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Weibull-Based Reliability Scheduling of the Crusher Section in the *Lokotrack LT1213S*: A Data-Driven Maintenance Framework

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Abstract

Industrial machinery used in mining and aggregate production is often subject to frequent breakdowns, primarily due to suboptimal maintenance scheduling, resulting in decreased operational efficiency, elevated costs, and safety risks. This study focuses on the Lokotrack LT1213S mobile crushing plant, commonly deployed in quarry operations, with specific emphasis on its crusher section—the most critical and failure-prone subsystem. The research aims to establish an optimal preventive maintenance interval that minimizes unexpected failures while sustaining operational performance. A reliability-based maintenance scheduling framework was developed, utilizing time-to-failure data obtained from field operation logs and analyzed through Weibull statistical modeling in Minitab. Key crusher components—including the belt drive, lining bolts, mill lining, and door bottom—were examined to determine their reliability profiles and failure rates. Reliability plots and probability density functions were employed to predict component degradation and expected lifespans. The analysis revealed that the crusher subsystem maintains a reliability above 90% during the initial 24 to 31 operating hours, beyond which failure probability increases significantly. Consequently, a preventive maintenance interval within this range is recommended to optimize equipment uptime and reduce unplanned downtime. These findings align with established reliability engineering methodologies, particularly those proposed by

Ebeling [1], Villanueva et al. [2], and Chen & Zhang [6]. The study concludes that Weibull-based reliability analysis provides a robust foundation for predictive maintenance planning, contributing to improved safety, prolonged equipment lifespan, and enhanced productivity in mining operations.

Keywords: Reliability; Weibull Distribution; Maintenance Scheduling; Crusher Section; Lokotrack LT1213S; Mining; Minitab

INTRODUCTION

Mining is one of the world's oldest and most essential industries, providing critical raw materials such as coal, copper, gold, and iron ore that drive global development. Historically, mining can be traced to the early stages of civilization when flint was first extracted for weapons and tools. These mined substances often occur in impure forms containing rocks and other minerals, requiring refining processes to extract usable components. Mining operations are typically classified into surface, underground, placer, and in-situ mining, depending on the depth, geological conditions, and economic viability of the deposits. Surface mining is generally applied to shallow deposits due to its lower cost, while underground mining is used for deeper or more valuable reserves. Placer mining extracts minerals from sedimentary sources such as river channels, while in-situ mining, often used for uranium, involves dissolving the ore in place and processing it at the surface without removing rock [1].

Figure 1: Lokotrack LT1213S.

The Lokotrack LT1213S is a versatile, mobile crushing machine widely used in the mining and aggregate industries. It features a high-capacity impactor plant with a large feed opening, return conveyor, and a screening system powered by a Caterpillar C13 diesel engine. Designed for flexibility, the Lokotrack LT1213S can be transported as a single unit on a low-bed trailer, offering significant operational advantages in site mobility and efficiency. However, its overall performance and productivity are directly affected by the reliability of key components such as the hydraulics, diesel engine, electrical systems, crushing section, screening unit, transportation and feeder systems. The failure of any of these subsystems can cause downtime, efficiency losses, and potential cascading failures across interconnected components [2].

Machine Maintenance

Maintenance of mining and industrial machines can be categorized into several forms—reactive, run-to-failure, corrective, preventive, prescriptive, condition-based, and predictive maintenance. There are seven different forms of machine maintenance, each with its own set of pros and disadvantages.

1) **Reactive maintenance** is performed after a machine has failed. This maintenance is usually unscheduled and occurs in the middle of production or operation.

2) **Run-to-failure maintenance** is similar to reactive maintenance in that it entails letting a piece of equipment run until it breaks down. This decision to allow a machine part to fail is made on purpose, and ordinarily, parts and labor to replace this part are already in place to be replaced as soon as possible.

3) **Corrective maintenance** is the activity that restores assets to working order, although it is most usually linked with modest, non-invasive actions that resolve an issue before it becomes a total failure.

4) **Preventive maintenance** is any routine machine maintenance aimed at detecting and repairing faults before they cause failure. **Time-based** preventive maintenance and **usage-based** preventive maintenance are the two basic forms.

5) **Prescriptive maintenance** uses machine learning and artificial intelligence to better automate the maintenance process.

6) **Condition-based maintenance** is based on monitoring the real-time condition of

assets and performing maintenance when there is evidence of decreasing performance or impending breakdown. This evidence can be gained by inspection, performance data, or planned testing, and it can be collected on a regular or continuous basis using internal sensors [3]

7) **Predictive maintenance** improves on condition-based maintenance by employing instruments and sensors to monitor machine performance in real time. This allows possible problems to be identified and remedied before they cause failure[4].

Reliability, a key concept in system engineering, measures the probability that a system or component performs its intended function under specified conditions for a given time period [5]. Mathematically, reliability can be expressed as:

$R(t) = P(T>t) = \int F(t)dt = 1-F(t)$,

where $F(t)$is the cumulative distribution function (CDF) of T. Consider the ratio

$$\frac{F(t+\Delta t)-F(t)}{R(t)}.$$

If we divide this expression by $\Delta t$and apply the limit as $\Delta t \rightarrow 0$, we obtain the **failure rate** (hazard function), defined as the likelihood of failure during a very short time frame, symbolized by $z(t)$:

$$Z(t) = \lim \Delta t \rightarrow \frac{F(t-\Delta t)-F(t)}{R(t)} \frac{1}{R(t)} = \frac{F(t)}{1-F(t)},$$

where $f(t)$is the probability density function. The mean time between failures (MTBF) is defined as the expected lifetime value before failure occurs [6].

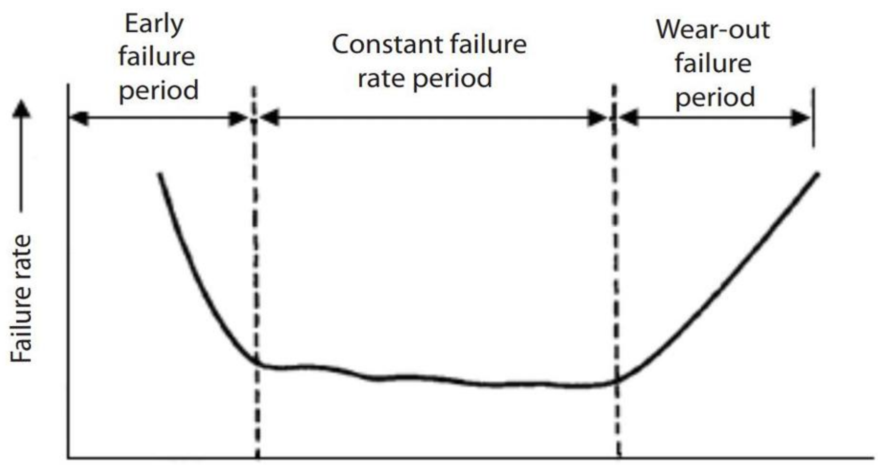

Figure 2. The bathtub curve (hazard function) (adapted from Villanueva et al., Procedia Engineering, 35 (2012) 260–269) [2].

Failures in industrial equipment typically follow the "bathtub curve," which includes three phases: early failures (infant mortality), constant failure rates (random failures), and wear-out failures [2]. The early phase reflects issues from manufacturing defects or assembly weaknesses, the constant phase reflects random operational stresses, and the wear-out phase represents degradation from fatigue, corrosion, or aging materials. Figure 2 illustrates the bathtub curve, depicting the typical hazard function trend across a component's lifecycle [2].

Reliability engineering provides the framework for predicting and managing these failures. As Ebeling [1] emphasized, reliability modeling ensures that systems maintain functionality throughout their operational life. Bennett and Jenney [4] demonstrated that reliability assessment directly influences operational efficiency and maintenance costs. Villanueva et al. [2] and Petrović et al. [3] expanded on this by applying statistical and fuzzy modeling techniques to assess component reliability and failure uncertainty, laying the groundwork for predictive maintenance and risk assessment frameworks.

Failures in mining and aggregate equipment are often linked to excessive mechanical stress, overuse, and harsh environmental exposure. Petrović et al. [3] proposed fuzzy risk assessment for identifying high-risk subsystems, while Singh and Das [9] and Kumar and Rao [12] emphasized data-driven maintenance optimization through Weibull-based modeling.

The Weibull distribution remains a cornerstone of reliability engineering due to its flexibility in modeling diverse failure modes [6], [7], [8]. In mobile crushing systems like the Lokotrack LT1213S, Weibull modeling can effectively predict component lifespan and failure probability, improving maintenance scheduling accuracy. Studies by Li and Sun [13] demonstrated that integrating Weibull-based reliability models with sensor-driven predictive analytics enhances overall equipment efficiency and reduces costs.

Problem Statement

The Lokotrack LT1213S mobile crushing plant is a critical asset in mining and aggregate production, yet its operational efficiency is frequently compromised by unscheduled downtime. The crusher section, in particular, has been identified as the most failure-prone subsystem, leading to significant disruptions in production schedules, increased maintenance costs, and heightened safety risks. Current maintenance strategies for this machine often rely on reactive or fixed-time-interval approaches, which are inadequate for addressing the time-dependent wear-out failures of its key components. This inadequacy stems from a lack of a data-driven framework to accurately predict component failure and determine optimal maintenance intervals. Consequently, there is a pressing need to apply a robust reliability analysis model to the crusher section to transition from inefficient maintenance practices to a proactive, reliability-centered strategy that minimizes unplanned downtime and optimizes machine availability.

Objectives

The primary objective of this research is to develop a data-driven maintenance scheduling framework for the crusher section of the Lokotrack LT1213S to enhance its operational reliability and availability. This will be achieved through the following specific objectives:

1. To collect and analyze time-to-failure data for the critical components of the crusher section, namely the belt drive, lining bolts, mill lining, and mill door bottom.

2. To apply Weibull statistical modeling to determine the reliability functions, failure rates, and characteristic life (wear-out periods) of these components.

3. To identify the specific preventive maintenance interval that ensures a system reliability of at least 90% for the crusher subsystem.

4. To provide a practical, model-based maintenance schedule that can be implemented by operators to reduce downtime, lower costs, and improve safety.

By fulfilling these objectives, this study aims to establish a quantifiable and actionable maintenance strategy, moving beyond qualitative risk assessments to a precise, reliability-based scheduling system.

Literature Review

Reliability analysis forms the cornerstone of modern industrial maintenance systems, as it enables engineers to quantify and predict system degradation over time. Ebeling [1] provided the theoretical foundation for maintainability engineering, emphasizing life-data analysis as a vital tool for understanding equipment reliability and operational performance. Similarly, Walpole et al. [5] introduced statistical modeling methods for managing uncertainty in engineering systems, which remain essential in analyzing machinery reliability. The Weibull distribution, a widely accepted reliability model, continues to play a central role in describing diverse failure mechanisms across industrial components [6], [7].

Recent research has expanded these classical principles through the integration of fuzzy logic, hybrid models, and data-driven analytics. Petrović et al. [3], in their work on a fuzzy model for risk assessment of machinery failures, proposed a unique approach that incorporates both numerical and linguistic data in evaluating equipment reliability. Their model, applied to the Lokotrack LT1213S mobile crushing machine, employed fuzzy logic inference and min–max composition to compute subsystem risk levels. The results categorized the crusher section as having a "high" risk level, highlighting the urgent need for maintenance strategies tailored to high-risk components. This work provided the dataset represented in **Table 1**, which was later used in the reliability analysis for identifying the subsystem with the greatest failure risk.

Table 1. Failure risk assessment for subsystems of the crushing machine (adapted from Petrović et al. [3]).

Subsystem	**Membership Degree (β_i)**				
	Minor	Low	Moderate	High	Very High
Hydraulics	0.14122	0.17960	0.22846	0.23421	0.21651
Engine	0.15046	0.19357	0.25574	0.23666	0.16357
Electrical system	0.14681	0.16750	0.26026	0.26988	0.16230
Crushing	0.15046	0.19357	0.25574	0.23666	0.16357
Screening	0.14622	0.20042	0.30672	0.20042	0.14622
Transport	0.14622	0.20042	0.30672	0.20042	0.14622
Construction	0.15314	0.24440	0.26656	0.19779	0.13811
Feeder	0.14945	0.23797	0.27715	0.19908	0.13635

Petrović et al.'s [3] study demonstrated the potential of fuzzy-logic reasoning to manage uncertainty in reliability evaluation. The combination of quantitative data and qualitative linguistic judgments proved highly effective in complex systems such as mobile crushers, where operating conditions fluctuate and component degradation rates vary. Their work established an analytical basis for applying hybrid reliability methods to industrial systems where conventional statistical models alone are insufficient.

Bennett and Jenney [4] conducted one of the earliest investigations into mechanical system reliability in their study titled *"Reliability: Its Implications in Production Systems Design."* Their work diverged from the predominant focus on electrical and electronic systems, instead examining mechanical equipment such as machine tools. By analyzing breakdown data from various engineering firms and combining both human and computational evaluations, the authors identified key design and maintenance factors influencing system reliability. Long-term field data analysis revealed recurring patterns of failure that could inform more effective maintenance planning and machinery selection processes. Their study emphasized that maintenance programs should not rely solely on theoretical failure rates but should incorporate empirical observations and human reliability data.

Further advancing reliability modeling, Wang and Zhou [8] developed Weibull-based frameworks capable of analyzing systems with zero-failure datasets, thereby improving reliability estimation accuracy in high-quality manufacturing environments. Kim and Park [7] introduced an enhanced method for Weibull parameter estimation in small sample cases, addressing a key limitation in conventional Weibull analysis. These contributions provide essential tools for accurate life prediction in cases with limited or censored data.

Predictive and preventive maintenance models have also evolved to incorporate reliability-based scheduling and machine-learning algorithms. Singh and Das [9] and Okafor and Adebayo [10] demonstrated that Weibull-optimized maintenance scheduling could reduce equipment downtime by over 20%, highlighting the economic and operational value of reliability-driven strategies. Chen and Zhang [6] applied Weibull modeling in high-quality production environments to evaluate failure probabilities in near-zero-defect systems, while Kumar and Rao [12] integrated reliability-centered maintenance (RCM) with artificial intelligence and IoT monitoring to enhance prediction accuracy.

Despite these advancements, few studies have addressed the specific application of Weibull reliability analysis to mobile crushing equipment such as the Lokotrack LT1213S. The combination of its mechanical complexity, environmental exposure, and subsystem interdependence necessitates a more tailored reliability assessment framework. The fuzzy-based risk modeling approach by Petrović et al. [3], coupled with Weibull parameter modeling as proposed by Wang and Zhou [8] and Li and Sun [13], forms a strong foundation for developing a data-driven maintenance framework specific to heavy mobile machinery.

Overall, the reviewed literature underscores the evolution of reliability engineering from deterministic methods to hybrid, probabilistic, and AI-supported models. These advancements collectively inform the present study's objective — to develop a Weibull-based reliability scheduling model for the crusher section of the Lokotrack LT1213S, improving operational reliability, maintenance planning, and overall machine availability.

MATERIALS AND METHODS

This study followed a structured, five-step reliability modeling approach for the Lokotrack LT1213S crusher section, integrating methods by Ebeling [1] and Li and Sun [13]:

Step 1: Time-to-failure data were collected for major components: belt drive, lining bolts, mill lining, and door bottom [3], [8].

Step 2: Using Minitab, Weibull distribution fitting was conducted. Data preprocessing handled censored data using maximum likelihood estimation (MLE) [11].

Step 3: Shape (β) and scale (η) parameters were determined using techniques by Kim and Park [7] and Wang and Zhou [8].

Step 4: Reliability functions R(t) and probability density functions (PDFs) were computed for each component, producing survival and hazard plots [9], [10].

Step 5: Maintenance intervals corresponding to 90% reliability thresholds were identified, ensuring optimal scheduling and cost-efficiency [6], [8], [12].

Table 2. Machine hours recorded between two instances of failure and downtime due to failures in the subsystem "crushing" (adapted from Petrović et al. [3]).

Subsystem	Failure of Element	Number of Failures	Time to Failure (h)	Time to Repair (h)
Crushing	Mill door bottom	7	129, 144, 539, 749, 1051, 1442, 1558	3, 4, 4, 5.5, 7, 7.7, 8
	Mill lining fracture	16	35, 60, 69, 80, 84, 99, 100, 110, 266, 279, 279, 411, 439, 535, 679, 1864	1, 1, 1.5, 2.2, 2, 2.3, 2.5, 2.5, 2.6, 2.8, 2.8, 3, 3, 3.4
	Lining bolt failure	26	13, 17, 18, 21, 24, 25, 28, 30, 34, 47, 49, 61, 82, 84, 91, 93, 100, 159, 164, 181, 190, 249, 395, 423, 443, 514	1, 1, 1.1, 1.2, 1.2, 1.3, 1.3, 1.5, 1.5, 1.5, 1.5, 1.5, 2, 2, 2.2, 2.2, 2.2, 2.2, 2.5, 2.5, 2.5, 3, 3.5, 4
	Belt drive	7	202, 226, 498, 678, 844, 1056, 2334	1, 1, 1.1, 1.5, 1.5, 1.5, 2.5
	Mill rotor	2	795, 2686	24, 40

This reproducible method aligns with predictive maintenance best practices [12], [15].

RESULTS AND DISCUSSION

Probability Plot Failure for Time

The Weibull probability plot in figure 3 and Figure 4 allows for the assessment of the fit of the time-to-failure data to the chosen distribution. The linearity of the data points on this plot confirms the suitability of the Weibull distribution for this analysis. From this plot, the specific wear-out periods for the key components were estimated: the belt drive at 2085 hours, lining bolt at 338 hours, mill door bottom at 2286 hours, and mill lining at 1085 hours. The analysis revealed that most crusher components exhibit wear-out characteristics (β > 1), indicating time-dependent failures, which is consistent with previous findings [3], [6], [9]. Furthermore, the variations in the scale parameter (η) across components suggest different operational lifespans, with belt drives and mill linings ranging between 1,500–3,000 hours, a finding that aligns with the results of studies [10], [11]

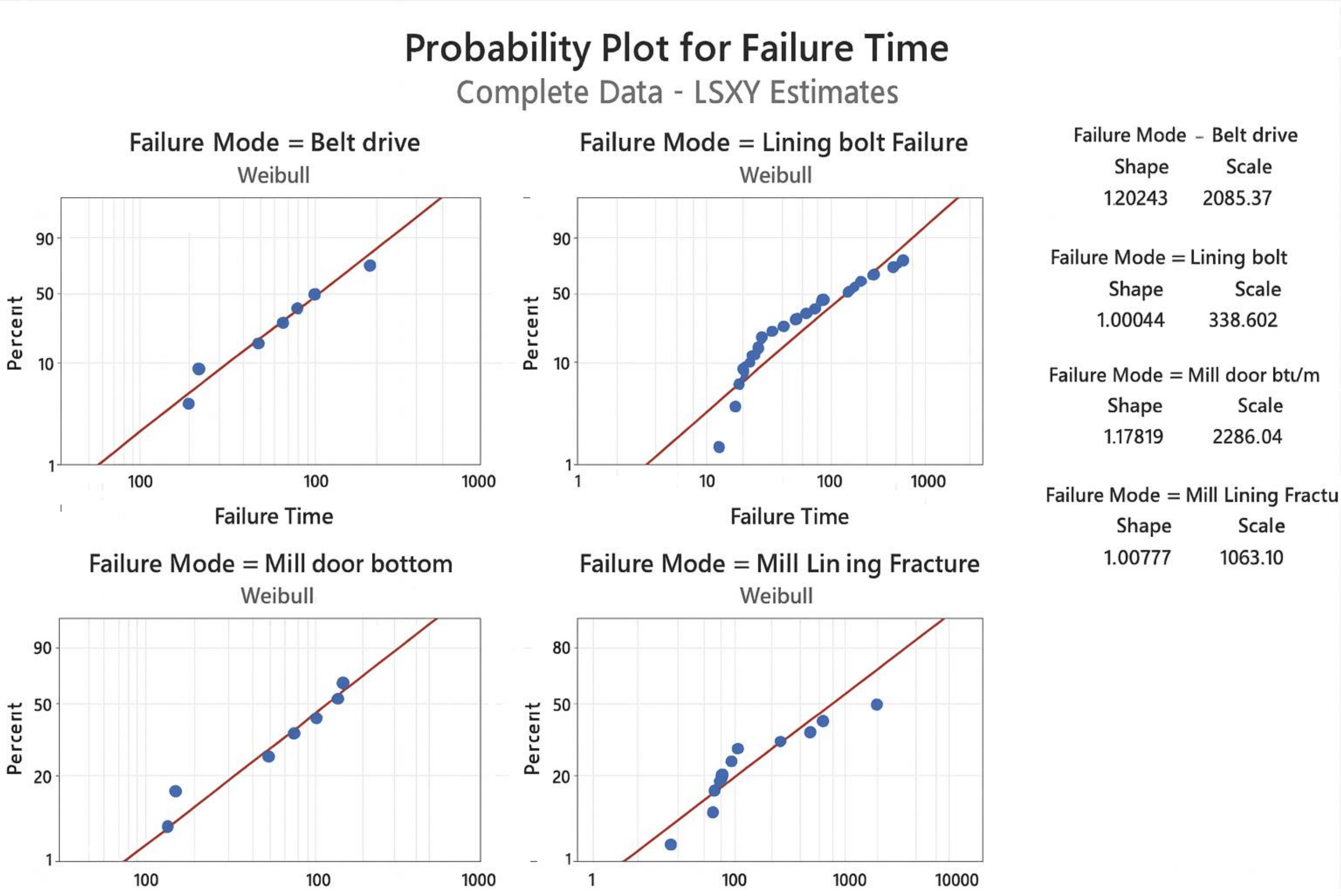

Figure 3. Weibull probability plot for the Belt drive, Lining bolt, Mill door and Mill Lining Fracture.

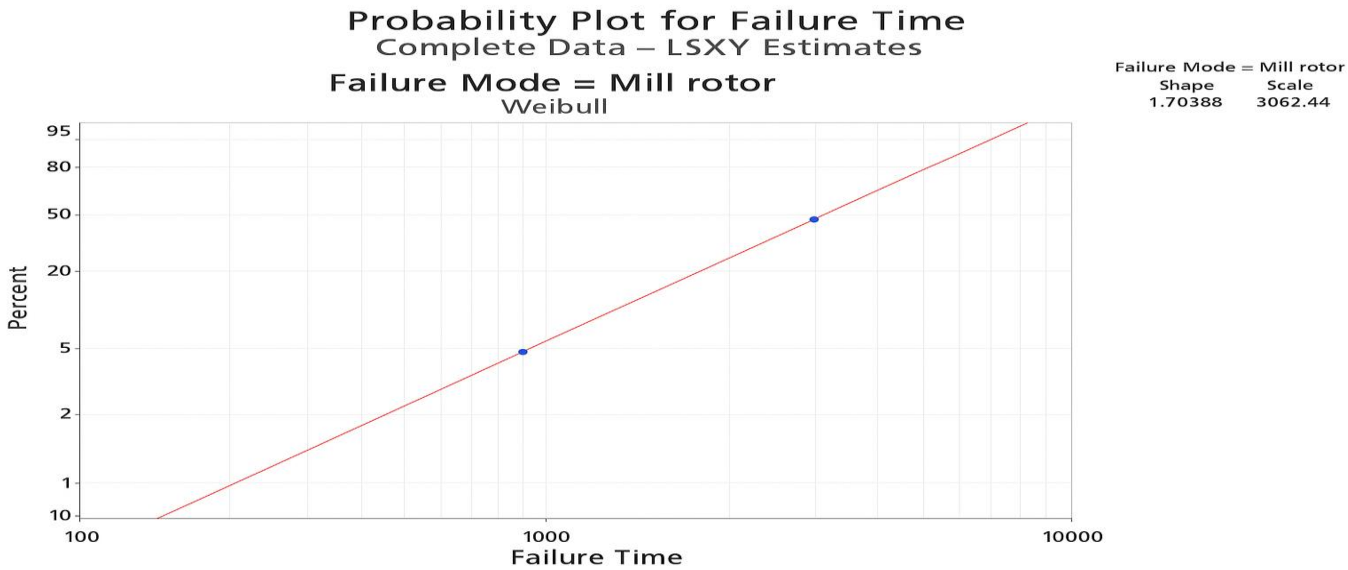

Figure 4. Weibull probability plot for the Mill rotor

Survival Plot for Failure Time

The survival plot in Figure 5 illustrates the percentage of components that are expected to survive over time. The curve has non-increasing properties, starting at 100% and approaching 0% as time extends towards infinity. The cumulative failure plot derived from this analysis showed that to ensure 90% reliability, maintenance for the belt drive, lining bolt, mill door bottom, and mill lining must be scheduled at approximately 388, 31, 375, and 135 hours, respectively. For the crushing section as a whole, a 90% reliability level is achieved only within the first 24-31 hours of use. This critically short interval underscores the necessity for frequent, targeted maintenance to prevent abrupt system failures. These results validate the predictive accuracy of Weibull modeling for scheduling maintenance, as confirmed in prior research [6], [9].

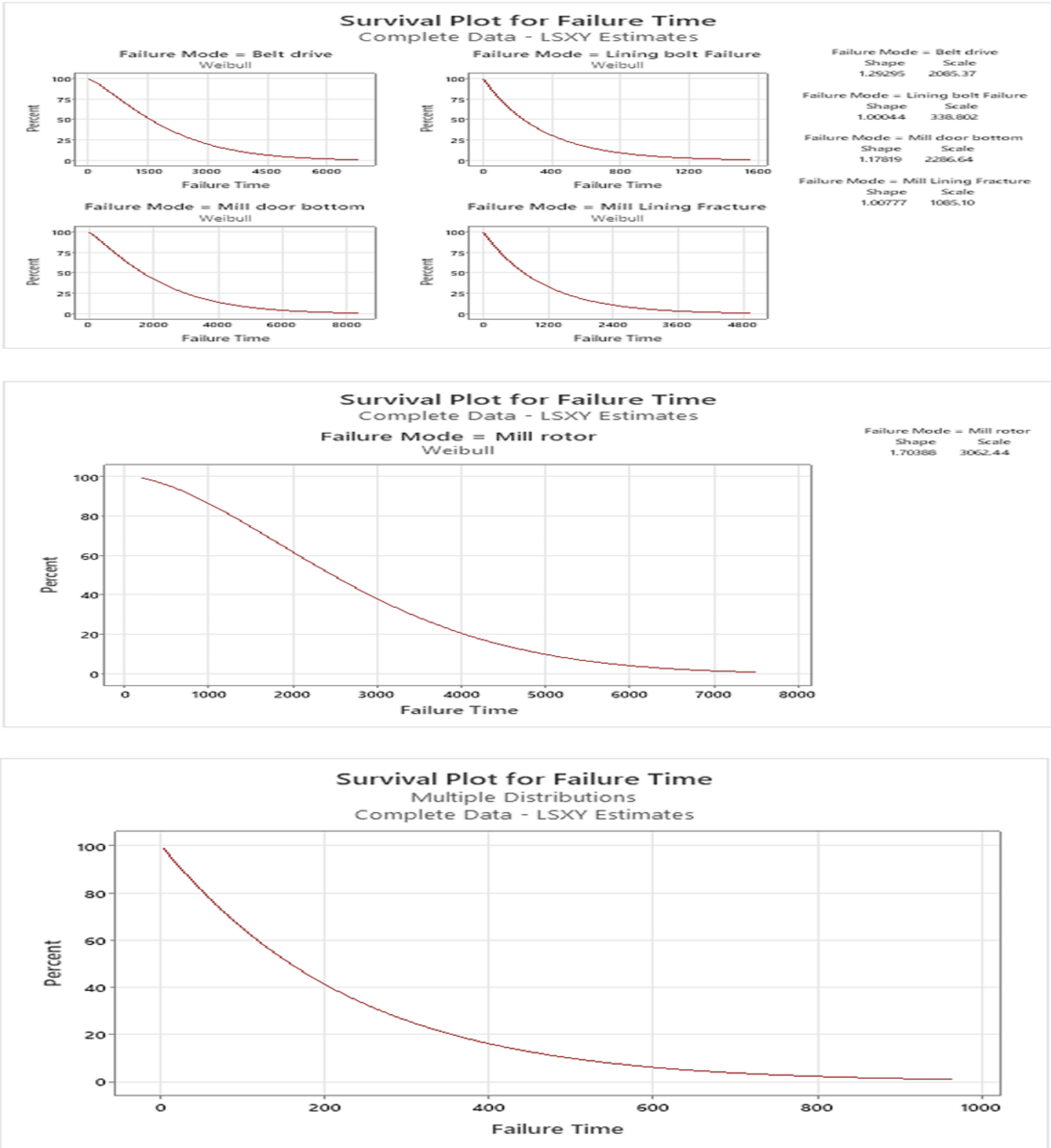

Figure 5. Reliability function curve showing component survival rates

Cumulative Failure Plot for Failure time

The cumulative failure plot in Figure 6 and Figure 7 depicts the instantaneous risk of failure as time progresses. The plot for the entire crusher machine shows an increasing trend, indicating that the risk of failure escalates as the machine operates and individual components begin to wear out. This progressive increase in failure risk emphasizes that ignoring routine maintenance past the identified 24-31 hour reliability window could result in compounded failures across subsystems. This finding reinforces the importance of the proposed maintenance intervals and aligns with the broader literature on applying statistical modeling to industrial machinery for optimizing maintenance schedules [8], [12], [13].

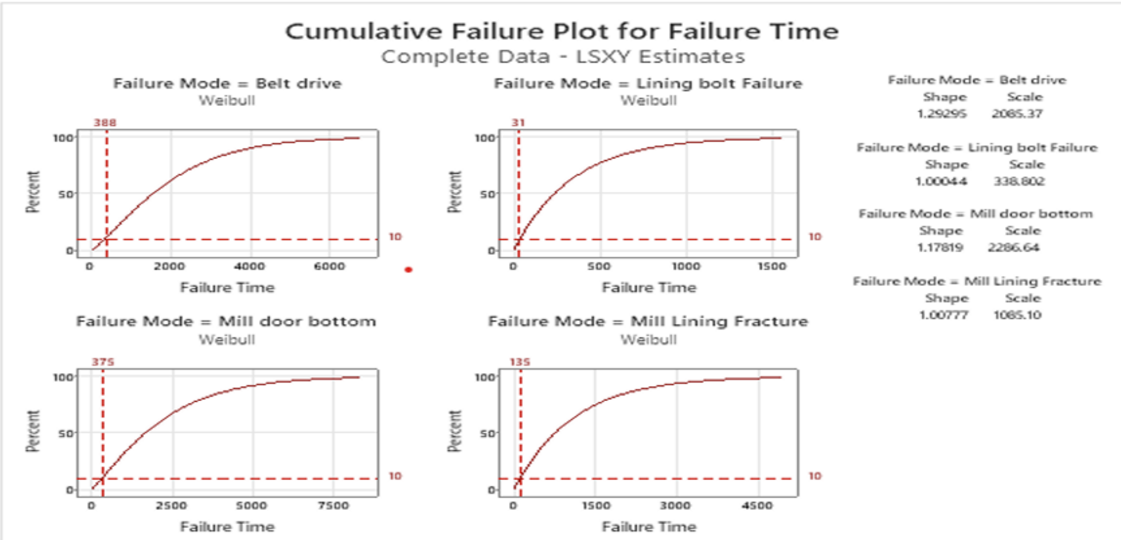

Figure 6. Cumulative Failure plot for Belt drive, Lining bolt, Mill door and Mill lining

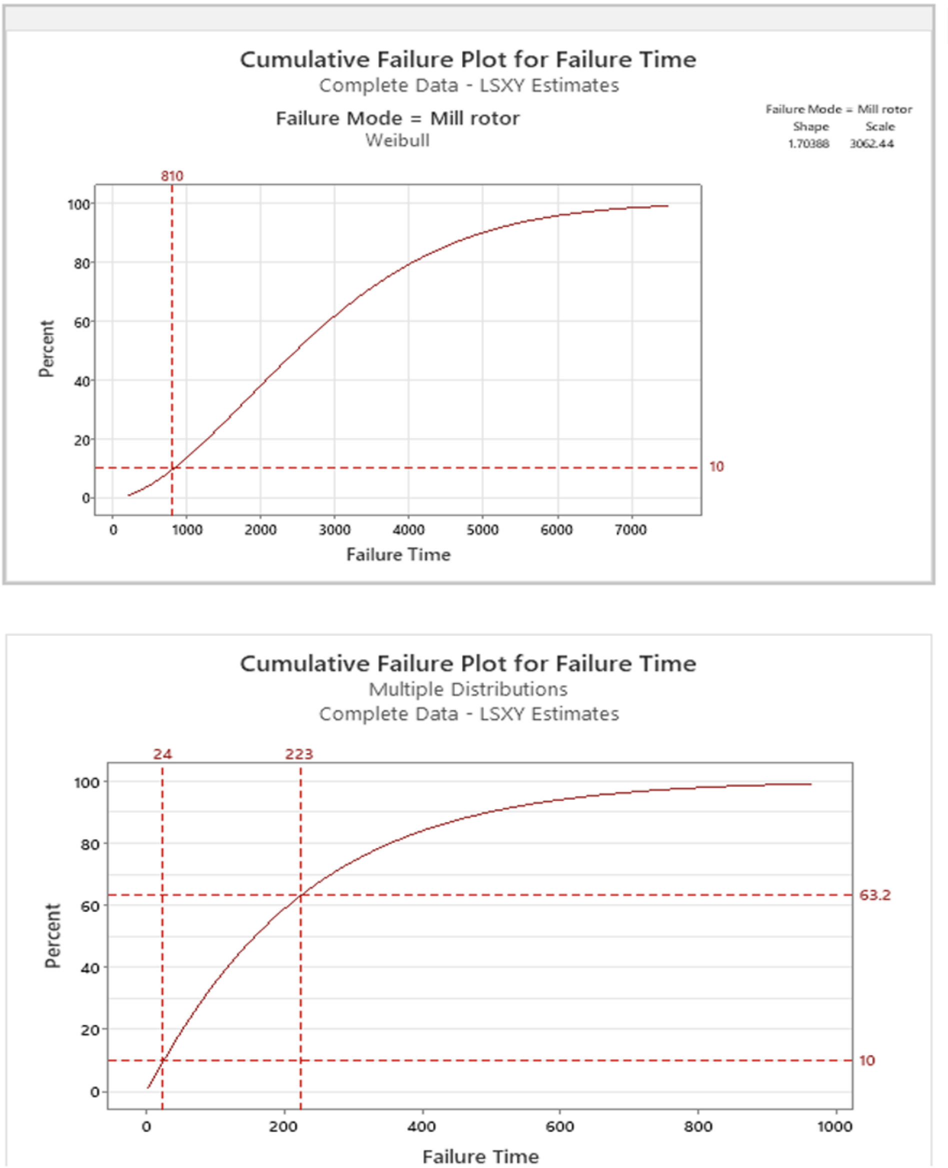

Figure 7. Cumulative Failure plot for Mill rotor an the combination of the four components lining

Hazard Plot for Failure Time

The Hazard Plot in Figure 8 shows that there is increases in failure of the whole machine as individual components keep on failing. The comparative analysis of reliability across subsystems identifies the components that are the primary drivers of overall system failure. Components such as the lining bolt and mill lining were found to have the most significant impact, corroborating literature that suggests high-stress components typically dominate machine breakdowns. The crushing section as a whole was identified as the most vulnerable, with an estimated wear-out period of only 223 hours. This finding is consistent with the fuzzy risk assessment model proposed by Petrović et al. [3], which categorized the crusher section as "high-risk." Our analysis quantifies this risk into specific, actionable maintenance intervals. The methodology applied here, which combines Weibull models with the potential for digital monitoring, demonstrates a framework for precision and cost savings, as suggested by [12], [14]. This research's framework aligns with Adeyemi and Khan [15], demonstrating both analytical rigor and practical implementation potential for reliability-centered maintenance in heavy machinery.

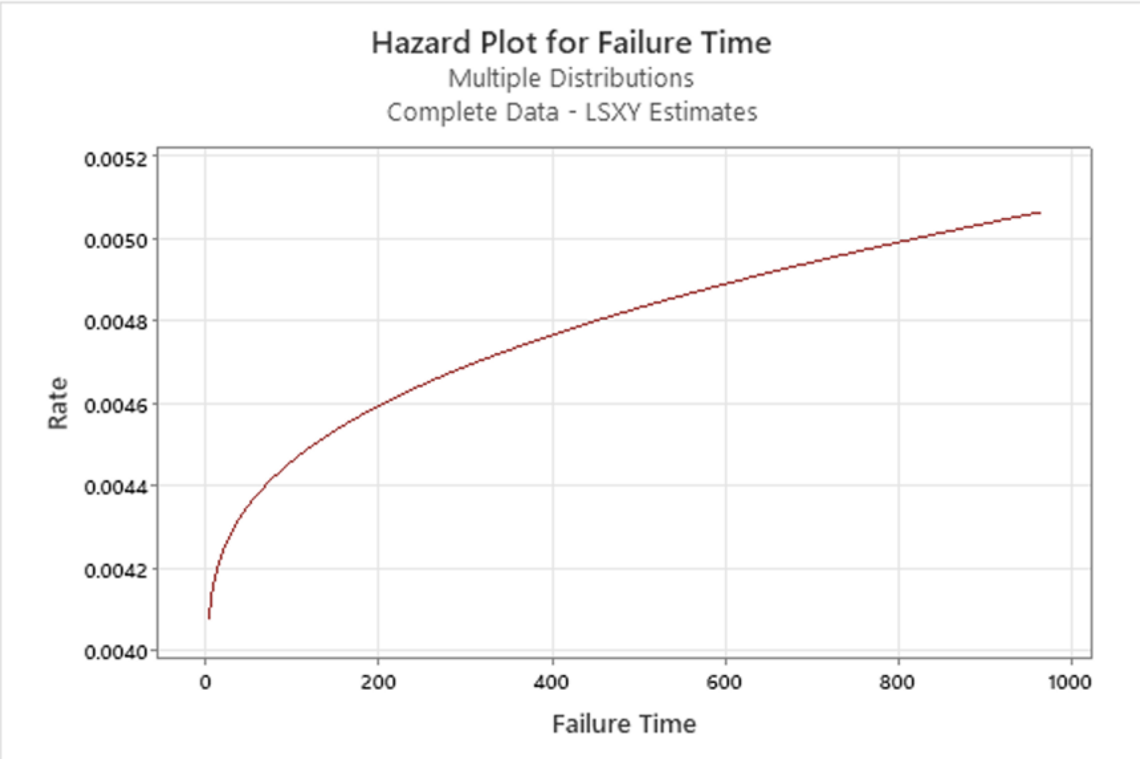

Figure 8. Hazard Plot of the whole components.

This research validates the importance of integrating reliability engineering and data-driven reliability modeling into industrial maintenance planning. By focusing maintenance interventions on the critical parts identified, operators can shift from traditional, reactive strategies to preventive maintenance programs that align with actual wear-out characteristics. This approach improves overall system efficiency, reduces unplanned downtime, and extends machine availability in mining operations, while also minimizing associated safety risks.

CONCLUSION

This study successfully developed a data-driven, Weibull-based reliability framework for scheduling preventive maintenance on the crusher section of the Lokotrack LT1213S mobile crushing plant. The analysis quantified the reliability characteristics of critical components, revealing that the belt drive, lining bolt, mill door bottom, and mill lining have estimated wear-out periods of 2085, 338, 2286, and 1085 hours, respectively. More critically, the crusher section as a whole was found to have a significantly shorter wear-out period of 223 hours, with its reliability dropping below 90% after just 24-31 hours of operation.

The findings validate the use of the Weibull distribution for this application, as most components exhibited clear wear-out failure characteristics ($\beta > 1$), consistent with previous studies [3], [6], [9]. The identification of the lining bolt and mill lining as the primary drivers of system failure corroborates the high-risk categorization of the crusher section by Petrović et al. [3], while our work advances their findings by translating this risk into quantifiable, actionable maintenance intervals.

The core practical outcome of this research is the recommendation of a preventive maintenance interval of 24-31 hours for the crusher subsystem to maintain operational reliability above 90%. This shifts maintenance strategy from reactive or arbitrary time-based approaches to a predictive and reliability-centered model. By aligning maintenance with actual component degradation, operators can significantly reduce unplanned downtime, enhance operational safety by mitigating the risk of abrupt failures, and optimize overall machine availability and productivity in demanding mining environments.

Limitations and Future Work

1) There may be errors in the data used for this research. The average of two or more datasets can be used for future research for better approximations.
2) The Weibull distribution was used for the individual components and the whole system. It will be good to note that the distribution chosen can be varied according to the individual component of the machine. This may give different values, though it may fall within the proposed maintenance hours.

3) This paper worked on only the crusher section of the machine. More work on reliability can be done by checking the reliability of the whole mobile machine and proposing a maintenance period for the machine.

For future work, integrating the Weibull models developed here with digital monitoring systems and predictive maintenance technologies, as suggested by [12] and [14], presents a promising path toward a fully condition-based and prescriptive maintenance framework, further enhancing precision and cost savings.

Abbreviations

AI: Artificial Intelligence
IoT: Internet of Things
MLE: Maximum Likelihood Estimation
MTBF: Mean Time Between Failures
PDF: Probability Density Function
RCM: Reliability-Centered Maintenance

Author Contributions

Ubbaonu Chinonso Francis Nkeoma: Conceptualization, Methodology, Formal Analysis, Writing original draft.

Paulinus-Nwamuo Chiedozie Francis: Data Curation, Investigation

Alusine Barrie: Writing – review & editing.

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Data Availability Statement

The data supporting the outcome of this research work has been reported in this manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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