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Optimization of Operational Risk in Ecuadorian Mining Using FMEA and Weibull Distribution to Reduce Critical Equipment Failures

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Abstract
Designing and implementing a preventive maintenance plan in the Ecuadorian mining industry requires systematic methodologies to reduce failures in crushing and grinding machines, improving operational availability and productivity. The main problem identified is reliance on corrective maintenance, with no historical failure records, which causes unexpected shutdowns. This study applies the FMEA (Failure Mode and Effects Analysis) methodology to evaluate the criticality of equipment using the Risk Priority Number (NPR), complemented with the Weibull distribution to model useful lifetimes. Key equipment such as the ball mill and jaw crusher at a mining beneficiation plant were analyzed. The results indicate that 25% of the subcomponents have NPR > 300 (unacceptable risk), mainly concentrated in structural elements subjected to severe operating conditions. A scenario analysis based on the fitted Weibull models and on reductions reported in the literature projects that implementation of the proposed preventive plan would reduce unplanned shutdowns by 40–50%, raising operational availability from the current 73% to approximately 90%; these figures are model-based projections and not post-implementation measurements. Weibull integration provides a robust statistical framework for the transition from reactive maintenance to predictive schemes, optimizing intervention intervals and extending the life of critical assets.

Keywords: *FMEA, Weibull, mining, operational risk, preventive maintenance, equipment reliability*

I. INTRODUCTION

The Ecuadorian mining industry plays a strategic role in the national economy, especially in the extraction and processing of metallic minerals such as gold, where crushing and grinding processes are critical for operational continuity. In this context, the high demand for machines and equipment, coupled with severe working conditions (dust, vibrations, variable loads), significantly increases the probability of failures, generating unforeseen downtime that reduces productivity and raises operational costs (Feyen et al., 2015; Li et al., 2026) .

Many mining companies still maintain a heavy reliance on corrective maintenance, performing interventions only when the breakdown occurs, resulting in prolonged downtime, loss of production, and accelerated wear and tear of key assets. The absence of structured systems for the recording and historical analysis of failures limits the ability to predict and plan maintenance. Faced with this scenario, preventive maintenance management has established itself as an

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essential strategy to guarantee the availability, reliability, and useful life of equipment. Various studies indicate that the application of preventive maintenance plans significantly reduces failure rates, reduces repair costs, and improves operational safety in production lines intensive in mechanical equipment (Odeyar et al., 2022; Uribe, 2020).

In the context of mining and grinding processes, preventive maintenance acquires special relevance due to the central role of the ball mill and the jaw crusher, whose unavailability directly impacts productivity and the fulfillment of production goals. The implementation of structured plans, with schedules for inspection, lubrication, adjustments, and replacement of critical components, is good practice to avoid recurrent failures and extend the useful life of this equipment. In addition, technical literature emphasizes the need to complement preventive maintenance with analysis tools that allow resources to be prioritized according to the importance and risk associated with each asset (Flores et al., 2020).

Among these tools, the Failure Mode and Effect Analysis (FMEA) is used to identify failure modes, evaluate their severity, frequency of occurrence, and detection capacity, allowing maintenance actions to be focused on the most vulnerable components (Lu et al., 2025; Zhou & Zhang, 2025). The use of criticality matrices and strategy assignment models based on availability and risk makes it possible to prioritize teams and define preventive interventions proportional to risk. In this way, maintenance management is no longer a reactive activity, but a planned process aligned with productivity and operational continuity objectives (Quisigüiña et al., 2021; Shafiee et al., 2019; Barros Enriquez et al., 2023).

In the context of Ecuadorian mining, where operations are exposed to various operational uncertainties, it is essential to have robust methodologies to anticipate and mitigate risks. The Weibull distribution, known for its ability to model the lifetime of components and equipment under various operating conditions, plays a key role in estimating the probability of failure of critical systems. Its application in risk management allows for precise adjustment of the expected useful life of equipment, improved maintenance times, and reduced likelihood of catastrophic failures (Bifásico et al., 2024).

The main purpose of this study is to design and implement a preventive maintenance plan for crushing and grinding machines in the Ecuadorian mining industry, combining FMEA and Weibull analysis, with the aim of reducing failure rates, improving operational availability, and increasing production efficiency. Through the diagnosis of the current state of critical machines, the systematic evaluation of failure modes and the statistical modeling of lifetimes, a replicable methodology is proposed that transforms reactive schemes into preventive-predictive approaches (Sanabria et al., 2020).

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The contribution of this study is applied rather than methodological. Although the combined use of FMEA and Weibull analysis is well established in the maintenance engineering literature, three specific aspects are highlighted: (i) the application of an integrated FMEA–Pareto–Weibull framework in the context of small and medium-scale Ecuadorian mining, characterized by scarce historical failure records and severe operating conditions; (ii) a transparent and replicable procedure that links NPR-based risk prioritization with statistically modeled intervention intervals; and (iii) a quantified projection of the expected improvement in availability, which is presented explicitly as an estimate to be validated after implementation. The study should therefore be read as an applied reliability engineering case study rather than as a methodological advance.

II. METHODS AND MATERIALS

A. Research Design

A descriptive field study was carried out and applied directly in a processing plant of the Ecuadorian mining industry. The approach was mixed, combining quantitative analyses of historical operational data with qualitative assessments based on multidisciplinary expert judgment. The analysis period covered twelve-month failure records before the study, supplemented by on-site technical inspections(Barros Enriquez et al., 2023; Feyen et al., 2015). Population and study sample: 74 occurrences of failures recorded in equipment in the crushing and grinding area were analyzed, distributed in eight main machines: ball mill, jaw crusher, conical crusher, conveyor belts, sorting screen, agitation tank, oxygenation blower, and feeding cart. 20 failure modes were identified in critical components of the ball mill and jaw crusher (Chica-Castro et al., 2024).

Times to failure (TTF) were computed from the maintenance logs as accumulated operating hours between consecutive functional failures of the same equipment. Of the 74 recorded occurrences, n = 20 times to failure were used for the ball mill and n = 18 for the jaw crusher; the remaining events, distributed among the other six machines, were used only for the Pareto frequency analysis given their small per-equipment sample sizes. The operating period between the last failure and the end of the observation window was treated as a right-censored interval; however, it was not incorporated in the fit, since the standard maximum-likelihood implementation used assumes complete samples. This simplification may slightly underestimate the scale parameter and is acknowledged as a limitation. Failure events were assumed to be independent and identically distributed within each equipment; preventive interventions during the observation period were minimal, since the plant operated under a predominantly corrective scheme during the observation window. The limited sample size per equipment is acknowledged as a source of statistical uncertainty and is discussed in the limitations section.

B. Instruments and tools

Data collection and analysis were supported by several instruments designed to ensure systematic equipment identification, failure assessment, and reliability evaluation. Inventory sheets were used to record machines, equipment, and tools, with alphanumeric codes assigned to maintain traceability throughout the analysis. Machinery data sheets documented operational specifications, nominal capacities, and design conditions, while historical maintenance reports provided information on recorded failures, downtime, failure causes, and previous corrective actions. Failure prioritization was performed using a Failure Mode and Effects Analysis (FMEA) matrix, in which each identified failure mode was evaluated according to severity (S), occurrence (O), and detectability (D) on a 1–10 scale. Pareto analysis was subsequently applied to identify dominant failures based on their frequency of occurrence, whereas a criticality matrix provided a complementary two-dimensional assessment based on failure frequency and consequence. Weibull analysis software was used for probability distribution fitting and parameter estimation through the Maximum Likelihood Estimation (MLE) method. The instruments and their respective functions are summarized in Table 1.

Table 1. Data Collection and Analysis Instruments

Instrument	Main Function
Inventory Sheets	Recording machines, equipment, and tools using alphanumeric identification codes to ensure traceability.
Machinery Data Sheets	Documenting operational specifications, nominal capacities, and design conditions.
Historical Maintenance Reports	Providing historical data on failures, downtime, causes, and previous corrective actions.
FMEA Matrix	Identifying and prioritizing failure modes based on severity (S), occurrence (O), and detectability (D).
Pareto Chart	Identifying dominant failures according to their frequency of occurrence.
Criticality Matrix	Evaluating and prioritizing risks according to failure frequency and consequence.
Weibull Analysis Software	Fitting failure-time distributions and estimating Weibull parameters using Maximum Likelihood Estimation.

C. FMEA Methodology

The FMEA was conducted by a multidisciplinary team consisting of personnel with experience in equipment operation, maintenance, engineering, and supervision. This multidisciplinary approach was adopted to ensure that failure modes were evaluated from both operational and technical perspectives (Dai & Pang, 2025; Basel et al., 2025). The analysis began with a functional decomposition of the critical equipment into components and subcomponents. For each element, its primary function, potential failure modes, effects on the production process, and possible root causes were identified. Each failure mode was subsequently assessed using three conventional FMEA indices: severity (S), occurrence (O), and detectability (D). All indices were rated on a scale from 1 to 10. Severity represented the magnitude of the potential impact on safety, production, and cost; occurrence represented the probability of a failure mode arising under normal operating conditions; and detectability represented the ability of existing inspection or monitoring systems to identify the failure mode before functional failure occurred. The assessment framework is summarized in Table 2.

Table 2. FMEA Evaluation Criteria

Index	Assessment Focus	Scale
Severity (S)	Magnitude of the consequences for safety, production, and cost	1–10
Occurrence (O)	Probability or frequency of the failure mode under operating conditions	1–10
Detectability (D)	Ability of existing inspection and monitoring systems to detect the failure before functional failure occurs	1–10

The Risk Priority Number was calculated for each failure mode using Eq. (1).

$$NPR = S \times O \times D \qquad (1)$$

The S–O–D scoring system was calibrated using descriptive criteria adapted from standard automotive and industrial FMEA rating practices and adjusted to the operating conditions of the plant. Occurrence scores were linked to failure frequencies observed in the 12-month maintenance records, severity scores were related to downtime and safety consequences, and detectability scores reflected the effectiveness of existing inspection and monitoring practices. Scores were assigned through facilitated multidisciplinary discussions. When evaluator scores differed by more than two points, the corresponding failure mode was reviewed until consensus was reached. Formal inter-rater agreement statistics were not calculated; therefore, the consensus-based scoring process represents a methodological limitation. Although this procedure was intended to improve consistency, expert judgment remains partly subjective, as is generally the case with classical FMEA. The resulting NPR values were classified into three risk categories, as presented in Table 3.

Table 3. Risk Classification Based on NPR

Risk Category	NPR Range	Interpretation
Acceptable	NPR < 150	Risk can be maintained under existing controls
Acceptable Reduction	150 ≤ NPR < 300	Risk reduction measures should be considered
Unacceptable	NPR ≥ 300	Corrective or preventive intervention is required

The cut-off values of 150 and 300 were adopted from ranges commonly applied in maintenance engineering using 1–10 FMEA scales. An NPR of 300 or higher, approximately corresponding to average index values near seven, was considered indicative of an unacceptable operational risk. These thresholds were additionally checked against the plant's internal safety and production-loss considerations. Nevertheless, the thresholds are convention-based rather than derived from a formal quantitative risk-acceptance model. The classical multiplicative NPR also has recognized limitations because it assigns equal importance to severity, occurrence, and detectability, allows identical NPR values to result from different combinations of S–O–D scores, and mathematically treats ordinal scores as though they were ratio-scale measurements. Although fuzzy FMEA and weighted FMEA can address some of these limitations, the classical method was retained because of its transparency, its familiarity to plant personnel, and the limited data available for calibrating more complex models. To reduce the effect of these limitations, the resulting prioritization was cross-checked using Pareto analysis and the criticality matrix.

D. Pareto Analysis

Pareto analysis was performed to identify the equipment and failure modes responsible for the largest proportion of recorded failures. Following the Pareto principle, the analysis focused on identifying approximately 20% of equipment contributing to approximately 80% of failure occurrences. This approach enabled maintenance efforts to be concentrated on assets with the greatest influence on operational readiness (Wu et al., 2013). Failure frequencies obtained from historical maintenance records were ranked from the highest to the lowest and subsequently expressed as cumulative percentages. Equipment appearing within the dominant cumulative range was considered a priority for further reliability analysis and preventive maintenance planning.

E. *Weibull Modeling*

Weibull analysis was used to characterize equipment failure behavior and estimate reliability parameters. The Weibull distribution parameters were estimated using the Maximum Likelihood Estimation (MLE) method (Arturo & Manuel, 2024). The probability density function of the two-parameter Weibull distribution is defined as Eq. (2).

$$f(x;\lambda,k) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}\exp\left(-\left(\frac{x}{\lambda}\right)^{k}\right) \quad (2)$$

Where λ is the scale parameter (characteristic life), and k is the shape parameter, which determines the dominant failure pattern: $k < 1$ indicates infant mortality (early failures), $k = 1$ indicates random failures with a constant hazard rate, and $k > 1$ indicates wear-out (aging-related) failures. For observed failure times, the corresponding log-likelihood function was maximized to obtain estimates of and (Knežević et al., 2022) using Eq. (3).

$$lnL(k,\lambda) = \sum_{i=1}^{n}\left[\ln(k) - k\ln(\lambda) + (k-1)\ln(x_i) - \left(\frac{x_i}{\lambda}\right)^{k}\right] \quad (3)$$

Numerical parameter estimation was implemented in Python using the `scipy.stats.weibull_min.fit()` function. Once the parameters had been estimated, reliability and failure-rate curves were generated for each critical item of equipment (Duffuaa et al., 2009).

F. Model Validation and Reliability Indicators

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Several reliability indicators were subsequently derived from the fitted parameters, including Mean Time Between Failures (MTBF), B10 life, and the recommended preventive intervention interval t^*. Their formulations are summarized in Table 4.

Table 4. Reliability Indicators Derived from the Weibull Model

Indicator	Equation	Interpretation
MTBF	$MTBF = \lambda\Gamma\left(1+\frac{1}{k}\right)$	Expected mean operating time between failures
B10 Life	$B10 = \lambda(-ln0.9)^{1/k}$	Time by which approximately 10% of units are expected to have failed
Preventive Intervention Interval	$t *= \lambda(-ln0.8)^{1/k}$	Intervention time corresponding to a reliability threshold of $(R(t^*) = 0.8)$

G. *Availability Estimation*

Operational availability was calculated using the relationship between Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) in Equation (4). MTBF and MTTR were derived from the 12-month maintenance records. When logistical and waiting times were included in the recorded downtime, mean downtime per failure was treated operationally as MDT.

$$A = \frac{MTBF}{MTBF + MTTR} \quad (4)$$

Post-implementation availability was subsequently projected under a preventive maintenance scenario in which failure modes classified as `unacceptable()` were mitigated. Availability was recalculated using the Weibull-based intervention intervals together with failure-rate reduction factors consistent with the 30–50% reductions reported in the literature for comparable preventive maintenance programs. Because this represents a projected rather than directly observed post-implementation condition, the resulting availability values were interpreted as scenario-based estimates.

H. *Design of the Preventive Maintenance Plan*

The preventive maintenance plan was developed by integrating the results of the FMEA prioritization, Pareto analysis, criticality assessment, and Weibull reliability analysis. Particular attention was given to subcomponents with high NPR values and comparatively low reliability (Rastayesh et al., 2019). The plan specified the maintenance task, intervention frequency, estimated intervention time, and responsible personnel. Maintenance activities included inspection, lubrication, adjustment, and component replacement, while intervention frequencies ranged from daily activities to scheduled maintenance every 4, 8, or 12 months. Responsibilities were assigned to appropriate personnel, including supervisors, mechanics, electricians, and assistants. The general structure of the preventive maintenance plan is presented in Table 5.

Table 5. Structure of the Preventive Maintenance Plan

Maintenance Element	Specification
Maintenance Activities	Inspection, lubrication, adjustment, and replacement
Intervention Frequency	Daily, monthly, and every 4, 8, or 12 months
Intervention Duration	Estimated according to the required maintenance activity
Responsible Personnel	Supervisor, mechanics, electricians, and assistants
Prioritization Basis	NPR classification, Pareto analysis, criticality, and Weibull reliability results

Detailed annual schedules were subsequently prepared for the ball mill and jaw crusher. These schedules were intended to reduce failure probability, improve equipment availability, and minimize unplanned production downtime. The FMEA format used during the assessment is illustrated in Figure 1, while the systematic procedure used to translate the analysis into preventive maintenance actions is presented in Figure 2.

FAILURE MODAL ANALYSIS AND EFFECTS OF FAILURE FMEA											
COMPANY NAME			Maintenance area		Code:						
			Date:	Edition :							
			Made by:		Approved by:						
Component	Sub-Component	Function	Potential Mode of failure	Potential effect of failure	Severity	Potential cause of the ruling	Occurrence	Medium of Verification	Detection	NPR	Status

Figure 1. FMEA Format

The FMEA results categorized the identified failure modes into acceptable, acceptable-reduction, and unacceptable risk levels. This classification identified several comparatively low-reliability components. For the ball mill, the sheet steel cylinder and mill caps produced NPR values of 480 and 500, respectively, while the crusher recorded an NPR of 360. In the jaw crusher, the side plates, positioning spring, and eccentric-shaft bearing were classified within the NPR range of 300–360 (Tazi et al., 2017).

The proportion of failure modes within each risk category was also calculated for every piece of equipment. This provided an aggregate representation of equipment reliability by quantifying the proportion of subcomponents classified as acceptable, acceptable reduction, or unacceptable. For example, 20% of the ball-mill subcomponents and 30% of the crusher subcomponents were categorized as unacceptable. Based on these results, annual maintenance schedules were established for the ball mill and jaw crusher to reduce failure probability, increase operational availability, and minimize unplanned downtime affecting production (Mecánica et al., 2015). The systematic process used for executing the resulting maintenance plan is illustrated in Figure 2.

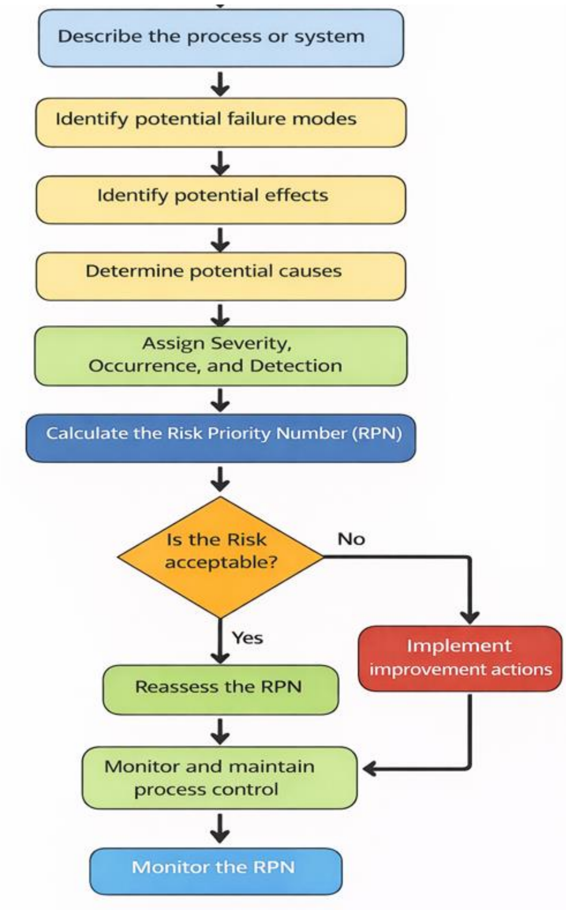

Figure 2. Systematic FMEA Analysis Process

III. RESULT AND DISCUSSION

A. Failure Distribution and Risk Prioritization

During the 12-month observation period, a total of 74 failure events were recorded across eight main pieces of equipment in the crushing and grinding area. The distribution was highly concentrated in several machines. The ball mill recorded the highest number of failures, with 20 events (27.0%), followed by the jaw crusher with 18 events (24.3%). Together, these two machines accounted for 51.4% of all recorded failures, indicating that they represented the primary targets for detailed reliability assessment and maintenance intervention.

The Pareto distribution presented in Figure 3 and Table 6 further illustrates this concentration. After the ball mill and jaw crusher, the conical crusher contributed 13 failures (17.6%), increasing the cumulative proportion to 68.9%, while conveyor belts contributed another nine events (12.2%), bringing the cumulative proportion to 81.1%. Thus, four of the eight equipment categories accounted for more than 80% of all recorded failures. This concentration supports the use of Pareto-based prioritization to direct maintenance resources toward the equipment contributing most strongly to operational interruptions.

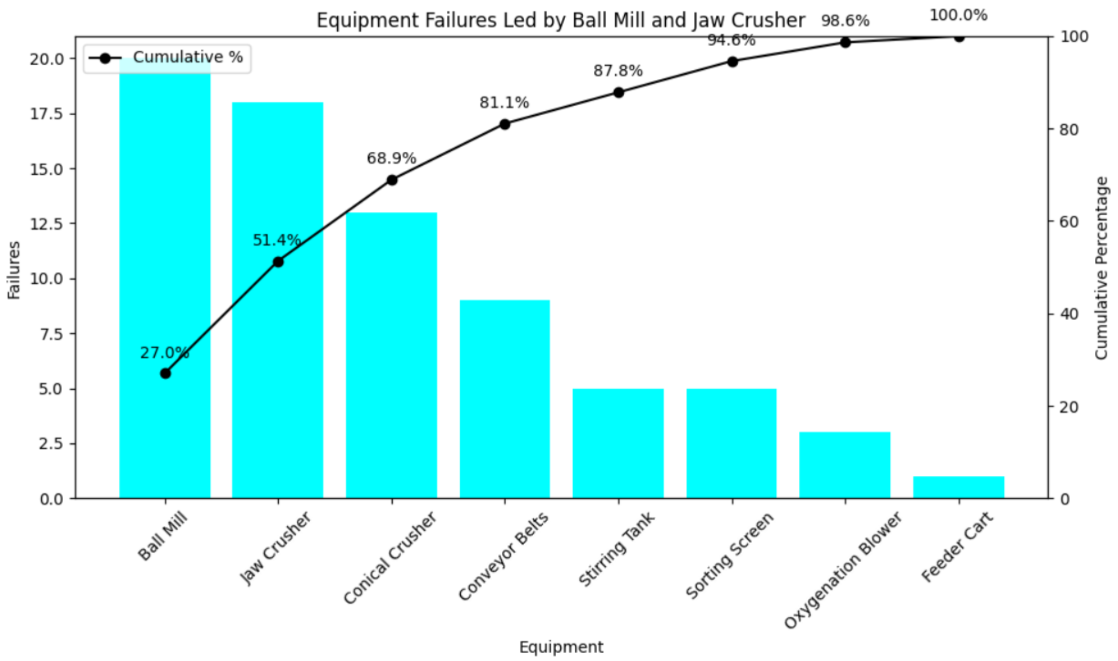

Figure 3. Pareto Occurrence of Failures

Table 6. Pareto Analysis of Failure Occurrences by Equipment During the 12 months

Equipment	Failures	% of Total	Cumulative %
Ball mill	20	27.0	27.0
Jaw crusher	18	24.3	51.4
Conical crusher	13	17.6	68.9
Conveyor belts	9	12.2	81.1
Agitation (stirring) tank	5	6.8	87.8
Sorting screen	5	6.8	94.6
Oxygenation blower	3	4.1	98.6
Feeding cart	1	1.4	100.0
Total	**74**	**100.0**	—

Note: Failure counts and cumulative percentages were calculated from the 74 failure events recorded during the 12-month maintenance observation period.

Based on this preliminary prioritization, the ball mill and jaw crusher were selected for more detailed FMEA and reliability analysis. Twenty failure modes associated with their critical components and subcomponents were assessed using severity, occurrence, and detectability scores. The analysis showed that approximately 25% of the evaluated subcomponents had an NPR greater than 300 and were therefore classified as presenting unacceptable risk.

The highest-priority failure modes were concentrated in structural and mechanical components exposed to severe operating conditions. For the ball mill, particularly high NPR values were identified for the sheet steel cylinder and mill caps, reaching values of 480 and 500, respectively. In the jaw crusher, critical elements included the side plates, positioning spring, and eccentric-shaft bearing, with NPR values within the range of 300–360. These results indicate that the most critical failures were not randomly distributed among components but were concentrated in elements subject to continuous mechanical stress, impact loading, friction, and wear. The overall classification of the identified failure modes according to NPR risk level is shown in Figure 4. Approximately 20% of the evaluated ball-mill subcomponents and 30% of those associated with the jaw crusher were classified within the unacceptable-risk category. This result provided a direct basis for defining preventive actions and prioritizing intervention frequencies.

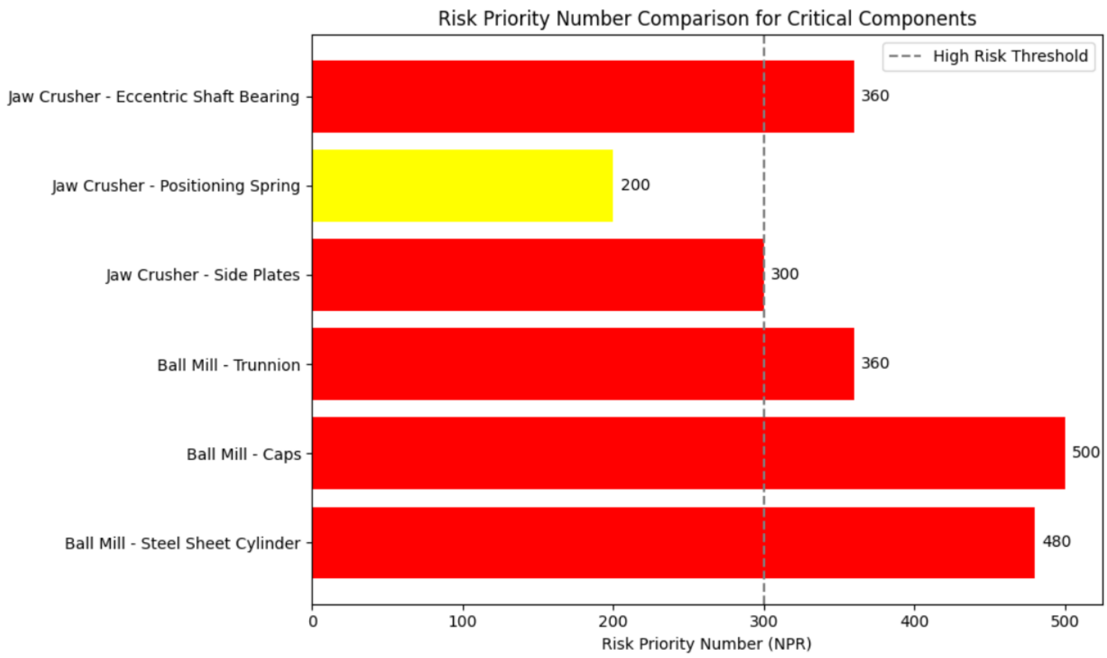

Figure 4. Classification of Mining Machinery Failures

The resulting maintenance plan, presented in Figure 5, was structured according to the identified risk levels. Higher-risk components were assigned more intensive inspection, lubrication, adjustment, or replacement activities, while intervention frequencies were aligned with their observed failure characteristics. In this way, the FMEA results were translated into actionable maintenance priorities rather than being used only as a descriptive risk-ranking instrument.

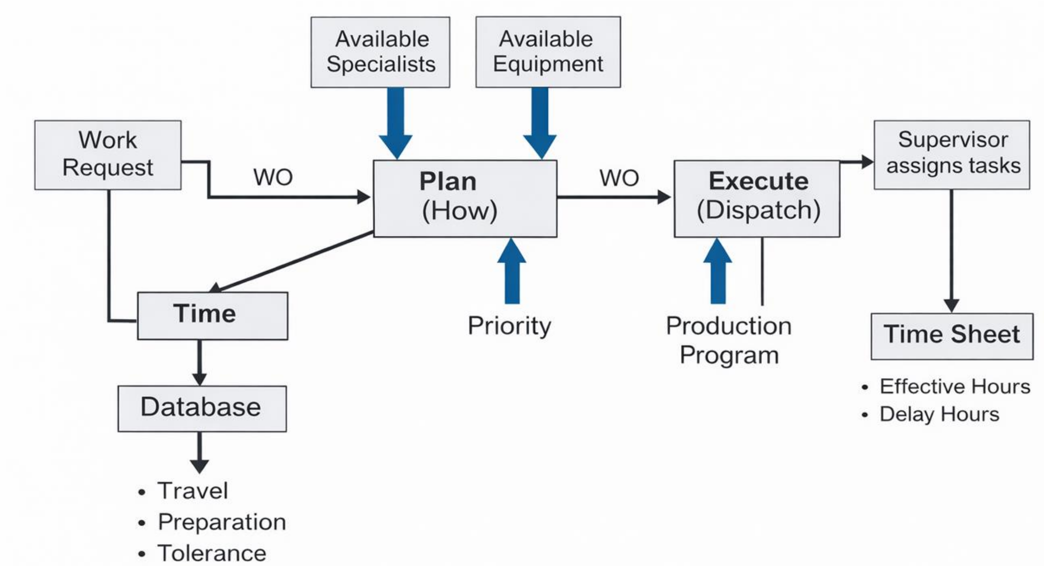

Figure 5. Maintenance Plan

B. Weibull Reliability Analysis

Following the FMEA-based prioritization, Weibull analysis was performed for the ball mill and jaw crusher using the observed times to failure. Parameter estimation was conducted using Maximum Likelihood Estimation (MLE), implemented in Python through the `scipy.stats.weibull_min.fit()` function. The resulting Weibull curves are presented in Figure 6, while the estimated parameters and derived reliability indicators are summarized in Table 7.

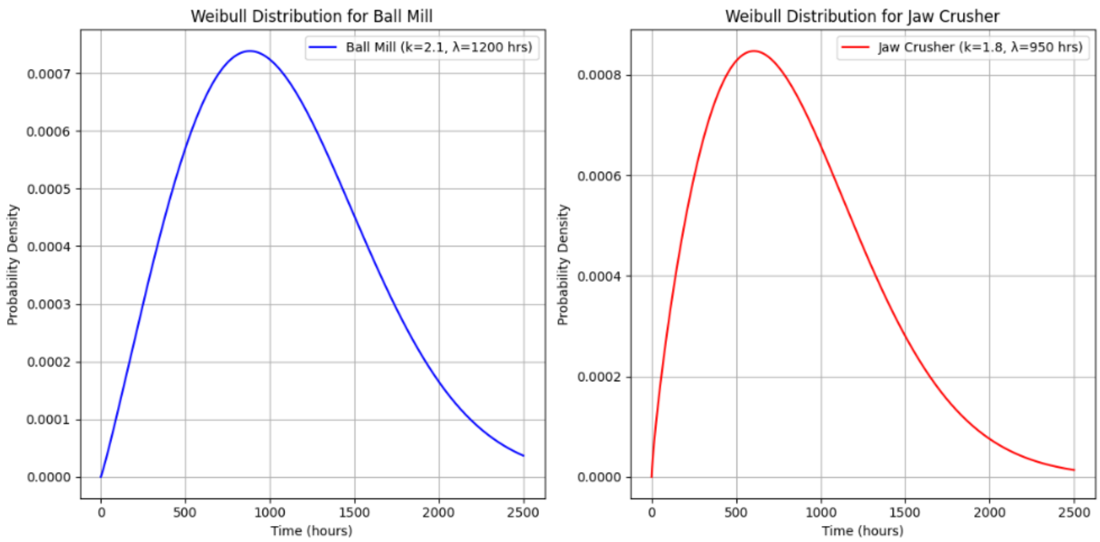

Figure 6. Weibull Curve

The ball mill produced an estimated shape parameter of $k = 21$, whereas the jaw crusher produced $k = 1.8$. Because both values are greater than one, the two machines exhibit an increasing failure rate with operating time. This behavior is characteristic of the wear-out region

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of the equipment life cycle and suggests that deterioration accumulates progressively rather than failures occurring at a constant random rate. From a maintenance perspective, this finding is important because equipment exhibiting $k > 1$ can benefit from scheduled preventive interventions before the probability of failure rises substantially. For the ball mill, the estimated characteristic life was $\lambda = 1{,}200\ h$, with an MTBF of 1,063 h. The estimated B10 life was 411 h, meaning that approximately 10% of comparable operating cycles would be expected to experience failure by this point under the fitted model. At the selected reliability threshold of $R(t) = 0.8$, the recommended preventive intervention interval was estimated at 588 h.

The jaw crusher showed a lower characteristic life of 950 h and an MTBF of 845 h. Its estimated B10 life was 272 h, while the intervention interval corresponding to $R(t) = 0.8$ was approximately 413 h. Compared with the ball mill, these shorter intervals indicate that the jaw crusher requires more frequent preventive attention to maintain the same reliability threshold.

Table 7. Weibull Parameters (MLE) and Derived Reliability Indicators for Critical Equipment

Equipment	k (95% CI)	λ, h (95% CI)	K–S test (α = 0.05)	MTBF (h)	B10 (h)	t* at R = 0.8 (h)
Ball mill (n = 20)	2.1 (1.38–2.82)	1,200 (936–1,464)	Not rejected (D < 0.294)	1,063	411	588
Jaw crusher (n = 18)	1.8 (1.15–2.45)	950 (693–1,207)	Not rejected (D < 0.309)	845	272	413

Note: k and λ correspond to the maximum-likelihood fits shown in Figure 6. Confidence intervals are asymptotic approximations derived from the observed Fisher information of the Weibull likelihood for the indicated sample sizes. D denotes the Kolmogorov–Smirnov statistic and the value in parentheses its 5% critical value for each n. $MTBF = \lambda\Gamma\left(1+\frac{1}{k}\right)$; $B_{10} = \lambda(-\ln 0.9)^{\frac{1}{k}}$; $t^* = \lambda \cdot (-\ln 0.8)^{\frac{1}{k}}$.

The Kolmogorov–Smirnov results did not reject the Weibull assumption at the 5% significance level for either machine, supporting its use as an approximate representation of the observed failure-time behavior. Nevertheless, these results should be interpreted cautiously because only 20 failure times were available for the ball mill and 18 for the jaw crusher. The relatively wide confidence intervals reflect this uncertainty and indicate that the estimated intervention intervals should initially serve as technical guidance rather than rigid maintenance limits.

The Weibull findings complement the FMEA results in an important way. FMEA identifies which components should receive priority, whereas Weibull analysis provides quantitative information regarding when intervention should be considered. Combining these two perspectives makes the maintenance decision more informative than using either risk ranking or failure-time modeling independently. This is consistent with reliability-centered maintenance approaches in which failure consequences and temporal failure behavior are jointly considered when defining intervention strategies (Duffuaa et al., 2009; Knežević et al., 2022; Zeng et al., 2020).

C. *Projected Impact on Availability and Downtime*

The potential operational effect of the proposed maintenance plan was evaluated by comparing the current condition with a projected post-implementation scenario. Current operational availability was estimated at 73%. At this availability level, approximately 27% of scheduled operating time is lost to downtime. For every 1,000 scheduled operating hours, this corresponds to approximately 270 h of downtime. Under the preventive-maintenance scenario, availability is projected to increase to approximately 90%, corresponding to approximately 100 h of downtime per 1,000 scheduled operating hours. The resulting difference is approximately 170 h of avoided downtime for every 1,000 scheduled operating hours.

Assuming 6,000 scheduled operating hours per year, the baseline condition corresponds to approximately 1,620 h of annual unplanned downtime. Under the projected scenario, annual downtime would decrease to approximately 600 h, representing an estimated reduction of approximately 1,020 h per year. The calculation follows: $Downtime = H(1 - A),$ where H represents scheduled operating time and A represents operational availability. The baseline and projected indicators are summarized in Table 8.

Table 8. Baseline Versus Projected Reliability and Availability Indicators

Indicator	**Baseline (current)**	**Projected (post-plan)**	**Change**
Scheduled operating time (h/year)	6,000 (assumed)	6,000 (assumed)	—
Unplanned failure events per year	74	≈ 41	−45% (range −40 to −50%)
Failure rate (events / 1,000 scheduled h)	12.3	≈ 6.8	−45%
Mean downtime per failure, MDT (h)	21.9	≈ 14.6	−33%
Plant-level MTBF (uptime h per event)	59.2	≈ 131.7	+122%
Availability A = MTBF/(MTBF + MDT)	73%	90% (projected)	+17 p.p.
Annual unplanned downtime (h)	1,620	≈ 600	≈ −1,020 h

At baseline, the estimated 1,620 h of downtime distributed among 74 recorded failures produced an MDT of approximately 21.9 h per event. Estimated uptime was 4,380 h, resulting in a plant-level MTBF of approximately 59.2 h per recorded failure event. These values reproduce the reported availability $A = \frac{59.2}{59.2+21.9} \approx 0.73$. Under the projected scenario, fewer failures combined with shorter intervention times and improved spare-part readiness increase the plant-level MTBF while reducing mean downtime per event. The resulting 90% availability therefore reflects improvements in both failure prevention and maintenance response. It is essential, however, to distinguish these projections from experimentally observed results. The preventive plan had not yet been fully implemented during the study period. Consequently, the projected reduction in failure events and increase in availability represent a scenario based on the Weibull model, NPR prioritization, and expected failure-rate reductions rather than direct post-intervention measurements.

D. Discussion

The concentration of 51.4% of recorded failures in the ball mill and jaw crusher demonstrates that maintenance problems within the plant were strongly associated with equipment that performs core crushing and grinding functions. When the conical crusher and conveyor belts are included, four equipment categories account for 81.1% of the recorded events. From an operational perspective, this means that maintenance resources do not need to be distributed uniformly across all equipment. Instead, interventions focused on a relatively small group of high-impact assets may produce a disproportionately large improvement in plant continuity.

This finding is particularly relevant in mineral-processing systems because crushing and grinding equipment generally operates under severe mechanical conditions involving vibration, abrasive materials, impact loading, and continuous operation. Previous reliability studies of mining equipment similarly emphasize that heavy mechanical components tend to dominate maintenance demand and that structured reliability analysis is necessary to reduce unexpected shutdowns (Odeyar et al., 2022). The present findings therefore reinforce the importance of shifting maintenance resources toward components with both high failure frequency and substantial operational consequences.

The FMEA analysis adds another dimension to the frequency results. Failure frequency alone does not necessarily indicate the most important maintenance target because relatively infrequent failures may still have severe safety or production consequences. By incorporating severity, occurrence, and detectability into NPR, the analysis identified components whose operational risk could not be explained by frequency alone. Approximately 25% of the evaluated subcomponents were classified as unacceptable, indicating that a meaningful proportion of the failure modes required intervention rather than continued corrective treatment.

The high NPR values associated with the ball-mill cylinder and caps and with the side plates, positioning spring, and eccentric-shaft bearing of the jaw crusher are technically consistent with the severe mechanical loading experienced by these elements. Similar FMEA-based approaches have shown that maintenance prioritization becomes more effective when criticality and failure consequences are considered together rather than relying exclusively on historical counts (Shafiee et al., 2019; Zeng et al., 2020). In the present study, cross-checking FMEA results against the Pareto and criticality analyses further reduced the dependence on a single ranking method.

The Weibull results provide additional evidence supporting preventive intervention. Shape parameters greater than one for both critical machines indicate increasing hazard rates and therefore deterioration associated with wear. This result is particularly important because purely reactive maintenance is poorly suited to equipment in an identifiable wear-out regime. Once the hazard rate begins to increase with operating time, waiting until functional failure occurs can lead to longer shutdowns and greater secondary damage. Weibull-based maintenance planning therefore provides a quantitative basis for scheduling interventions before equipment enters a higher-risk operating period (Knežević et al., 2022).

The different Weibull characteristics of the ball mill and jaw crusher also demonstrate why a uniform maintenance interval would be inappropriate. The recommended interval at $R(t) = 0.8$ was approximately 588 h for the ball mill but only 413 h for the jaw crusher. The jaw crusher should therefore receive more frequent preventive attention if the same reliability criterion is maintained. This equipment-specific scheduling is an improvement over calendar-based maintenance programs that assign identical frequencies without considering actual failure behavior.

When considered jointly, Pareto analysis, FMEA, criticality assessment, and Weibull modeling provide complementary information. Pareto analysis identifies where failures are concentrated, FMEA evaluates the consequence and detectability of specific failure modes, the criticality matrix supports risk-based prioritization, and Weibull modeling estimates how failure probability evolves with operating time. Their integration therefore establishes a practical pathway from historical failure records to maintenance decisions.

The projected availability improvement from 73% to approximately 90% demonstrates the potential operational significance of this integrated approach. Under the assumed 6,000 annual operating hours, the difference represents approximately 1,020 h of potentially avoided downtime per year. Such an improvement would be especially relevant for a beneficiation plant because interruptions in crushing or grinding can constrain downstream processes and affect the continuity of the entire mineral-processing line.

Nevertheless, the 90% availability value should be interpreted as a target scenario rather than a demonstrated post-implementation outcome. Its realization depends on whether the proposed interventions actually reduce the identified failure modes, whether spare parts are available when required, and whether maintenance activities are executed according to schedule. Post-implementation monitoring is therefore necessary before the projected improvement can be treated as an observed performance gain.

From a broader maintenance-management perspective, the proposed framework supports a transition from predominantly corrective maintenance toward a preventive-predictive approach. Under the corrective model, resources are mobilized after functional failure has already interrupted production. In the proposed approach, high-risk components are identified in advance and intervention times are informed by both risk assessment and statistical reliability behavior. This transition is consistent with preventive-maintenance principles intended to improve

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equipment availability, reduce repair-related uncertainty, and support operational continuity (Flores et al., 2020; Sanabria et al., 2020; Uribe, 2020).

The contribution of the study is therefore primarily practical. The combination of established reliability tools does not constitute a new mathematical maintenance model; rather, its value lies in demonstrating how FMEA, Pareto prioritization, criticality assessment, and Weibull modeling can be integrated in an Ecuadorian mining environment characterized by limited historical records and strong dependence on mechanical crushing and grinding equipment. The resulting framework can potentially be transferred to comparable mining operations, provided that risk scales, failure histories, and intervention intervals are recalibrated according to local operating conditions.

E. Limitation

Several limitations should be considered when interpreting these findings. The first concerns sample size. Although 74 failure events were available for the overall Pareto analysis, the Weibull models were based on only 20 failure times for the ball mill and 18 for the jaw crusher. These relatively small samples increase the sensitivity of parameter estimates to individual observations and contribute to the wide confidence intervals obtained for and . The reliability estimates and recommended intervention intervals should therefore be updated as additional failure-time observations become available.

A second limitation concerns the expert-based nature of FMEA. Although severity, occurrence, and detectability ratings were calibrated and established through multidisciplinary consensus, some degree of subjectivity remains unavoidable. Furthermore, the conventional multiplicative NPR can produce identical scores from different combinations of severity, occurrence, and detectability and gives equal mathematical weight to all three dimensions. Advanced approaches such as fuzzy or weighted FMEA could be considered in future studies to address these limitations.

The third limitation concerns the projected maintenance outcomes. The estimated 40–50% reduction in failure events and increase in availability from 73% to approximately 90% were not measured after implementation. They represent model-based scenarios that require validation using subsequent maintenance records. Their achievement may also be affected by spare-part availability, personnel turnover, maintenance discipline, logistical delays, and production pressures that can postpone scheduled interventions.

Finally, the study was conducted at a single beneficiation plant. Direct statistical generalization to the entire Ecuadorian mining industry is therefore limited. Nevertheless, the analytical procedure itself is transferable and may be applied to other plants after adjustment to their equipment configuration, failure histories, and operating conditions.

F. Economic Feasibility

The economic justification of the proposed plan depends on whether the cost of preventive intervention is lower than the economic value of the downtime and corrective maintenance that can be avoided. Based on the availability scenario, increasing availability from 73% to 90% corresponds to approximately 170 h of avoided downtime per 1,000 scheduled operating hours, or approximately 1,020 h annually under the assumed 6,000-h operating schedule. The basic economic feasibility condition can be expressed as:

$$C_{prev} < \Delta T\left(c_{prod} + c_{corr}\right)$$

where C_{prev} represents the incremental annual cost of the preventive maintenance program, ΔT is the estimated downtime avoided, c_{prod} is the contribution margin associated with one hour of recovered production, and c_{corr} represents the average cost associated with corrective intervention. Accordingly, the proposed plan can be considered economically attractive when the annual costs of planned labor, spare parts, inspections, and scheduled intervention remain below the value of recovered production and avoided corrective repair. This consideration is particularly important in crushing and grinding operations because the unavailability of critical equipment can interrupt subsequent stages of the beneficiation process.

However, the present study did not include sufficiently detailed plant accounting data to calculate a complete net economic benefit or return on investment. Therefore, the economic analysis should currently be regarded as a feasibility framework rather than a definitive cost–benefit assessment. Future post-implementation evaluation should integrate actual preventive-maintenance costs, corrective-repair costs, production contribution margins, and observed downtime reductions to quantify the economic return of the proposed strategy.

IV. CONCLUSION

The combined application of FMEA, criticality analysis, Pareto analysis, and Weibull modeling provided a systematic basis for identifying and prioritizing operational risks in the crushing and grinding equipment. Approximately 25% of the evaluated subcomponents were classified as having unacceptable risk levels (NPR > 300), with the highest risks concentrated in structural and mechanical elements of the ball mill and jaw crusher operating under severe conditions. The proposed preventive maintenance plan translated these findings into scheduled maintenance tasks, intervention frequencies, and assigned responsibilities focused on the least reliable subcomponents. Based on the model-based scenario, implementation of the plan is expected to reduce unplanned downtime by approximately 40–50% and increase operational availability from 73% to about 90%. The Weibull analysis further strengthened the maintenance strategy by providing a quantitative basis for estimating failure behavior and defining appropriate preventive intervention intervals, thereby supporting the transition from predominantly corrective maintenance toward a preventive-predictive approach.

The integrated framework developed in this study is potentially applicable to other Ecuadorian mining operations that rely heavily on crushing and grinding equipment, particularly where historical maintenance data are limited and operating conditions are severe. However, the projected improvement in availability and downtime should be validated through post-implementation monitoring of actual failure events, maintenance duration, and equipment performance. To improve the sustainability and accuracy of the proposed maintenance strategy, future implementation should strengthen historical failure and maintenance-record systems, provide continuous training for personnel in reliability-analysis tools, and progressively incorporate digital condition-monitoring technologies such as sensors and equipment-condition analysis. These measures would allow the maintenance plan to be continuously updated using operational evidence and support a more data-driven approach to reliability and operational risk management.

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