineering asset performance, ensuring alignment between industry objectives and asset management goals [3].

The industry consists of different types of equipment that work together synchronously to form a network of equipment, which can deliver the desired output with maximum efficiency. To maintain maximum equipment efficiency, it is important to understand the criticality of every network element. Criticality is a means of assessing the effect of each failure mode within the equipment portfolio and assessing their associated risks. Criticality analysis can be an essential step in reliability engineering, providing a systematic way to identify high-risk assets and prioritize maintenance efforts. The key factors which might help to assess the criticality are failure likelihood, failure consequences, interdependency of the systems and sub-systems, cost implications and associated risks.

Risk is a very subjective topic and a very important at the same time. The understanding of the risk of a failure mode depends on the perspective of the observer which can also influence the criticality of that failure mode. Risk can be driven by one or multiple defined factors and must be assessed against these to determine the level of focus necessary to manage it. Risk management includes the application of logical and systematic methods for establishing the process of identifying, analysing, evaluating, treating, monitoring, reviewing, reporting, and recording risks. Risk assessment is that part of risk management which will help to identify and analyse the criticality of a failure mode and its consequences [4]. Risk assessment involves identifying, evaluating, and communicating the presence, characteristics, extent, frequency, influencing factors, and uncertainties associated with potential losses [5]. It has been considered a powerful approach to address public concerns and to develop sound policy and design strategy [6]. Several benchmark studies have shown that risk assessment results might differ depending on the industry professionals performing the analysis and the clients requesting them [7]. This subjectivity in the assessment process raises the question of uncertainties. Also, the future development and maintenance of the infrastructure of society will even more likely demand an intensified and quantified focus on risk [7]. Thus, due to tremendous demand of risk-based decision-making in engineering applications and a significant lack of recognition of risk analysis as a necessary discipline, there has been development of a range of practices for risk analysis [7]. These practices have been published and well defined by author Valis and Koucky [4].

In this paper we have proposed a novel means of applying common Failure Mode and Effects Analysis (FMEA)/ Failure Mode, Effects, and Criticality Analysis (FMECA) – centred tools to identify ‘critical’ process systems. This multi-layered risk assessment practice will be applied to a critical system to evaluate the influence of individual equipment failure risks within it. The paper uses a case study data for implementing the novel approach of risk assessment and compare various risk assessment methods, and parameters evaluated for the implementation of multi-stage risk assessment framework. The paper critically reviews all the results derived through different implemented risk assessment methods in this paper and showcases the advantages and limitations of the proposed novel approach.

2. Review of FMEA and FMECA methods

The advancement of mining technology has led to the creation of complex technical systems that require a systematic analytical and methodological approach to be properly understood. These systems have emerged due to the increasing demand for and interest in resource extraction. Effective risk analysis and management play a crucial role in ensuring quality and reliability within the mining industry. However, one of the main challenges in technical systems is conducting thorough risk assessments. Historically, risk management in mining has not been given sufficient attention, but there is now an urgent need for change [8]. A key approach to risk analysis involves proactive error identification through methods such as FMEA and FMECA. These methodologies break down systems at a functional level, considering failure modes as the loss of specific component functions.

The concept of FMEA originated in the 1940s within the U.S. military and was later adapted by the aerospace, automotive, and manufacturing industries [9]. FMEA is a methodology designed to identify the ways in which components, systems, or processes can fail. FMEA identifies all the potential failure modes associated with core function/s of a system or process and their effects respectively. It also evaluates the risk of each failure mode that may disrupt any such function. A failure mode is the observed reason of failure or the reason of incorrect performance [4]. To avoid failures above a nominated risk threshold, appropriate corrective actions are drafted as outputs for implementation. As per McDermott, et al. [10], FMEA has evolved into a widely used technique for improving quality and minimizing failures in both product and process design. Generally, FMEA's are performed during the design or process development of a greenfield project or modification stages.

The applications of FMEA can be found across many industries like machinery [11-14], electronics [15], chemical [16], medicine [17, 18], textile [19, 20], aerospace, nuclear, mining and other manufacturing industries [8, 21-23]. Focusing more closely on the mining industry as an application, these practices demand strong, decision-making criteria to help define site-relevant factors that influence the detectability, severity and occurrence of each failure mode; many of which are complex and multi-dimensional in nature. These criteria help to define and understand the availability, reliability, maintainability and overall criticality of the systems. In the mining industry, this decision-making process is challenging and complex, as failure of a single item of equipment can lead to a sudden or delayed system-wide stoppage. Furthermore, buffers may also exist between adjacent systems (for example, stockpiles) which make the actual effect of a failure difficult to determine across the broader process at large. In such cases, decisions are likely focused around the system's availability, with maintenance strategy improvement and subsequent reliability gains acting as controls to mitigate associated risks. Currently, in the mining industry decision-making processes for asset investment are largely qualitative, with assets being monitored and managed via qualitative FMEA tools or other risk-based methods [3]. Author Duda and Juzek [24] illustrates the application of FMEA method for hazard identification and process risk assessment in a coal mine which is a crucial step in risk assessment and safety management, helping to prevent accidents and ensure operational reliability. Paper [25] highlights the use of FMEA to overcome the uncertainty in the decision-making process of an underground coal mine. Most recent application of FMEA method is highlighted in a case study on risk analysis of a machine breakdown in a cement factory in Indonesia [26].

When used as a top-down analysis tool, FMEA may only identify the most significant failure modes within a system. However, when applied as a bottom-up approach, FMEA can complement Fault Tree Analysis method by uncovering additional causes and failure modes that contribute to top-level system issues. Despite its widespread adoption, traditional FMEA has limitations, including subjectivity in RPN scoring (different assessors may assign different scores), lack of consideration for failure interdependencies and inability to predict unknown failure modes. It cannot effectively detect complex failure modes involving multiple failures within a subsystem or predict the failure intervals of specific failure modes at higher system levels. Additionally, the method of calculating the Risk Priority Number (RPN) by multiplying severity, occurrence, and detection rankings can lead to inconsistencies, sometimes assigning a higher RPN to a less critical failure mode than a more severe one. This issue arises because these rankings use an ordinal scale, where the numerical values indicate relative order but not precise magnitude. For example, a ranking of "2" is not necessarily twice as severe as a ranking of "1", nor is an "8" necessarily twice as bad as a "4". However, multiplication treats them as if they are proportional, leading to misleading prioritization [27].

To address these limitations, modern approaches like FMECA offers an extension to FMEA theory, allowing each failure mode to be ranked according to its importance or criticality. This critical analysis is usually qualitative or semi-quantitative but may be quantified using actual failure rates [27]. The FMECA is the result of two steps: – Failure Mode and Effect Analysis (FMEA) and Criticality Analysis (CA). The CA can be aligned with two distinct alternatives: qualitatively or quantitatively. The implementation of the quantitative analysis method is well explained by author Lipol and Haq [27]. FMEA and FMECA are methodologies used to identify potential failures in a product or process. While both follow the same fundamental approach, they differ in key aspects. FMEA provides qualitative insights, whereas FMECA incorporates some quantitative data that can be measured. FMEA is commonly used in industries as a "what-if" analysis tool and is an integral part of NASA's flight assurance program for spacecraft. On the other hand, FMECA assigns a criticality level to failure modes and is used by the U.S. Army to evaluate mission-critical equipment and systems [27]. FMECA is essentially an extended version of FMEA. To conduct FMECA, analysts first perform an FMEA and then carry out a CA. FMEA identifies failure modes and their effects, while CA ranks these failures based on their severity and occurrence rate, prioritizing the most critical ones [27].

The most recent application of FMECA can be found in the field of medicine [28, 29], manufacturing [30-34], machinery [35-38], aerospace [39, 40], and automobile [41]. Cheng, et al. [42] applied FMECA to assess the reliability of a metro door system. They compiled failure statistics for various metro door subsystems and determined their criticality levels. The analysis identified the EDCU function as the most critical subsystem. Ćatić, et al. [43] conducted a criticality analysis of the steering tie-rod joint. They first created a layout of the joint using a tree diagram, outlining its various components. Subsequently, they performed a Fault Tree Analysis (FTA) for the steering tie-rod joint. Focusing on the recent applications of FMECA in mining industry, paper [44] successfully assessed the criticality of dumper subsystems using the FMECA methodology. Criticality indices for each failure mode were determined based on failure rate, frequency, and operating time. The impact of different operating time modes on criticality rankings was also analysed. Among the eight dumper subsystems, the engine component was identified as the most critical, ranking first. Additionally, the relationship between failure occurrences and criticality was examined and validated using Spearman's correlation test, confirming that higher failure occurrence values correspond to greater criticality. Paper [45] highlights the application of FMECA to assess and design the reliability of the coal system in the Oslomej surface mine. This approach helped identify potential failure modes, enhance reliability evaluation, and conduct a qualitative criticality analysis. As a result, key insights were gained, guiding attention toward the highest-risk areas. Paper [46] introduces a method for supporting occupational risk management in quarry blasting operations using a modified FMECA algorithm. The proposed approach systematically identifies risks and highlights key occupational hazards that should be prioritized for preventive measures. These preventive actions can be incorporated during the design phase by modifying technology or work organization, depending on the specific quarry's available options. Table 1 summarises the reviewed literature and their corresponding research gaps, and highlights how the proposed research offers improvements over existing approaches.

While the reviewed literature provides valuable contributions, the comparison in Table 1 underscores a clear and recurring gap across existing studies. These gaps collectively point to the need for a more comprehensive and data-driven approach to maintenance decision-making, one that aligns more closely with the operational realities of the mining industry. This broader need forms the foundation and motivation for the present study. As mining operations grow increasingly complex and cost-sensitive, the ability to make informed, data-driven maintenance decisions has become more critical than ever. Traditional tools such as FMEA and FMECA, while widely adopted, often rely on static and qualitative assessments that do not fully capture the dynamic and economic nature of equipment failures. There is a growing need for approaches that can translate real-world failure behaviour into actionable insights for minimizing downtime, reducing costs, and improving asset reliability. This study responds to that need by proposing a novel multi-stage quantitative risk assessment framework centred around a unique application of conventional FMEA/FMECA theory. This practice will be used to compare the influence of equipment failure modes on the overall criticality of the system in which they function. The multi-stage quantitative risk assessment framework assesses failure rate (likelihood), downtime and cost (Consequence) as quantitative elements in the FMECA framework. The work is focused on the mining industry and the data for the study was sourced from a gold mining company in Australia.

Table 1. Summary of reviewed literature and their corresponding research gaps

Reviewed literature	Contribution	Research gaps	Benefits of proposed research over existing approaches
Duda and Juzek [24]	Applies traditional FMEA for hazard identification in mining roadway development. Uses RPN scores based on severity, occurrence, and detection.	Static model with subjective RPN; lacks cost, downtime, and interdependency modelling.	Dynamic FMECA with cost/failure/downtime metrics. Supports risk updates and optimal strategy choice.
Shariati [25]	Introduces a fuzzy FMEA approach for mining hazard analysis using linguistic variables to address uncertainty.	Handles uncertainty but lacks integration of cost/downtime and real-time data feedback.	Quantitative integration of failure data and cost; enables uncertainty-aware decision optimization.
Fithri, et al. [26]	Conducts risk analysis of machine breakdown in a cement factory using traditional FMEA with RPN rankings.	No quantitative modelling or optimization; analysis is one-time and based on subjective scores.	Quantifies criticality using downtime/cost. Supports real-time updates and decision optimization.
Kumar and Kumar [8]	Uses FMEA/FMECA to assess mining excavator risks and prioritize components for preventive maintenance.	Semi-quantitative; lacks cost integration and dynamic reassessment or optimization.	Adds cost/failure data into strategy prioritization with multi-stage adaptability.
Franceschini and Galetto [21]	Applies traditional RPN using a qualitative scale method to reflect criticality.	Improves scoring logic but lacks real-world failure/cost data or dynamic system updates.	Complements scoring improvements with cost-driven maintenance optimization framework.
KUMAR, et al. [44]	Applies FMECA to dumper subsystems using failure frequency and operating time in criticality ranking.	Based only on historical frequency and does not adapt dynamically or optimise strategy.	Integrates cost/time impact dynamically; enables adaptive criticality ranking and optimization.
Rika, et al. [45]	Conducts FMECA for mechanical failures in a surface mine coal system; prioritizes failure modes qualitatively.	Focuses only on qualitative failure ranking; lacks cost/time modelling or iterative strategy.	Introduces economic logic to FMECA prioritization with cost-driven maintenance feedback.
Dworzak [46]	Modifies FMECA for occupational risk in quarry blasting, emphasizing safety-based preventive strategies.	Targets safety hazards but not broader reliability, cost, or system-wide performance.	Expands scope from safety to asset-level cost-reliability prioritization under dynamic inputs.
Daya and Leonard [47]	Proposes maintenance planning using FMECA and optimal replacement time in mining with historical failure data.	Uses historical failure data only; does not optimize across maintenance strategies.	Supports maintenance scheduling using real-world failure data and downtime cost modelling.
Chennoufi and Chakhrit [48]	Develops a multi-dimensional, fuzzy-AHP-enhanced FMECA prioritization method across several impact domains.	Prioritization is multi-dimensional but does not account for evolving failure data or budget.	Aligns risk prioritization with multiple impact areas, adaptable to cost-aware extensions.

ElKasrawy, et al. [49]	Implements modified FMECA with operational factors to optimize maintenance schedules in industrial case study.	No dynamic updating; cost savings shown but not embedded in a strategic decision framework.	Provides a quant model framework to balance failure impacts, operational needs, and cost.
Zhu, et al. [50]	Proposes a multi-stage stochastic program for optimizing component maintenance over a planning horizon.	Addresses maintenance optimization but lacks component interaction and cost breakdown.	Multi-stage decision-making framework for failure-based strategy optimization.
Zhu and Xiang [51]	Presents a CBM optimization model for multi-component systems using a multi-stage stochastic framework.	Focuses on CBM but does not link with broader FMECA or cost-centric prioritization models.	Condition-based maintenance over time optimized with real-time system health and strategy cost.

3. Data

The work presented in the paper is based on the case study of a gold mining company in Australia. The industry failure data was collected from two different sources, one providing maintenance work order information and another providing downtime information. These were labelled 'Selective work orders.xlsx' and 'Downtime.xlsx' respectively. The raw data was recorded manually over different periods for different systems, downloaded in comma-separated value (CSV) format, and was initially analysed in MS Excel. Through this process, a new dataset was created which was largely tailored to this undertaking. The initial exploratory analysis using information originally from the 'Downtime.xlsx' client spreadsheet. The major focus was on extracting variables like failure modes, downtime associated with those failure modes and finally the downtime cost associated with each failure mode. As the industry manually records the data, it was difficult to find consistency in the data across the time frames as highlighted in Table 2.

Table 2. Data summary

System	Time stamp
Mill	January 2021 – October 2021
Crusher 1	July 2021 – April 2022
Modular crusher	January 2021 – April 2022
Nolans crusher	January 2021 – April 2022

The identified critical system based on downtime from Table 2 is Modular Crusher as highlighted in Fig. 1, with its year-wise downtime bifurcation. The downtime history of individual systems presented in Fig. 1 are in minutes.

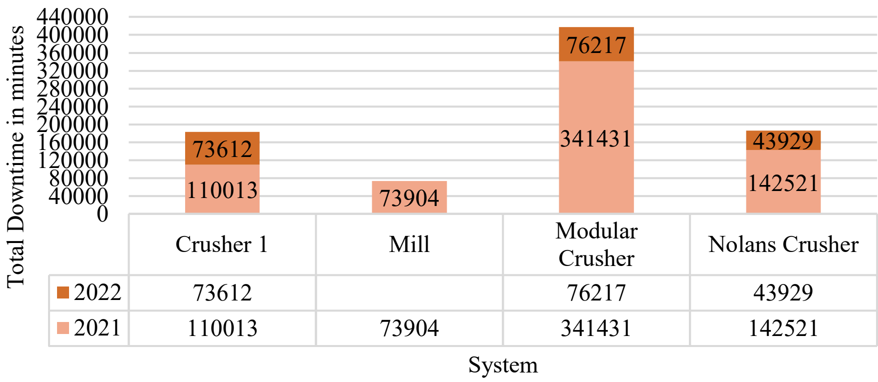

Fig. 1. Analysis of system downtime

Table 3 shows the different failure modes of all the equipment associated with the Modular Crusher system.

Table 3. Failure modes of all the equipment associated within the critical system

Critical system	Equipment	Failure modes
Modular crusher	Crusher	Blocked Jaw
		Grizzly Bar Breakdown
		Electrical fault
		Hydraulic Leak
		Liners /Bolts
		Motor Breakdown
		Oil & Lubrication
		Bins Issue
		Maintenance
		Other
	CV 201	Belt damaged
		Chute Issues
		Electrical fault
		Mechanical Fault
		Bins Issue
		Other
	Feeder	Blockage
		Mechanical Fault
		Bins Issue
		Electrical Fault
		Maintenance
		Liners/Bolts
		Others
	Fines conveyor	Belt damaged
		Conveyor bogged
		Electrical Fault
		Truck delay
		Others
	Loader	Loader Unavailable
		Maintenance
		Hydraulic leak
		Low Manning
		Others
	Product stacker	Conveyor bogged
		Electrical Fault
		Commissioning
		Others
	Reject stacker	Bearings failure
		Belt damaged
		Blockage
		Conveyor bogged
		Electrical fault
		Maintenance
		Mechanical fault
		Liners/Bolts
		Others
	Rock breaker	Hydraulic leak
		Noise
		Others
	Screen	Bearings failure
		Belt damaged

		Conveyor bogged
		Maintenance
		Electrical fault
		Liners/Bolts
		Mechanical fault
		Oil & Lubrication
		Blockage
		Screen mats
		Others
	Total circuit	Belt damaged
		Blocked Jaw
		Conveyor bogged
		Maintenance
		Commissioning
		Electrical fault
		Low Manning
		Liners/Bolts
		Mechanical fault
		Noise
		Screen mats
		Others

Some commonly observed failure modes were blockage of jaws, damaged belt, bogged conveyor, bearing failure, liners/bolts failure, oil and lubrication issues, chute issues, electrical issues, etc.

However, ‘Total Circuit’ does not resemble any equipment but rather it was a qualitative choice made by the operator to record a downtime event. for instance, if a conveyor bearing fails and interrupts the entire circuit, some operators recorded this as a ‘Total Circuit’ failure. from an asset criticality perspective, it had to be assigned to ‘conveyor’ otherwise it had no use. Some of the undefined failure modes were listed under ‘others’, and were omitted as they could not be processed.

4. Comparison of risk assessment frameworks

Using a dataset derived from the equipment listed in Table 3, outcomes from two, industry-adopted qualitative risk assessment processes will be compared against a novel, multi-stage quantitative approach. Firstly, risk assessment outcomes forwarded by traditional FMEA practices will be shown. These will be followed by outcomes from a common industry-based method. Lastly, a novel, multi-stage quantitative FMECA practice will be introduced for comparison. Not only will this highlight the influence of ‘subjectivity’ in the repeatability of qualitative risk assessment outcomes, but it will also help us understand the concept of risk by looking through different lenses.

4.1. Traditional FMEA (Failure modes and effect analysis)

The implementation of FMEA is a structured and progressive process, where each step directly influences the overall outcome. Research indicates that the effectiveness of FMEA throughout a product’s life cycle hinges on two critical factors: ensuring a comprehensive system that accurately identifies all potential failure modes and scientifically assessing the risk levels associated with these failures [52]. The traditional FMEA process follows a structured methodology consisting of seven key steps, as recommended by AIAG and VDA [53]. First step is to identify product, system, or process to be analysed. Later defining the scope, operating conditions, limitations, customer requirements and system boundaries. The next step is to identify and listing all potential failure modes for each component. Followed by determining failure effects by identifying consequences of each failure mode. Also, define the severity levels based on type of impact (Low, Medium, High). The next step is to identify failure causes and determine the root cause of each failure mode. in the next step, Risk Priority Numbers (RPN) are assigned, where risk is evaluated using three parameters; Severity (S), Occurrence (O) and Detection (D). Basically, RPN is the product of the Severity (S), Occurrence (O) and Detection (D) of a failure. (RPN = O * S * D). Higher RPN values indicate high-risk failure modes requiring immediate action. The next step is to develop risk mitigation strategies by proposing corrective actions to reduce S, O, D. Lastly, implement the corrective actions, monitor the effectiveness of risk reduction measures and conduct periodic reviews. To showcase the subjectivity of traditional FMEA risk scores, this paper reveals results from the same dataset that was analysed by three individuals, highlighted in Table 4. Due to this observed difference of opinion between the three individuals, there is always presence of uncertainties in the decision-making process. This subjectivity is largely adjudicated by those more senior in both equipment knowledge and experience. Subsequent outcomes typically form the baseline of the decisions regarding maintenance activities.

Table 4. Qualitative Analysis – Standard FMEA of industry failure data from the mining company

Equipment	Failure modes	Standard FMEA								
		1st Person			2nd Person			3rd Person		
		Likelihood	Consequence	RPN	Likelihood	Consequence	RPN	Likelihood	Consequence	RPN
Crusher	Blocked Jaw	9	9	81	8	9	72	7	7	49
	Grizzly Bar Breakdown	7	9	63	9	7	63	7	8	56
	Electrical fault	9	10	90	9	9	81	8	10	80
	Hydraulic Leak	3	8	24	2	8	16	3	6	18
	Liners /Bolts	10	5	50	7	4	28	9	7	63
	Motor Breakdown	3	10	30	2	8	16	5	5	25
	Oil & Lubrication	7	7	49	5	6	30	5	5	25
	Bins Issue	7	7	49	7	7	49	5	6	30
	Maintenance	5	5	25	5	5	25	5	5	25
	Other	5	5	25	5	5	25	5	5	25
CV 201	Belt damaged	5	9	45	6	10	60	7	9	63
	Chute Issues	5	6	30	3	4	12	4	5	20
	Electrical fault	9	10	90	9	9	81	8	10	80
	Mechanical Fault	10	7	70	8	7	56	9	7	63
	Bins Issue	7	7	49	7	7	49	5	6	30
	Other	5	5	25	5	5	25	5	5	25
Feeder	Blockage	9	9	81	8	9	72	7	7	49
	Mechanical Fault	10	7	70	8	7	56	9	7	63
	Bins Issue	7	7	49	7	7	49	5	6	30
	Electrical Fault	9	10	90	9	9	81	8	10	80
	Maintenance	5	5	25	5	5	25	5	5	25
	Liners/Bolts	10	5	50	7	4	28	9	7	63
	Others	5	5	25	5	5	25	5	5	25
Fines conveyor	Belt damaged	5	9	45	6	10	60	7	9	63
	Conveyor bogged	5	9	45	6	10	60	7	9	63
	Electrical Fault	9	10	90	9	9	81	8	10	80
	Truck delay	5	5	25	5	5	25	5	5	25
	Others	5	5	25	5	5	25	5	5	25
Loader	Loader Unavailable	9	8	72	7	8	56	7	9	63
	Maintenance	5	5	25	5	5	25	5	5	25

	Hydraulic leak	3	8	24	2	8	16	3	6	18
	Low Manning	5	5	25	5	5	25	5	5	25
	Others	5	5	25	5	5	25	5	5	25
Product stacker	Conveyor bogged	5	9	45	6	10	60	7	9	63
	Electrical Fault	9	10	90	9	9	81	8	10	80
	Commissioning	5	5	25	5	5	25	5	5	25
	Others	5	5	25	5	5	25	5	5	25
Reject stacker	Bearings failure	1	10	10	3	8	24	4	8	32
	Belt damaged	5	9	45	6	10	60	7	9	63
	Blockage	9	9	81	8	9	72	7	7	49
	Conveyor bogged	5	9	45	6	10	60	7	9	63
	Electrical fault	9	10	90	9	9	81	8	10	80
	Maintenance	5	5	25	5	5	25	5	5	25
	Mechanical fault	10	9	90	8	7	56	9	7	63
	Liners/Bolts	10	5	50	7	4	28	9	7	63
	Others	5	5	25	5	5	25	5	5	25
Rock breaker	Hydraulic leak	3	8	24	2	8	16	3	6	18
	Noise	10	9	90	9	9	81	9	10	90
	Others	5	5	25	5	5	25	5	5	25
Screen	Bearings failure	1	10	10	3	8	24	4	8	32
	Belt damaged	5	9	45	6	10	60	7	9	63
	Conveyor bogged	5	9	45	6	10	60	7	9	63
	Maintenance	5	5	25	5	5	25	5	5	25
	Electrical fault	9	10	90	9	9	81	8	10	80
	Liners/Bolts	10	5	50	7	4	28	9	7	63
	Mechanical fault	10	9	90	8	7	56	9	7	63
	Oil & Lubrication	7	7	49	5	6	30	5	5	25
	Blockage	9	9	81	8	9	72	7	7	49
	Screen mats	8	6	48	5	5	25	5	6	30
	Others	5	5	25	5	5	25	5	5	25
Total circuit	Belt damaged	5	9	45	6	10	60	7	9	63
	Blocked Jaw	9	9	81	8	9	72	7	7	49
	Conveyor bogged	5	9	45	6	10	60	7	9	63
	Maintenance	5	5	25	5	5	25	5	5	25
	Commissioning	5	5	25	5	5	25	5	5	25
	Electrical fault	9	10	90	9	9	81	8	10	80
	Low Manning	5	5	25	5	5	25	5	5	25
	Liners/Bolts	10	5	50	7	4	28	9	7	63
	Mechanical fault	10	9	90	8	7	56	9	7	63
	Noise	10	9	90	9	9	81	9	10	90
	Screen mats	8	6	48	5	5	25	5	6	30
	Others	5	5	25	5	5	25	5	5	25

4.2. Generic risk assessment framework implemented by the mining company

The gold mining company examined in this paper adopts a generic risk assessment framework which follows a risk matrix based on consequence and likelihood. Table 5 shows the supporting information table used to determine the overall consequence score that should be applied to a risk matrix when assessing each failure mode. a series of metric that aligns with the greatest 'fears' of the business and are separately assessed. Depending on the process adopted by an organisation, either the average score of all metrics becomes the 'overall' consequence rating, or the most severe rating of any one metric. Table 6 also shows a similar information table to assist with 'likelihood' ratings. in this case, both 'likelihood' and 'consequence' tables offer 5 possible rating scores; leading to a 5x5 risk matrix with 25 possible risk score outcomes.

Table 5. Generic risk consequence matrix used by the mining company

Description			
Consequence	Injury or Illness	Environment	Property damage
Insignificant	No treatment required	Category 1 - Little or no environmental impact (e.g. Minor contained spill)	< $20,000
Minor	First aid treatment required	Category 2 - Small and/or localised impact. Large, contained spill. (e.g. mill spillage outside bund)	$20,000 - $200,000
Moderate	Medical treatment required	Category 3 - Substantial environmental impact. (e.g. Breach of license conditions)	$200,000 - $2,000,000
Major	Hospitalisation and/or specialist treatment required	Category 4 - Serious environmental impact. May impact off-lease areas	$2,000,000 - $10,000,000
Catastrophic	Fatality or Permanently Disabling Injury	Category 5 - Disastrous and/or widespread environmental impact. (Tails dam beach)	> $10,000,000

Table 6. Generic risk likelihood matrix used by the mining company

Likelihood	Description	
Almost certain	The event is most likely to occur in most circumstances	> once per week
Likely	The event will probably occur in most circumstances	> once per month
Possible	The event might occur at some point	> once per year
Unlikely	The event could occur at some time	> once per two years
Rare	The event may occur only in exceptional circumstances	< once per two years

Once the consequence of the risk has been established, the risk ranking can be obtained by aligning this with the probability of the consequence being realised. The subsequent information table to determine the probability is provided in Table 7.

Table 7. Generic risk matrix

Likelihood	Consequence				
	Insignificant	Minor	Moderate	Major	Catastrophic
Almost certain	H(11)	H(16)	E(20)	E(23)	E(25)
Likely	M(7)	H(12)	H(17)	E(21)	E(24)
Possible	L(4)	M(8)	H(13)	E(18)	E(22)
Unlikely	L(2)	L(5)	M(9)	H(14)	E(19)
Rare	L(1)	L(3)	M(6)	H(10)	H(15)

Risk Score is derived by combining estimates of consequence and likelihood (probability) in the context of existing control measures. The results of the risk assessment are then compiled into a ranked list for further evaluation. Following this, appropriate controls are determined for risks above a predefined level of business exposure. Table 8 highlights the results of the qualitative risk assessment procedure performed on the same identified failure modes using the company's generic approach.

Table 8. Qualitative analysis – company's generic framework

Equipment	Failure modes	Generic procedure		
		Likelihood	Consequence	Risk score
Crusher	Blocked Jaw	Almost Certain	Major	E23
	Grizzly Bar Breakdown	Possible	Insignificant	L4
	Electrical fault	Almost Certain	Major	E23
	Hydraulic Leak	Possible	Major	E18
	Liners /Bolts	Almost Certain	Moderate	E20
	Motor Breakdown	Rare	Major	H10

	Oil & Lubrication	Almost Certain	Minor	H16
	Bins Issue	Likely	Minor	H12
	Maintenance	Possible	Moderate	H13
	Other	Possible	Moderate	H13
CV 201	Belt damaged	Rare	Major	H10
	Chute Issues	Likely	Minor	H12
	Electrical fault	Almost Certain	Major	E23
	Mechanical Fault	Almost Certain	Moderate	E20
	Bins Issue	Likely	Minor	H12
	Other	Possible	Moderate	H13
Feeder	Blockage	Almost Certain	Major	E23
	Mechanical Fault	Almost Certain	Moderate	E20
	Bins Issue	Likely	Minor	H12
	Electrical Fault	Almost Certain	Major	E23
	Maintenance	Possible	Moderate	H13
	Liners/Bolts	Almost Certain	Moderate	E20
	Others	Possible	Moderate	H13
Fines conveyor	Belt damaged	Rare	Major	H10
	Conveyor bogged	Almost Certain	Major	E23
	Electrical Fault	Almost Certain	Major	E23
	Truck delay	Possible	Minor	M8
	Others	Possible	Moderate	H13
Loader	Loader Unavailable	Almost Certain	Major	E23
	Maintenance	Possible	Moderate	H13
	Hydraulic leak	Possible	Major	E18
	Low Manning	Possible	Minor	M8
	Others	Possible	Moderate	H13
Product stacker	Conveyor bogged	Almost Certain	Major	E23
	Electrical Fault	Almost Certain	Major	E23
	Commissioning	Rare	Minor	L3
	Others	Possible	Moderate	H13
Reject stacker	Bearings failure	Almost Certain	Catastrophic	E25
	Belt damaged	Rare	Major	H10
	Blockage	Almost Certain	Major	E23
	Conveyor bogged	Almost Certain	Major	E23
	Electrical fault	Almost Certain	Major	E23
	Maintenance	Possible	Moderate	H13
	Mechanical fault	Almost Certain	Moderate	E20
	Liners/Bolts	Almost Certain	Moderate	E20
	Others	Possible	Moderate	H13
Rock breaker	Hydraulic leak	Possible	Major	E18
	Noise	Almost Certain	Minor	H16
	Others	Possible	Moderate	H13
Screen	Bearings failure	Almost Certain	Catastrophic	E25
	Belt damaged	Rare	Major	H10
	Conveyor bogged	Almost Certain	Major	E23
	Maintenance	Possible	Moderate	H13
	Electrical fault	Almost Certain	Major	E23
	Liners/Bolts	Almost Certain	Moderate	E20
	Mechanical fault	Almost Certain	Moderate	E20
	Oil & Lubrication	Almost Certain	Minor	H16
	Blockage	Almost Certain	Major	E23
	Screen mats	Likely	Moderate	H17
	Others	Possible	Moderate	H13
Total circuit	Belt damaged	Rare	Major	H10
	Blocked Jaw	Almost Certain	Major	E23

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	Conveyor bogged	Almost Certain	Major	E23
	Maintenance	Possible	Moderate	H13
	Commissioning	Rare	Minor	L3
	Electrical fault	Almost Certain	Major	E23
	Low Manning	Possible	Minor	M8
	Liners/Bolts	Almost Certain	Moderate	E20
	Mechanical fault	Almost Certain	Moderate	E20
	Noise	Almost Certain	Minor	H16
	Screen mats	Likely	Moderate	H17
	Others	Possible	Moderate	H13

4.3. Multi-stage quantitative FMECA (failure modes, effects and criticality analysis) - a novel approach

The multi-stage quantitative FMECA framework introduced in this paper has been designed in multiple stages and is a novel quantitative way to remove uncertainties from the decision-making process. It also offers a means of ranking the most critical equipment of an identified critical system. Multi-stage quantitative FMECA framework is essential because it provides a comprehensive, structured, and adaptive approach to identifying, analysing, and mitigating risks. It enhances thoroughness, prioritization, and adaptability, making it an essential strategy for effective risk management. It reduces uncertainties, improves system reliability, and helps organizations take proactive, data-driven decisions to prevent failures and accidents. While traditional FMEA and standard FMECA are widely used for risk assessment, they have certain limitations, such as subjectivity, lack of dynamic analysis, and difficulty in handling complex failure interactions. A multi-stage quantitative FMECA framework approach helps overcome these challenges in the following ways by filtering a failure mode through different quantitative elements. This helps in reducing the uncertainty in the decision-making process, addresses complex failure interactions, improves risk prioritisation and decision-making, enhances adaptability to different risk environments, etc. Each stage of this process is designed to assess failure rate (likelihood), downtime and cost (Consequence) as presented in Table 9.

The framework is designed by defining the system and functional decomposition; where the identified critical system is analysed and breakdown into subsystems, components, and failure modes. Later, assess the failure rate (likelihood) of failure modes with the help of Table 6. Followed by the assessment of the event total downtime in hours. Lastly, the cost parameter is evaluated with the help of Table 5 to assess the total loss per event which is the consequence of the failure mode. Finally, the risk score is evaluated by referring the 'Generic Risk Matrix' highlighted in Table 7.

Table 9. Quantitative Analysis – Multi-Stage FMECA (A novel approach)

Equipment	Failure modes	Quantitative Analysis								Risk score
		Failure rate (likelihood)			Event total downtime in minutes	Event total downtime in Hrs	Total loss/event (consequence)			
Crusher	Blocked Jaw	183	> once per week	Almost Certain	11167	186.12	$18,306.56	<$20K	Insignificant	H11
	Grizzly Bar Breakdown	10	> once per month	Likely	3105	51.75	$93,150.00	$20K - $200K	Minor	H12
	Electrical fault	27	> once per week	Almost Certain	1833	30.55	$20,366.67	$20K - $200K	Minor	H16
	Hydraulic Leak	1	> once per week	Almost Certain	180	3.00	$54,000.00	$20K - $200K	Minor	H16
	Liners /Bolts	9	> once per month	Likely	5400	90.00	$180,000.00	$20K - $200K	Minor	H12
	Motor	15	> once per	Likely	6193	103.22	$123,860.00	$20K -	Minor	H12

	Breakdown		month					$200K		
	Oil & Lubrication	2	> once per month	Likely	110	1.83	$16,500.00	<$20K	Insignificant	M7
	Bins Issue	19	> once per month	Likely	337	5.62	$5,321.05	<$20K	Insignificant	M7
	Maintenance	8	> once per month	Likely	1123	18.72	$42,112.50	$20K - $200K	Minor	H12
	Other	16	> once per month	Likely	1691	28.18	$31,706.25	$20K - $200K	Minor	H12
CV 201	Belt damaged	12	> once per month	Likely	7060	117.67	$176,500.00	$20K - $200K	Minor	H12
	Chute Issues	32	> once per month	Likely	410	6.83	$3,843.75	<$20K	Insignificant	M7
	Electrical fault	45	> once per week	Almost Certain	1594	26.57	$10,626.67	<$20K	Insignificant	H11
	Mechanical Fault	2	> once per year	Possible	30	0.50	$4,500.00	<$20K	Insignificant	L4
	Bins Issue	1	> once per year	Possible	720	12.00	$216,000.00	$200K - $2000K	Moderate	H13
	Other	7	> once per month	Likely	651	10.85	$27,900.00	$20K - $200K	Minor	H12
Feeder	Blockage	23	> once per week	Almost Certain	2293	38.22	$29,908.70	$20K - $200K	Minor	H16
	Mechanical Fault	12	> once per week	Almost Certain	5118	85.30	$127,950.00	$20K - $200K	Minor	H16
	Bins Issue	99	> once per week	Almost Certain	1705	28.42	$5,166.67	<$20K	Insignificant	H11
	Electrical Fault	10	> once per week	Almost Certain	6497	108.28	$194,910.00	$20K - $200K	Minor	H16
	Maintenance	1	> once per year	Possible	300	5.00	$90,000.00	$20K - $200K	Minor	M8
	Liners/Bolts	1	> once per year	Possible	390	6.50	$117,000.00	$20K - $200K	Minor	M8
	Others	5	> once per month	Likely	44	0.73	$2,640.00	<$20K	Insignificant	M7
Fines Convey or	Belt damaged	1	> once per year	Possible	75	1.25	$22,500.00	$20K - $200K	Minor	M8
	Conveyor bogged	1	> once per year	Possible	15	0.25	$4,500.00	<$20K	Insignificant	L4
	Electrical Fault	8	> once per week	Almost Certain	416	6.93	$15,600.00	<$20K	Insignificant	H11
	Truck delay	1	> once per year	Possible	720	12.00	$216,000.00	$200K - $2000K	Moderate	H13
	Others	9	> once per month	Likely	159	2.65	$5,300.00	<$20K	Insignificant	M7
Loader	Loader Unavailable	72	> once per week	Almost Certain	1123	18.72	$4,679.17	<$20K	Insignificant	H11
	Maintenance	2	> once per year	Possible	29	0.48	$4,350.00	<$20K	Insignificant	L4
	Hydraulic leak	2	> once per year	Possible	85	1.42	$12,750.00	<$20K	Insignificant	L4
	Low Manning	11	> once per month	Likely	427	7.12	$11,645.45	<$20K	Insignificant	M7
	Others	19	> once per month	Likely	231	3.85	$3,647.37	<$20K	Insignificant	M7
Product stacker	Conveyor bogged	1	> once per year	Possible	60	1.00	$18,000.00	<$20K	Insignificant	L4
	Electrical Fault	3	> once per year	Possible	60	1.00	$6,000.00	<$20K	Insignificant	L4
	Commissioning	1	> once per year	Possible	730	12.17	$219,000.00	$200K - $2000K	Moderate	H13
	Others	5	> once per month	Likely	42	0.70	$2,520.00	<$20K	Insignificant	M7
Reject Stacker	Bearings failure	2	> once per year	Possible	1140	19.00	$171,000.00	$20K - $200K	Minor	M8
	Belt damaged	5	> once per year	Possible	2838	47.30	$170,280.00	$20K - $200K	Minor	M8
	Blockage	13	> once per	Almost	692	11.53	$15,969.23	<$20K	Insignificant	H11

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			week	Certain						
	Conveyor bogged	38	> once per week	Almost Certain	2143	35.72	$16,918.42	<$20K	Insignificant	H11
	Electrical fault	42	> once per week	Almost Certain	1551	25.85	$11,078.57	<$20K	Insignificant	H11
	Maintenance	9	> once per month	Likely	898	14.97	$29,933.33	$20K - $200K	Minor	H12
	Mechanical fault	3	> once per month	Likely	740	12.33	$74,000.00	$20K - $200K	Minor	H12
	Liners/Bolts	1	> once per year	Possible	70	1.17	$21,000.00	$20K - $200K	Minor	M8
	Others	14	> once per month	Likely	421	7.02	$9,021.43	<$20K	Insignificant	M7
Rock Breaker	Hydraulic leak	1	> once per year	Possible	60	1.00	$18,000.00	<$20K	Insignificant	L4
	Noise	1	> once per year	Possible	720	12.00	$216,000.00	$200K - $2000K	Moderate	H13
	Others	1	> once per year	Possible	5	0.08	$1,500.00	<$20K	Insignificant	L4
Screen	Bearings failure	12	> once per week	Almost Certain	8180	136.33	$204,500.00	$200K - $2000K	Moderate	E20
	Belt damaged	5	> once per week	Almost Certain	1730	28.83	$103,800.00	$20K - $200K	Minor	H16
	Conveyor bogged	15	> once per week	Almost Certain	945	15.75	$18,900.00	<$20K	Insignificant	H11
	Maintenance	22	> once per week	Almost Certain	2202	36.70	$30,027.27	$20K - $200K	Minor	H16
	Electrical fault	4	> once per month	Likely	185	3.08	$13,875.00	<$20K	Insignificant	M7
	Liners/Bolts	4	> once per month	Likely	312	5.20	$23,400.00	$20K - $200K	Minor	H12
	Mechanical fault	33	> once per week	Almost Certain	18720	312.00	$170,181.82	$20K - $200K	Minor	H16
	Oil & Lubrication	1	> once per year	Possible	120	2.00	$36,000.00	$20K - $200K	Minor	M8
	Blockage	3	> once per month	Likely	78	1.30	$7,800.00	<$20K	Insignificant	M7
	Screen mats	7	> once per month	Likely	1810	30.17	$77,571.43	$20K - $200K	Minor	H12
	Others	6	> once per month	Likely	230	3.83	$11,500.00	<$20K	Insignificant	M7
Total Circuit	Belt damaged	5	> once per month	Likely	1039	17.32	$62,340.00	$20K - $200K	Minor	H12
	Blocked Jaw	9	> once per week	Almost Certain	448	7.47	$14,933.33	<$20K	Insignificant	H11
	Conveyor bogged	15	> once per month	Likely	1234	20.57	$24,680.00	$20K - $200K	Minor	H12
	Maintenance	226	> once per week	Almost Certain	40065	667.75	$53,183.63	$20K - $200K	Minor	H16
	Commissioning	7	> once per year	Possible	4445	74.08	$190,500.00	$20K - $200K	Minor	M8
	Electrical fault	28	> once per week	Almost Certain	3098	51.63	$33,192.86	$20K - $200K	Minor	H16
	Low Manning	16	> once per week	Almost Certain	4904	81.73	$91,950.00	$20K - $200K	Minor	H16
	Liners/Bolts	6	> once per month	Likely	3270	54.50	$163,500.00	$20K - $200K	Minor	H12
	Mechanical fault	29	> once per week	Almost Certain	16416	273.60	$169,820.69	$20K - $200K	Minor	H16
	Noise	294	> once per week	Almost Certain	203155	3385.92	$207,301.02	$200K - $2000K	Moderate	E20
	Screen mats	1	> once per year	Possible	105	1.75	$31,500.00	$20K - $200K	Minor	M8
	Others	792	> once per month	Likely	30052	500.87	$11,383.33	<$20K	Insignificant	M7

5. Comparison of the three methods

The three different approaches explained in this paper yields three different results. to understand these better, this section, compares each of these approaches by focusing on a specific critical equipment, the 'Screen'. Table 10 displays the standard FMEA process results. as mentioned earlier in Section 4.1, the RPN is the product of the occurrence (O), severity (S) and detection (D) of a failure (RPN = O * S * D). in this example, we will focus on the occurrence (O) and severity (S) to measure the likelihood and consequence of the failure mode respectively. Further to this, detectability is an additional measure associated with the 'monitoring effectiveness' of a failure mode. It requires an intricate knowledge of the maintenance strategies that safeguard the failure mode to be applied consistently. This factor has been omitted from this study due to this 'intricate knowledge' being largely unavailable. if the data is more granular and if more strategy information is available then 'detectability' should be included, unfortunately that is the constraint of this study.

According to the 1st person, risk-prone failure modes include 'Electrical fault' and 'Mechanical fault' which have been assigned an RPN of 90. Conversely, the 2nd and 3rd identify the most risk-prone failure modes to be 'conveyor bogged' and 'belt damaged' respectively. Along with the inconsistency in identifying the most risk-prone failure mode, there is also widespread variation when the RPN value is ranked highest to lowest in each case. This indicates that there is significant uncertainty in the maintenance decision-making process.

Table 10. Analysis of standard FMEA process results of critical equipment "Screen"

Equipment	Failure modes	Standard FMEA								
		1st person			2nd person			3rd person		
		Likelihood	Consequence	RPN	Likelihood	Consequence	RPN	Likelihood	Consequence	RPN
Screen	Bearings failure	1	10	10	3	8	24	4	8	32
	Belt damaged	5	9	45	6	10	60	8	9	72
	Conveyor bogged	5	9	45	9	10	90	7	9	63
	Maintenance	5	5	25	5	5	25	5	5	25
	Electrical fault	9	10	90	9	9	81	8	7	56
	Liners/Bolts	10	5	50	7	4	28	9	7	63
	Mechanical fault	10	9	90	8	7	56	9	7	63
	Oil & Lubrication	7	7	49	5	6	30	5	5	25
	Blockage	9	9	81	8	9	72	7	7	49
	Screen mats	8	6	48	5	5	25	5	6	30
	Others	5	5	25	5	5	25	5	5	25

Table 11 highlights the application of the company's generic process to the same piece of critical equipment, the 'Screen'. According to generic approach the most risk-prone is 'bearings failure' with risk score as E25.

Table 11. Result analysis of company's generic process applied on critical equipment, the "Screen"

Company's generic procedure				
Equipment	Failure modes	Likelihood	Consequence	Risk score
Screen	Bearings failure	Almost Certain	Catastrophic	E25
	Belt damaged	Rare	Major	H10
	Conveyor bogged	Almost Certain	Major	E23
	Maintenance	Possible	Moderate	H13
	Electrical fault	Almost Certain	Major	E23
	Liners/Bolts	Almost Certain	Moderate	E20

	Mechanical fault	Almost Certain	Moderate	E20
	Oil & Lubrication	Almost Certain	Minor	H16
	Blockage	Almost Certain	Major	E23
	Screen mats	Likely	Moderate	H17
	Others	Possible	Moderate	H13

Before explaining the proposed approach of this paper, which is known as multi-stage quantitative FMECA, the different parameters of this framework are analysed. This is important for understanding, as there are specific factors that are assessed individually using a more defined classification system. This helps to significantly improve decision-making uncertainty from the previous approach.

Turning our attention to the novel approach, the failure modes will be assessed quantitatively using two parameters. the first being 'failure rate', which is a 'likelihood' measure, and the second being 'downtime', which is often a dominant measure for 'consequence' in the context of equipment failure modes. Initially, the failure rate of all failure modes in the example will be calculated, followed by its corresponding downtime in hours. Table 12 and Table 13 display the corresponding results.

Thus, in the first stage, 'Mechanical fault' failure mode is of high priority with 33 failure occurrences over an annualised period. This corresponds to an 'Almost Certain' rating when the company's generic (industry-aligned) risk likelihood matrix is applied.

Table 12. Analysis of failure rate

Equipment	Failure modes	Failure rate (likelihood)		
Screen	Bearings failure	12	> once per week	Almost Certain
	Belt damaged	5	> once per week	Almost Certain
	Conveyor bogged	15	> once per week	Almost Certain
	Maintenance	22	> once per week	Almost Certain
	Electrical fault	4	> once per month	Likely
	Liners/Bolts	4	> once per month	Likely
	Mechanical fault	33	> once per week	Almost Certain
	Oil & Lubrication	1	> once per year	Possible
	Blockage	3	> once per month	Likely
	Screen mats	7	> once per month	Likely
	Others	6	> once per month	Likely

If the company's generic (industry-aligned) consequence matrix is applied, a 'high' consequence rating is appropriate to this failure mode given it has amassed a total of 312 hours of downtime per event. as highlighted in Fig. 2, the top three critical failure modes based on their likelihood are 'Mechanical fault', 'Maintenance activities' and 'bogged conveyor'.

If a decision-maker had to rely on just the likelihood score, then the most frequently occurring failure mode will be attended first. in this case the 'Mechanical fault' followed by the other in sequential order. But if a different person tries to analyse the same failure modes through the lens of 'downtime' alone, the priority changes. as seen in the Fig. 3, the topmost critical failure modes coincidently reoccur, but this time they are reordered, "mechanical fault", "bearing failure" and then "maintenance activities". Thus, both the parameters yield different priorities thus creating uncertainties in the decision-making process.

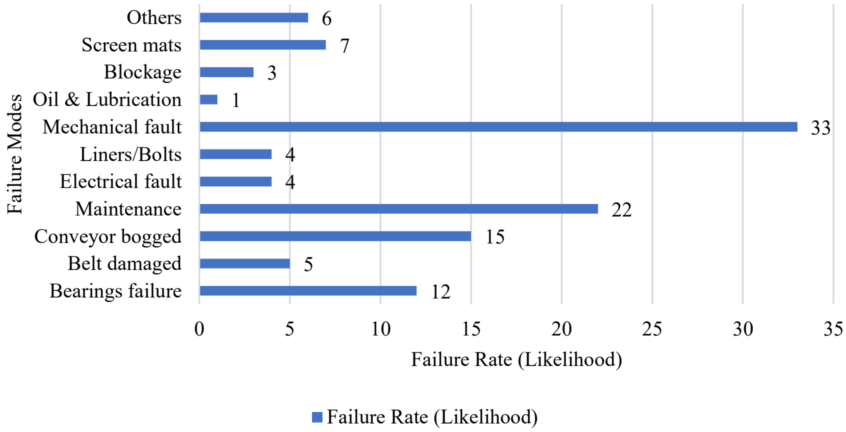

Fig. 2. Analysis of failure rate (likelihood)

Table 13. Analysis of downtime

Equipment	Failure modes	Event total downtime in minutes	Event total downtime in Hrs
Screen	Bearings failure	8180	136.33
	Belt damaged	1730	28.83
	Conveyor bogged	945	15.75
	Maintenance	2202	36.70
	Electrical fault	185	3.08
	Liners/Bolts	312	5.20
	Mechanical fault	18720	312.00
	Oil & Lubrication	120	2.00
	Blockage	78	1.30
	Screen mats	1810	30.17
	Others	230	3.83

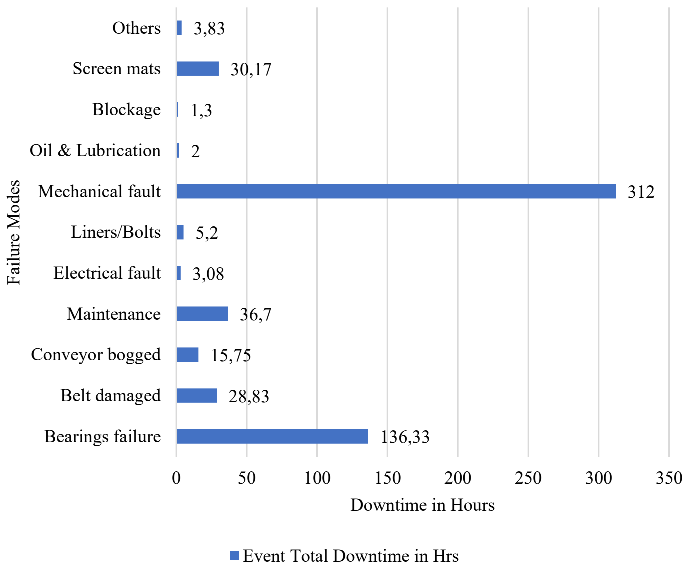

Fig. 3. Analysis of failure modes of an identified critical equipment

After this individual analysis of this parameters, Table 14 showcases their role in the novel quantitative approach proposed in this paper.

This approach reveals why it is important to consider both 'failure rate' and 'downtime' to highlight the likelihood and consequences of the risk associated with an event caused by each particular failure mode. It is important to understand that we are analysing historical data, and we are analysing risk per event as we do not want another event to occur. Risk is an event-based measure, and a quality decision-making process must therefore assess the risk associated with each unique event-type.

The higher the frequency of failure in a particular period of time then it is more likely that event is to occur again. The risk matrix (Likelihood x Consequence) presented in this framework indicates the risk per event. The downtime parameter is important, but it doesn't belong in likelihood space. Only the failure rate belongs in the likelihood space because its matrix describes classifies the time period between failure events due to a specific failure mode. Similarly, the downtime is important when we are discussing consequence. The consequence is described by the cost parameter because the cost is inherently related to the production downtime per event, contributed by the same failure mode.

Table 14. Analysis of multi-stage quantitative FMECA (A novel approach) process results of critical equipment "Screen"

Equipment	Failure modes	Quantitative analysis								
		Failure rate (likelihood)			Event total downtime in minutes	Event total downtime in Hrs	Total loss/event (consequence)			Risk score
Screen	Bearings failure	12	> once per week	Almost Certain	8180	136.33	$204,500.00	$200K - $2000K	Moderate	E20
	Belt damaged	5	> once per week	Almost Certain	1730	28.83	$103,800.00	$20K - $200K	Minor	H16
	Conveyor bogged	15	> once per week	Almost Certain	945	15.75	$18,900.00	<$20K	Insignificant	H11
	Maintenance	22	> once per week	Almost Certain	2202	36.70	$30,027.27	$20K - $200K	Minor	H16
	Electrical fault	4	> once per month	Likely	185	3.08	$13,875.00	<$20K	Insignificant	M7
	Liners/Bolts	4	> once per month	Likely	312	5.20	$23,400.00	$20K - $200K	Minor	H12
	Mechanical fault	33	> once per week	Almost Certain	18720	312.00	$170,181.82	$20K - $200K	Minor	H16
	Oil & Lubrication	1	> once per year	Possible	120	2.00	$36,000.00	$20K - $200K	Minor	M8
	Blockage	3	> once per month	Likely	78	1.30	$7,800.00	<$20K	Insignificant	M7
	Screen mats	7	> once per month	Likely	1810	30.17	$77,571.43	$20K - $200K	Minor	H12
	Others	6	> once per month	Likely	230	3.83	$11,500.00	<$20K	Insignificant	M7

This framework generates a risk score which is basically dependent on the total loss per event (Consequence). The total loss is basically the downtime in hours due to each occurred event which is then multiplied by the production loss cost per hour. Thus, by using Table 5, 6 and 7 we can evaluate the risk per failure mode, per event. The risk score of the 'Bearing failure' event is 'E20' which is a high priority considering the consequence of that failure mode. By comparing it with the individual parameter analysis; with respect to failure rate displayed in Table 12, a 'Bearing failure' was not even in the top three in the priority list, but with respect to downtime it would have been addressed, but not as a high priority. This shows how much the cost parameter makes difference in the perspective of decision-makers, as it results in the development of more robust maintenance strategies and utilises funds in a more efficient and effective way.

The findings of this research contribute meaningfully to both theoretical development and practical decision-making in the context of maintenance management within the mining industry. The proposed multi-stage risk assessment approach based on quantitative FMECA framework introduces a novel way to assess failure criticality by incorporating failure rate, downtime, and cost into a dynamic and repeatable analysis process. This approach moves beyond the limitations of traditional RPN-based methods, which often rely on static, subjective evaluations, and instead supports a continuous reassessment of risk as operational conditions evolve. From a theoretical perspective, this research enhances the existing body of work on reliability-centered maintenance by integrating data-driven, multi-criteria decision-making into the FMECA process. The inclusion of time-sensitive and cost-related parameters makes the framework especially relevant to industries like mining, where equipment downtime directly impacts productivity and revenue. On the managerial side, the framework provides maintenance planners and operations managers with a transparent and systematic tool to prioritise interventions based on measurable outcomes. By linking technical degradation with economic impact, it facilitates more accurate forecasting, targeted resource allocation, and improved maintenance planning. This alignment between technical risk and financial consequence also enables better justification of maintenance strategies to senior management, reinforcing accountability and supporting long-term asset performance optimisation.

6. Conclusions

The aim of every industry is to reduce the risk associated with their assets operation. the risk generally increases with the ageing of the assets and every industry has a different approach towards assessing this risk. Assessing risk is a crucial phase of the maintenance decision-making process and it is very important to complete this process as consistently as possible. There are different qualitative and quantitative risk assessment techniques adopted throughout industry to help reduce uncertainty. Each of these techniques are often universally applied to equipment and systems; regardless of criticality. Every technique has some level of uncertainty or limitation. for example, different likelihood and consequence factors may be relevant to different organisations, or, different organisations may record events differently or inadequately, which may influence the risk assessment approach that can be applied. Without question, it can be stated that a lack of quality data increases the challenges of the risk assessment process.

Risk assessment is a very time consuming, and a costly process and every industry adopts, to some extent, a fixed annual budget for asset maintenance and improvement activities. in such scenarios, industries go for the most affordable and quick options to arrive at a decision, which is not always a recommended approach. This is a widespread problem that is a result of pace of development, production targets and ever-changing market demands. in this style of workplace, it is very important to equip the decision-making process or the decision-maker with multiple decision parameters which can be selected based on data that is readily available throughout industry at a relatively high quality (i.e. availability, downtime and budget figures).

The aim of this paper was to design a framework based on multiple quantitative parameters. in this paper, a novel quantitative risk assessment approach has been introduced. This approach is based on quantitative FMECA. The entire framework is designed with different decision-making parameters, represented as a standalone individual decision-making practice. This gives flexibility to the decision-making committee to plan the maintenance activities in accordance with time and budget availability. The novel risk assessment approach considers assessing, analysing and prioritising the failure modes using a multi-stage, quantitative approach. Whilst it is important to note that all three approaches yield results that will reduce overall risk, the cost and timeframe needed to do so will vary dramatically. Ultimately, the management team can select an option that better suits their needs and maturity. However, this paper has determined that a quantitative influence is required to streamline decision-making processes and reduce outcome subjectivity.

By breaking down risk assessment into distinct stages, this methodology addresses key limitations of traditional FMEA/FMECA. The inclusion of failure rate in the first stage helps to quantify the likelihood of failures occurring. The second stage, which assesses downtime, allows for a more comprehensive understanding of how failures impact system availability and overall productivity. Finally, integrating cost analysis in the third stage provides financial justification for prioritizing maintenance and reliability improvements. This multi-dimensional approach ensures a balanced decision-making process that aligns with both technical performance and economic feasibility. Furthermore, applying multi-stage quantitative FMECA in industries such as mining, manufacturing, and aerospace can significantly reduce unplanned downtime, optimize maintenance planning, and enhance system reliability. As industries continue to adopt data analytics and predictive maintenance, this approach can be further refined by integrating machine learning algorithms and real-time monitoring to improve risk prediction accuracy.

In conclusion, the multi-stage quantitative FMECA methodology presented in this paper represents a critical advancement in reliability engineering and risk management. By systematically analysing failure rate, downtime, and cost, organizations can enhance safety, improve asset performance, and reduce operational losses, leading to more efficient and sustainable industrial operations. It also shows how important it is to filter the failure modes through an economic lens along with other quantitative risk assessment parameters which yield results in a more effective and efficient way.

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Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author contributions

Sagar More: writing-original draft preparation, conceptualization, methodology. William Milne: writing-review and editing, conceptualization, methodology. Rabin Tuladhar: writing-review and editing

Conflict of interest

The authors declare that they have no conflict of interest.

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