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Lifecycle-Based Maintenance Optimisation for Aging Mining Assets

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Abstract

As mining operations age, they face increasing pressure to enhance efficiency, reduce costs and extend asset lifecycles. Effective maintenance management becomes essential for sustaining operational performance, as equipment failures and unplanned downtime can significantly impact productivity and profitability. This study investigates how aligning maintenance strategies with asset lifecycle stages can improve operational performance in aging mining assets. The research utilised real operational data from a mining operation and applied Weibull analysis to evaluate asset reliability behaviour across lifecycle stages. A quantitative approach was used, analysing downtime records, shift-based performance patterns and asset failure rates. The analysis identified trends in downtime behaviour and variations in failure patterns as assets progressed through different lifecycle phases. The findings demonstrate that maintenance strategies guided by asset lifecycle stages significantly enhance equipment reliability and operational efficiency, particularly for critical assets prone to failure. The study establishes a strong relationship between tactical maintenance decisions and overall operational performance. The results indicate that aligning maintenance strategies with asset lifecycle stages resulted in an estimated 30% reduction in downtime, demonstrating the effectiveness of lifecycle-informed maintenance planning. The study supports the transition from reactive maintenance practices toward proactive, data-driven maintenance strategies that integrate preventive and predictive approaches. When effectively implemented, these strategies can reduce unplanned downtime, extend asset lifespans and improve operational sustainability and cost-effectiveness.

Keywords
Asset Lifecycle Analysis, Weibull analysis, Condition Based Monitoring, Preventive and Predictive Maintenance Strategies, Downtime Analysis

1. Introduction
Maintenance is a critical component in the lifecycle management of physical assets, ensuring efficient, safe and reliable operations while minimising downtime, operational costs and safety risks. In mining operations, where harsh environmental conditions and heavy reliance on critical equipment are common, effective maintenance tactics are essential to sustain productivity, improve equipment efficiency and extend asset lifespan. Studies such as Cao et al. (2021) have shown that equipment failures significantly hinder mining operations, yet many organisations continue to rely on reactive maintenance strategies.

Company A has been experiencing operational challenges within one of its wet concentrating plants. Maintenance activities have largely followed a reactive approach, addressing failures only after they occur. This has resulted in unplanned downtime, loss of production and increased operational costs (Mobley, 2002; Al-Najjar, 2007). Despite the recognised importance of structured maintenance strategies, existing practices have not adequately mitigated these recurring operational challenges.

This research is motivated by the need to evaluate current maintenance tactics, assess their impact on overall asset performance and explore data-driven methods, specifically Weibull analysis, to support more proactive maintenance planning (Abernethy, 2006; Jardine, Lin and Banjevic, 2006). The study investigates how maintenance frequency influences reliability and uptime, identifies the lifecycle stage of assets based on the bathtub curve and proposes targeted improvements informed by lifecycle insights (Dhillon, 2006; Ben-Daya, Kumar and Murthy, 2016). By bridging theoretical principles with practical implementation, this research provides valuable guidance for enhancing asset management practices in mining operations.

1.1. Objectives

In response to the need to transition from reactive to proactive maintenance practices, this study aims to identify the most suitable maintenance tactics for equipment and infrastructure at Company A. The overall objective is to improve asset reliability, extend equipment lifespan and maximise operational efficiency (Ben-Daya, Kumar and Murthy, 2016). By evaluating the influence of specific maintenance management strategies on performance, the research provides a data-driven framework that supports continuous improvement in maintenance planning and execution (Alsyouf, 2007; Tsang, 2002).

The study focuses on three key objectives:

- Investigate and determine the impact that different frequencies of maintenance interventions have on the performance, reliability and operational uptime of critical assets.
- Determine the stage of the bathtub curve which represents the empirical data of the asset.
- Identify and propose maintenance strategies tailored to the specific stage of the asset's life cycle to enhance reliability and overall performance.

2. Literature Review and Case Study Context

Asset management strategies such as Reliability-Centered Maintenance (RCM), Risk-Based Maintenance (RBM) and Total Productive Maintenance (TPM) provide structured frameworks for optimising asset performance and ensuring operational reliability. RCM focuses on identifying and managing potential failure modes to improve system reliability (Smith and Hinchcliffe, 2004; Moubray, 1997). RBM prioritises maintenance efforts based on the likelihood and consequences of asset failure, enabling more efficient allocation of maintenance resources (Dhillon, 2006; Kelly, 2006). TPM promotes a proactive maintenance culture by involving frontline employees in routine maintenance activities, with the objective of reducing downtime and improving overall equipment effectiveness (Nakajima, 1988; Ahuja and Khamba, 2008).

While these strategies have proven effective across various industries, there remains a gap in the literature regarding their practical application within mining operations, where asset performance must be aligned with lifecycle stages (Amadi-Echendu et al., 2010; Jardine, Lin and Banjevic, 2006). The complex and harsh operating environments found in mining operations make it essential to adapt maintenance strategies according to asset maturity. However, existing studies do not fully address how these methodologies integrate with lifecycle-based frameworks such as the bathtub curve (Dhillon, 2006), or how analytical tools such as Weibull analysis can enhance maintenance decision-making (Abernethy, 2006; Jardine, Lin and Banjevic, 2006).

This study addresses this gap by examining the practical application of maintenance management strategies within real mining operations, using operational data collected at Company A as a case study. By applying Weibull analysis, the research aims to improve understanding of how maintenance strategies can be tailored to asset reliability patterns, ultimately supporting enhanced operational performance and cost efficiency (Ben-Daya, Kumar and Murthy, 2016).

2.1 Overview of the Mineral Processing Plant Process

A mineral processing plant is designed to systematically extract and refine valuable minerals from dredged ore through a series of integrated processing steps. According to Rahman et al. (2019), the process begins with dredging, where raw materials are collected and pumped to the Wet Concentrator Plant (WCP). At this stage, oversized materials are removed and heavy mineral concentrate (HMC) is separated from lighter materials such as silica sand and clay. The remaining tailings are rehabilitated through co-deposition, reshaping and revegetation processes.

The heavy mineral concentrate is subsequently transported to the Mineral Separation Plant (MSP), where advanced separation techniques such as Wet High-Intensity Magnetic Separation (WHIMS) and electrostatic separation are applied to isolate valuable minerals, including ilmenite, rutile and zircon. As described by Murty, Natarajan and Rao (2023), the final mineral products are dried, classified and stored before being prepared for transportation and distribution to downstream processing facilities (Figure 1).

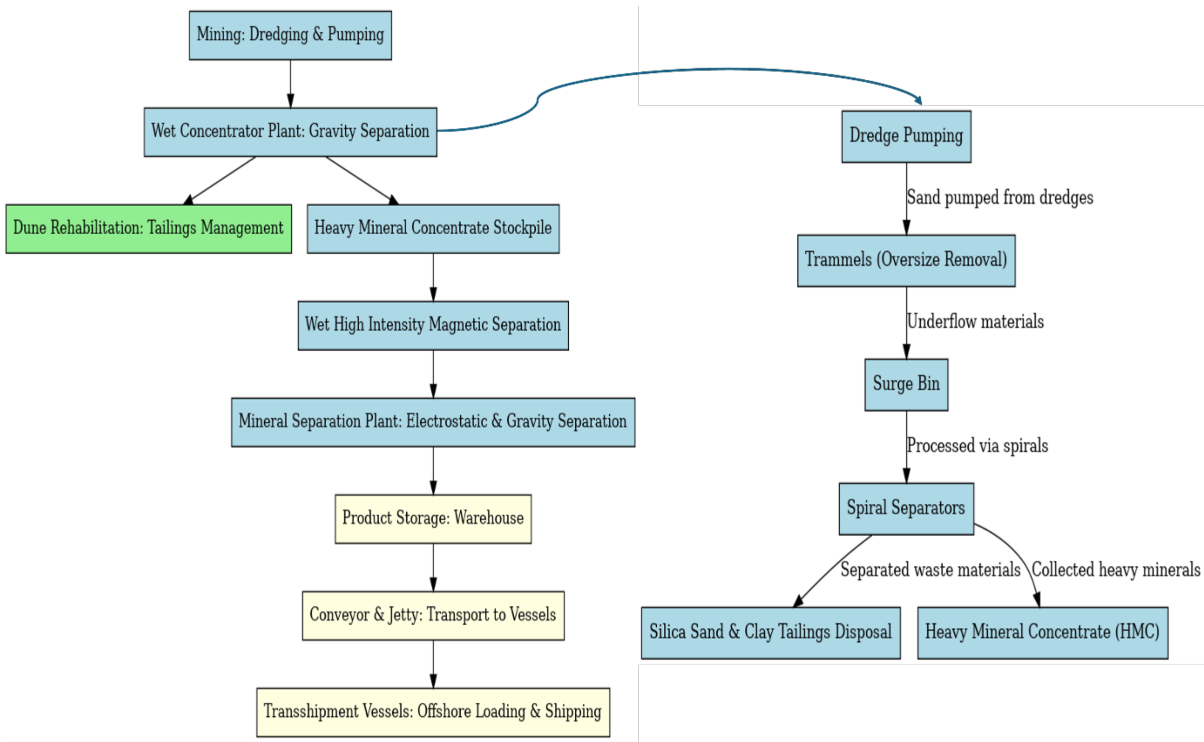

Figure 1. Process flow overview of the wet concentrator plant showing material flow from mining to shipment

2.2 Asset Maintenance Strategies

Asset maintenance involves a set of strategic approaches aimed at improving the reliability, efficiency and lifespan of physical assets. Effective maintenance requires a clear understanding of asset types, their current condition and the most suitable maintenance practices. The main strategies include:

- Preventive Maintenance - Scheduled interventions aimed at preventing potential failures before they occur (Mobley, 2002).
- Predictive Maintenance - Data-driven approaches that use condition monitoring and analytics to anticipate failures and optimise intervention timing (Jardine, Lin and Banjevic, 2006).
- Corrective Maintenance - Reactive responses to failures, where maintenance is performed after a breakdown or fault has occurred (Ben-Daya, Kumar and Murthy, 2016).

To support these strategies, organisations often implement Maintenance Management Systems or Computerised Maintenance Management Systems. These digital tools help streamline maintenance processes by scheduling tasks, tracking asset performance, managing spare parts inventory and providing data insights for informed decision-making. By automating and integrating maintenance activities, these systems contribute significantly to improving overall maintenance efficiency and effectiveness (Lu et al., 2020).

Challenges in Maintaining Assets at Company A's Wet Concentrator Plant
As Company A's Wet Concentrator Plant continues to age, maintaining its assets has become increasingly critical. Key challenges include the complexity of equipment requiring specialized expertise, harsh environmental conditions that accelerate wear and corrosion, limited availability of spare parts and a shortage of skilled maintenance personnel (Patil et al., 2024; Islam et al., 2024). These challenges are further intensified by safety and environmental compliance requirements, which not only increase technical complexity but also escalate the urgency and workload for maintenance personnel, placing additional demands on the maintenance function (Kumar et al., 2019).

These factors have contributed to increased downtime and financial strain, emphasising the need for more effective maintenance strategies tailored to the plant's context(Figure 2). Such challenges are consistent with the bathtub curve concept, which illustrates how equipment experiences varying maintenance demands throughout its lifecycle. The lifecycle of an asset is typically represented by the bathtub curve, which illustrates three primary stages: infant mortality, normal life and wear-out. Each phase requires tailored maintenance strategies (Kolehmainen, 2021).

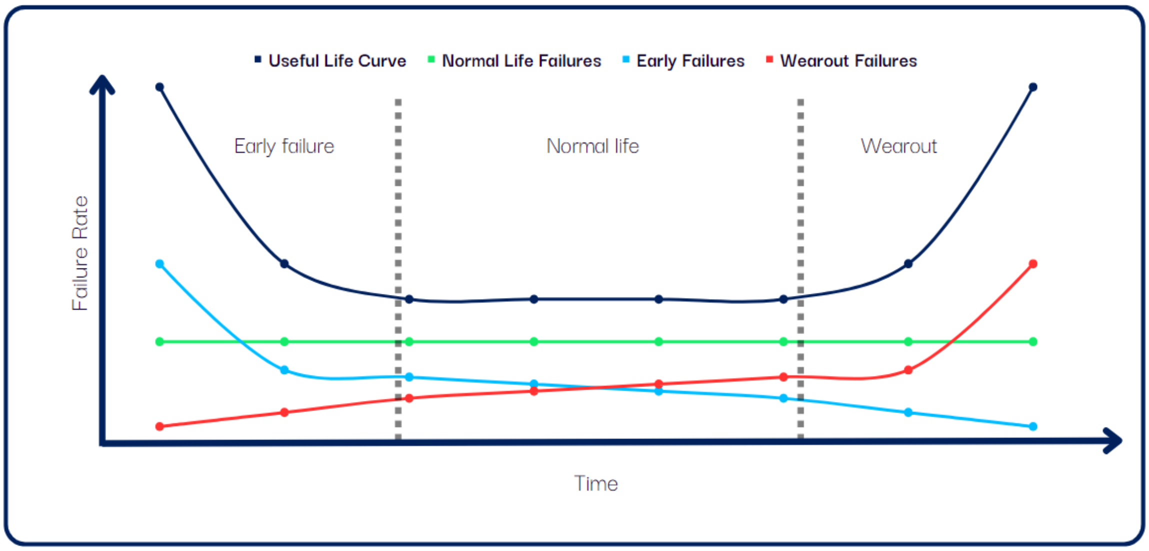

Figure 2. Bathtub curve model of equipment failure rates over time

2.3 Application of Weibull Analysis

Several studies have applied Weibull analysis to examine failure patterns and inform maintenance strategies in industrial and mining contexts. This approach classifies failures into key asset lifecycle phases, each requiring tailored maintenance interventions.

- Early-Life Failures: Early-life (infant mortality failures) are commonly attributed to manufacturing defects, improper installation or misalignment (e.g., Kolehmainen, 2021). These failures often occur within the initial operating hours and decline over time. Literature suggests that improving quality control during production and implementing rigorous commissioning and testing procedures can reduce the frequency of such failures.
- Random Failures: Failures that occur at a constant rate throughout an asset's useful life are often considered random and are typically linked to human error, inadequate operating conditions or inconsistent maintenance practices (Smith & Hinchcliffe, 2019). Condition-Based Maintenance (CBM) enables early detection and reduces unnecessary interventions while extending asset life.
- Wear-Out Failures: In the wear-out phase, failure rates increase due to accumulated wear and degradation over time. Research indicates that predictive maintenance and partial replacement strategies can be effective in mitigating risks associated with aging equipment (Mobley, 2002).
- Asset Lifecycle and Maintenance Strategy: Literature supports integrated maintenance strategies combining predictive, preventive and condition-based approaches aligned to lifecycle stages. This aligns with Reliability-Centred Maintenance (RCM), which matches maintenance to failure characteristics (Nowlan & Heap, 1978).

- Strategic Prioritisation of High-Risk Assets: Literature also highlights the importance of prioritising maintenance efforts on high-risk or critical assets, especially those prone to early-life or wear-out failures. Risk-Based Maintenance (RBM) improves resource allocation by focusing on assets with the highest safety, cost or operational impact (Dhillon, 2006).

The application of Weibull analysis highlights the importance of understanding failure patterns across the asset lifecycle. These insights support targeted, cost-effective and reliability-focused maintenance strategies, improving maintenance management in complex environments such as mining. Recent studies emphasise data-driven maintenance frameworks, with predictive analytics improving scheduling accuracy (Väyrynen et al., 2020) and lifecycle-based decision models addressing aging infrastructure challenges (Patil et al., 2024). These findings reinforce the need for advanced reliability modelling techniques, such as Weibull analysis, to enhance maintenance planning.

3. Research Methodology

This study adopted a quantitative approach to assess the impact of asset tactics on the overall asset performance at Company A's Wet Concentrator Plant. Data were obtained from the Asset Management System (AMS), including key indicators such as failure rates, maintenance schedules and repair histories. Weibull analysis was applied to model asset reliability and lifecycle, providing insights into the effectiveness of preventive, predictive and corrective maintenance strategies (Meeker & Escobar, 1998; Lee & Goh, 2017; Xu et al., 2015). The case study examined operational challenges such as harsh environmental conditions and equipment complexity and their influence on maintenance practices. Historical and real-time condition monitoring data were integrated to support comprehensive asset performance analysis, improving prediction accuracy of asset health and failure probabilities (Bajpai et al., 2019; Väyrynen et al., 2020). Statistical methods were used to evaluate relationships between maintenance strategies and performance outcomes, providing empirical evidence applicable to similar operational contexts (Yin, 2018). The dataset included 24 months of maintenance and failure records for 96 critical assets, including failure timestamps, downtime duration, maintenance type and equipment classification. Weibull analysis was conducted to estimate shape (β) and scale parameters, enabling classification of assets by lifecycle phase and determination of appropriate maintenance strategies.

4. Findings and Discussions

4.1. Downtime Analysis

The downtime analysis at Company A identified key trends across shifts, disciplines and circuits. A notable finding was the higher failure rate during night shifts, with mechanical breakdowns (44%), power faults (21%) and instrumentation issues (15%) as the main contributors to downtime. Further analysis by discipline and shift showed that mechanical and production functions experienced the highest frequency of interruptions, with downtime increasing significantly during night shifts. This trend may be linked to reduced staffing levels, limited availability of skilled personnel and low supervision. Key findings include:

Downtime by Discipline: Production accounted for the largest share of downtime (40.2%), followed by mechanical systems (25%). Mechanical failures were identified as highly preventable through predictive maintenance technologies such as vibration monitoring, thermal imaging and pressure sensors. Literature indicates that these technologies can reduce mechanical downtime by approximately 30–50% through early fault detection and timely intervention. (Figure 3).

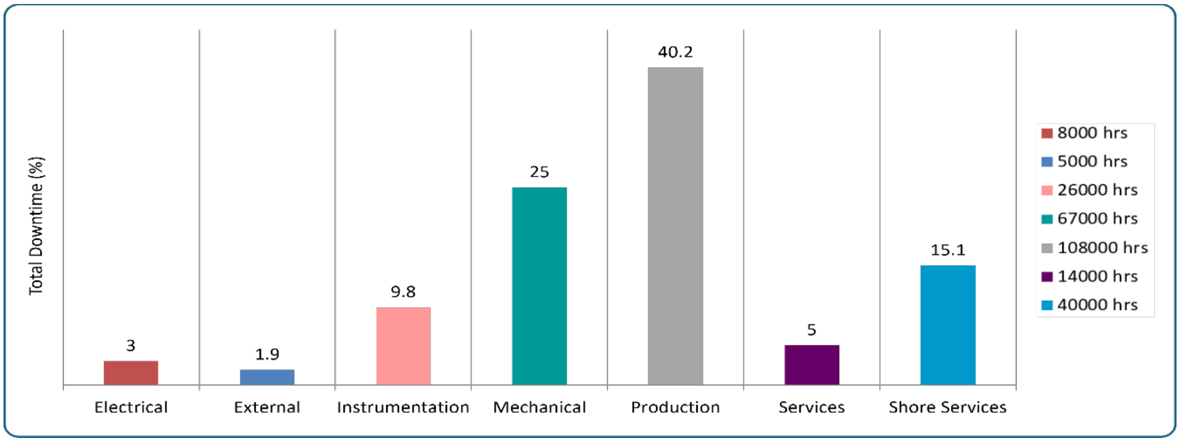

Figure 3. Breakdown of total equipment downtime across maintenance disciplines

Downtime by Circuit: Certain processing circuits notably A Side, DMB and DMA were responsible for a disproportionately high share of total downtime(Figure 4). These circuits exhibited frequent equipment failures, often linked to aging infrastructure and inadequate preventive maintenance. Focused maintenance efforts, including targeted inspections and component upgrades, may help mitigate these recurring issues and improve overall circuit reliability.

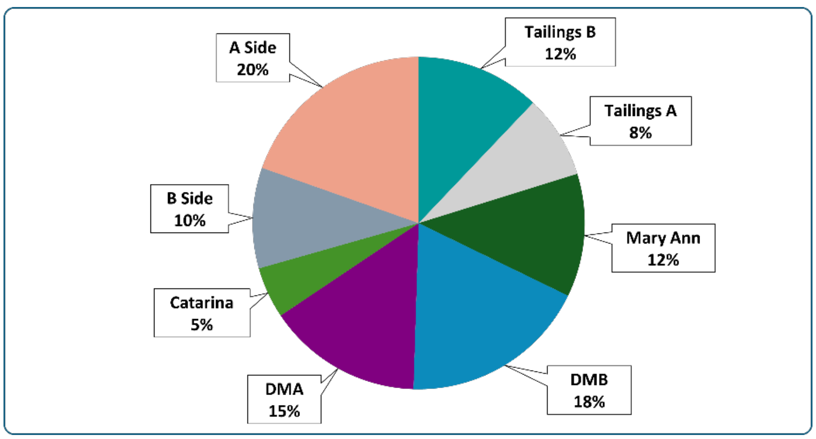

Figure 4. Percentage contribution of each circuit to total equipment downtime

Downtime by Shift: Night shifts consistently recorded higher levels of downtime compared to day shifts. Contributing factors may include reduced workforce availability, limited access to specialized maintenance personnel and slower response times for unplanned failures. The introduction of remote monitoring systems, automated alerts and enhanced night shift supervision could support more proactive fault identification and response during these hours(Figure 5).

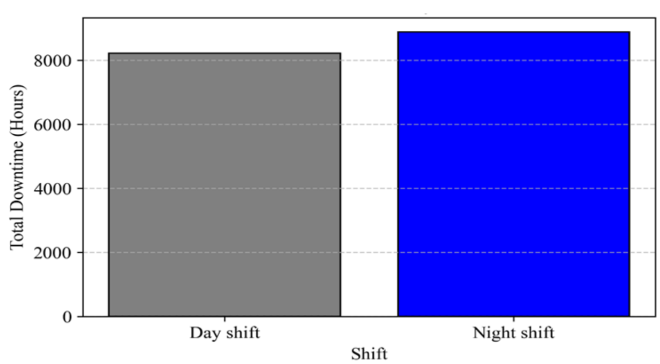

Figure 5. Breakdown of total equipment downtime by shift

Operational downtime was categorized into four types: Breakdown Loss (11,500 occurrences, 89,085.3 total hours, averaging 7.75 hours per event), Operational Delay (11,624 occurrences, 90,088.5 total hours, averaging 7.75 hours per event), Other Unplanned Loss (9,279 occurrences, 72,041.9 total hours, averaging 7.76 hours per event) and Standing Time (13,897 occurrences, 107,779.2 total hours, averaging 7.76 hours per event). Among these, Standing Time emerged as the category with the highest total downtime, contributing 107,779.2 hours, followed by Operational Delays at 90,088.5 hours. Breakdown Loss accounted for 89,085.3 hours and Other Unplanned Loss contributed the least, with 72,041.9 hours of total downtime. Overall, the four categories exhibited similar proportions in their contribution to the total downtime. (Figure 6).

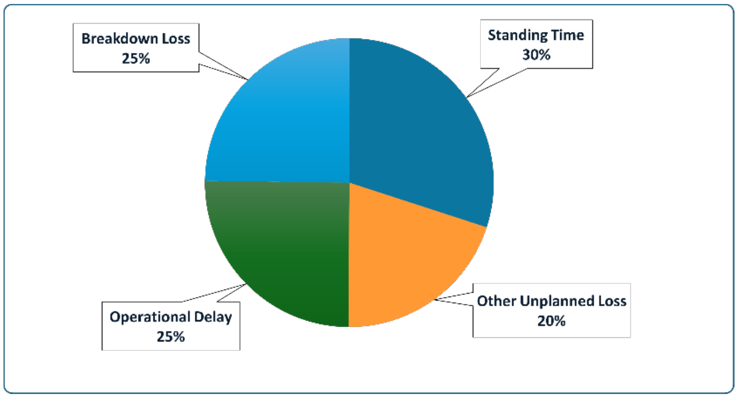

Figure 6. Percentage Contribution to Total Downtime by Classification (hours)

4.2. Weibull analysis throughout the stages (cycle) of the assets

The assets at Company A, which include dredge, pumps, transformers, air compressors, pumps, electrical motors and various other equipment, totalling 96 items, were analysed across different stages of their life cycle. A Weibull analysis was used to model and interpret time-to-failure data for these assets. The objective of the analysis was to generate insights that could inform predictive maintenance strategies, helping to determine optimal maintenance schedules, as well as guiding decisions on whether to buy new assets or repair existing ones, based on parameters such as the mean time to failure and other relevant metrics. As shown below in the Weibull log plot for assets in the early-life failure phase, the data follows a straight line without concavity on a log-log graph. This indicates that a Weibull distribution is suitable for modelling the time-to-failure data. The close alignment with the straight line further supports the use of the Weibull distribution to describe the observed failure patterns(Figure 7).

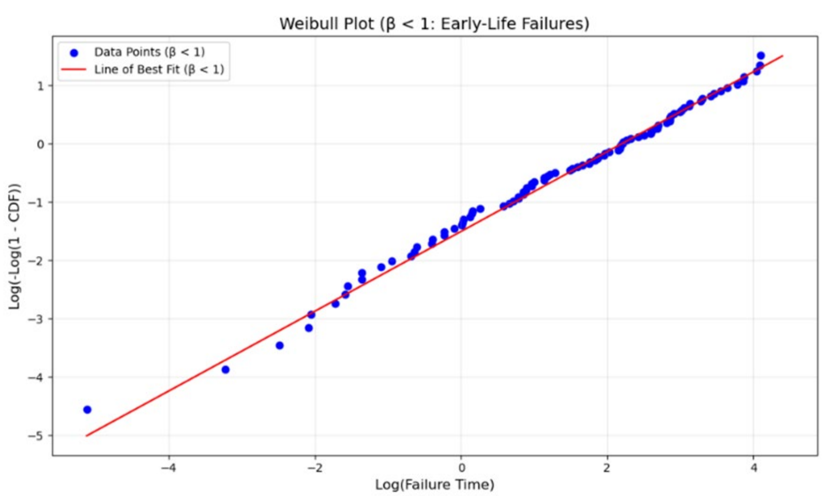

Figure 7. Weibull log plot showing assets in the early-life failure phase

The hazard function illustrates infant mortality failures, with a failure rate during the early-life phase indicated by a $\beta < 1$, reflecting a high occurrence of early failures. The function shows a decreasing trend over time, signifying higher failure rates in the initial stages of the asset lifecycle. These early failures are likely due to factors such as manufacturing defects or improper alignments. To mitigate these, enhancing initial testing procedures and strengthening quality control measures are crucial. The decreasing hazard function further suggests that the failure rate will likely decline as the assets age (Figure 8).

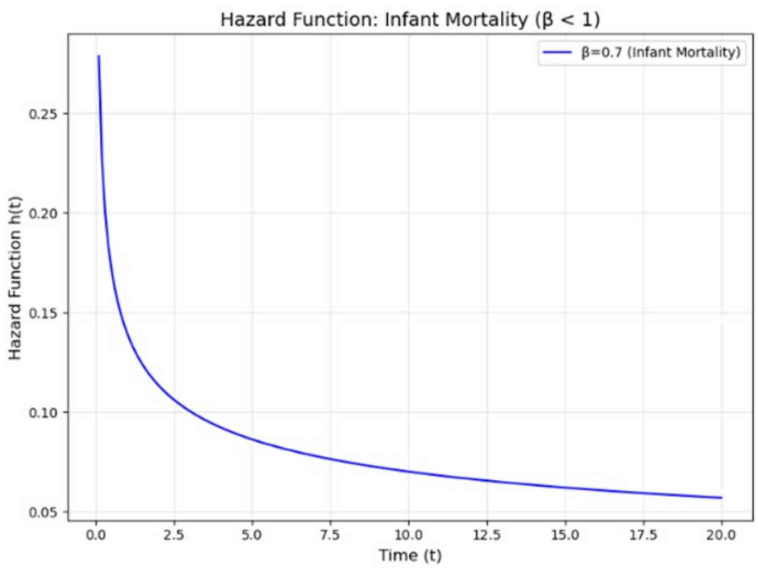

Figure 8. Hazard function showing infant mortality failure behaviour

The hazard function for random failures reflects failures occurring during the useful life of assets, with a constant failure rate over time. In this phase, assets are in their operational stage and failures are random. Contributing factors may include inadequate quality control, inefficient fault detection, human error, or suboptimal operational processes. Condition-based maintenance strategies can be effective in identifying potential issues early, enabling timely interventions (Figure 9).

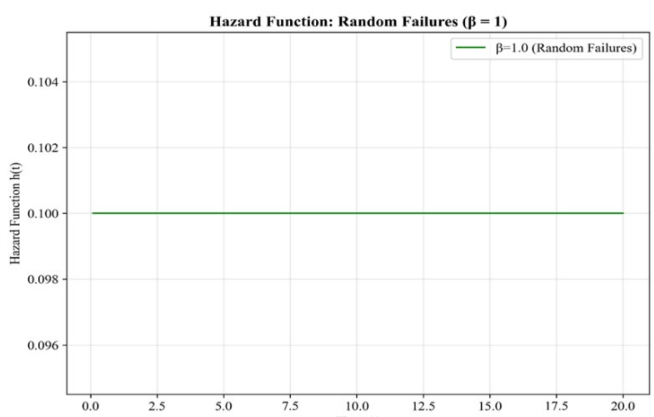

Figure 9. Hazard function showing random failure behaviour

The hazard function for wear-out failures at Company A (WCP A) shows that the assets are in the wear-out phase, as indicated by a $\beta = 1.41$, greater than 1. This phase is marked by an increasing failure rate as assets age, with a sharp rise in failure density beyond 15 hours. The consistent upward slope and $\beta > 1$ suggest accelerated failures due to aging, corrosion and accumulated operational stress, common in the later stages of an asset's lifecycle.

Given these findings, Company A should prioritize asset replacement and proactive maintenance before failures occur. Managing aging assets effectively is key to minimising unplanned downtime and maintaining operational efficiency. This approach aligns with Reliability-Centered Maintenance (RCM), which advocates for a data-driven, proactive maintenance strategy tailored to each asset's lifecycle stage. By identifying failure modes and applying preventive or predictive strategies, companies can enhance asset reliability and reduce maintenance costs. Moreover, Ben-Daya et al. (2016) found that predictive maintenance can reduce downtime by 30-50%. Techniques like condition monitoring and time-to-failure predictions enable early maintenance interventions, extending asset life and optimising maintenance efforts (Figure 10).

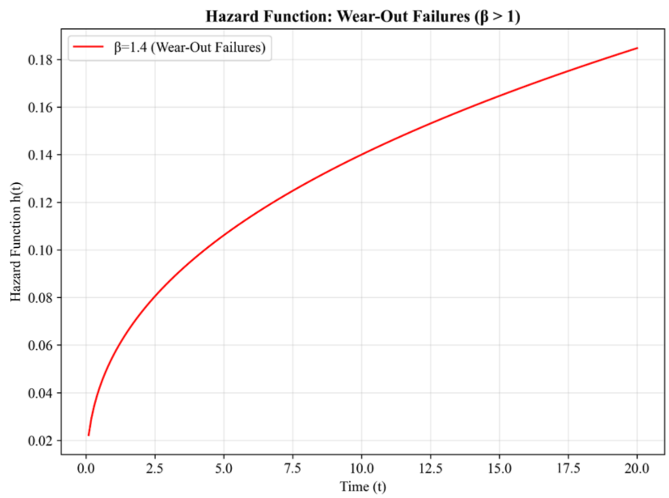

Figure 10. Hazard function showing wear-out failure behaviour

The Weibull distribution with $\beta = 0.68$ ($\beta < 1$) indicates a decreasing failure rate over time, characteristic of early-life failures. Assets are most likely to fail within the first 9.00 hours, after which the failure risk declines. The mean time to failure of 11.88 hours suggests vulnerability during the initial phase, highlighting the need for rigorous commissioning, testing and quality control to reduce infant mortality. For $\beta = 0.99$, the distribution approximates an exponential pattern, indicating random failures with a constant failure rate. These assets show increased failure likelihood after 9.08 hours, with a mean time to failure of 9.25 hours. Condition-based maintenance is recommended to support early fault detection and timely intervention. Assets with $\beta = 1.54$ ($\beta > 1$) represent the wear-out phase, characterised by an increasing failure rate over time. The scale parameter of 11.08 hours suggests low early failure probability; however, failure risk increases with age due to wear, corrosion and accumulated stress. The mean time to failure of 9.83 hours supports the use of predictive maintenance and targeted replacement strategies(Figure 11).

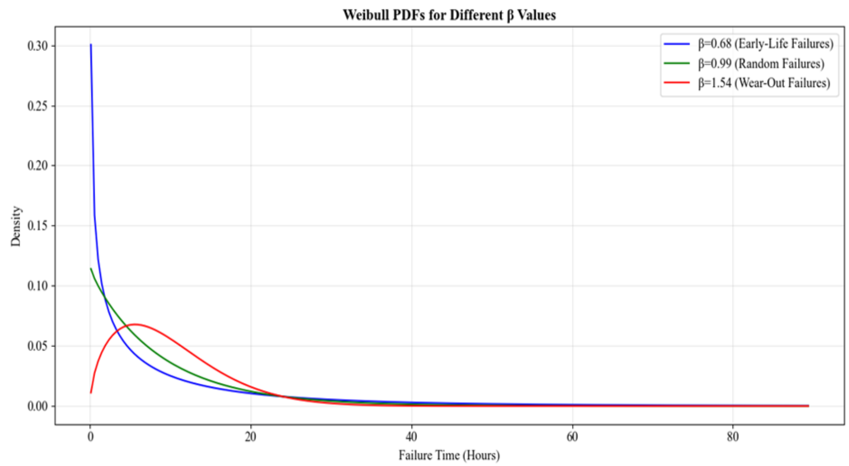

Figure 11. Weibull function illustrating early-life, random and wear-out failure phases

4.3. Secondary Data Analysis

The secondary data analysis revealed three key themes: asset maintenance tactics, overall asset performance evaluation and the relationship between asset maintenance and performance.

- Asset Maintenance Tactics: The study identified preventive, predictive and corrective maintenance as essential tactics. Issues such as operating delays, mechanical breakdowns and resource shortages caused significant downtime, especially during dredge repositioning and pump inspections. Standing time, often caused by bottlenecks, further exacerbated inefficiencies, highlighting the need for proactive maintenance to reduce these delays.
- Overall Asset Performance Evaluation: Maintenance strategies were found to positively impact asset uptime, with preventive and predictive maintenance reducing downtime. Reactive maintenance, however, contributed to unplanned losses and performance degradation. Unplanned losses were linked to service delays and equipment unavailability, affecting overall performance, particularly during peak periods.
- Relationship Between Maintenance and Performance: Preventive maintenance was crucial but often delayed by resource shortages, while predictive maintenance showed promise but suffered from data gaps and lack of expertise. Corrective maintenance, though essential for emergencies, resulted in higher costs and inefficiencies, emphasising the need for better planning and resource allocation.

4.4. Maintenance Strategy Effectiveness

The analysis indicated that the current preventive maintenance strategy applied uniformly across all assets may not be suitable for all stages of the asset lifecycle. Key observations from the case study included:

- Tailored maintenance tactics were associated with a reduction in downtime of approximately 30%.
- Preventive maintenance appeared to be more effective when aligned with the asset's specific lifecycle stage.
- Predictive strategies and real-time condition monitoring demonstrated performance improvements when compared to traditional reactive maintenance methods.

These findings suggest that lifecycle-aligned maintenance strategies can improve operational performance and reduce equipment downtime. The integration of predictive tools and real-time monitoring supports a more proactive, data-driven maintenance approach.

Maintenance interventions based on lifecycle phase and risk profile were associated with improved reliability, reduced unplanned downtime and potential extension of asset lifespan. The results support further development of a Lifecycle-Based Asset Management (LBAM) approach, including prioritisation of critical assets and adoption of Risk-Based Maintenance (RBM) to optimise resource allocation and cost efficiency. Overall, the findings are consistent with existing literature, particularly regarding early-life and wear-out failure patterns (Kolehmainen, 2021) and align with Asset Management Optimisation (AMO) principles that promote integrated preventive and predictive maintenance strategies tailored to asset conditions.

5. Conclusion and Recommendations

The implementation of lifecycle-based maintenance strategies resulted in measurable operational improvements, including an estimated 30% reduction in downtime and improved alignment between maintenance activities and asset reliability behaviour. Weibull modelling identified assets operating in wear-out phases ($\beta > 1$), supporting proactive maintenance planning and targeted replacement decisions. These results demonstrate the value of integrating lifecycle-based reliability modelling into maintenance management.

The findings also indicate benefits from predictive maintenance technologies such as vibration analysis, oil analysis and infrared thermography for early fault detection and reduced failure risk. Enhancing workforce capability through training in early fault recognition can further minimise unplanned downtime. The use of key performance indicators (KPIs) is recommended to support performance monitoring and continuous improvement. Overall, transitioning from uniform preventive maintenance to lifecycle-based strategies supported by predictive monitoring can enhance asset reliability and operational efficiency. Further validation through wider implementation is recommended. Based on the study's findings, the following recommendations are proposed:

- Develop maintenance schedules aligned with asset lifecycle stages to improve maintenance effectiveness.
- Integrate predictive tools such as vibration analysis, oil analysis and infrared thermography to support early fault detection.
- Train shift teams in early failure detection and basic maintenance practices to reduce unplanned downtime.
- Establish well-defined KPIs to monitor maintenance effectiveness and support continuous improvement.

Limitations of the Study

- The study depended on the availability and quality of historical maintenance and failure data; incomplete or inconsistent records may affect the accuracy of Weibull modelling and lifecycle predictions.
- The findings are based on a single wet concentrating plant, which may limit generalisation to operations with different equipment, conditions, or maintenance practices.
- The analysis focused on selected critical assets due to data availability and operational priorities; broader datasets and longer observation periods could provide more comprehensive reliability insights.

Despite these limitations, the study provides a foundation for lifecycle-based maintenance optimisation and highlights the importance of reliable data systems in supporting predictive maintenance. The proposed framework may also be adapted to other asset-intensive industries such as manufacturing, energy and processing operations.

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Biographies

Shoni Whitney Mathivha is a Professional Certificated Engineer (Pr.Cert. Eng) registered with the Engineering Council of South Africa and holds Government Certificates of Competency (GCC) for Mines and Works as well as Factories. She is a member of the Association of Mine Resident Engineers (AMRE) and the Southern African Asset Management Association (SAAMA). She has over 12 years of experience in maintenance, reliability engineering, physical asset management, project management and change management across mining and processing operations. She holds a Master of Philosophy in Engineering Management, a Diploma in Corporate Governance and is currently pursuing a Doctor of Philosophy in Mechanical Engineering. Her work focuses on the application of reliability engineering principles to maintenance and operational practices, supported by data-driven methodologies such as condition monitoring, root cause failure analysis and predictive maintenance techniques. Her research interests include reliability engineering, maintenance optimisation, Weibull analysis and asset lifecycle management. She is engaged in academic research on the impact of asset tactics on the overall asset performance, based on a mining case study.

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Prof Dr Leon Pretorius has over 45 years of academic and professional experience. He served as Dean of Engineering at Rand Afrikaans University and Executive Dean at the University of Johannesburg. He is currently Professor Emeritus at the University of Pretoria and a research supervisor at multiple institutions. He has supervised over 270 postgraduate students, including 69 PhDs, examined more than 30 doctoral theses internationally and authored over 350 peer-reviewed papers. He serves on international editorial boards and is an Honorary Fellow of SAIMechE and Fellow of SAIIE and IAMOT.