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Reliability Assessment through MTBF, MTTR and Availability in Industrial Wood Chippers: A Case Study

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ABSTRACT

Given the need to produce products such as paper, pellets, biomass, and other wood-derived materials in the form of chips, it is essential that key equipment, particularly wood chippers, operate reliably and efficiently. In this context, the present study aims to analyze the reliability and performance of two wood chippers operating continuously in an industrial unit over a twelve-month period. The methodology was based on the analysis of historical maintenance records and the application of classical performance indicators, namely Mean Time Between Failures (MTBF), Mean Time To Repair, and Availability. In parallel, statistical analysis tools, such as the Weibull distribution, were used to characterize failure regimes, while the Kaplan–Meier estimator was applied to evaluate the empirical survival function of the equipment. The results obtained reveal high levels of operational availability, ranging between 92% and 97%, with MTBF varying between 38 and 105 operating hours. Failure analysis identified the most impactful failure modes, highlighting blade replacement and jamming events as the main causes of downtime. Based on the obtained results, operational improvements and preventive and condition-based maintenance strategies were proposed, aiming to increase reliability, reduce unplanned downtime, and improve the overall efficiency of the wood-chip production process.

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1. Introduction

The forestry sector plays a fundamental role in the global economy, particularly in the processing and recovery of timber and its byproducts. Among the critical operations in this sector is the production of wood chips, in which wood chippers play an essential role [1]-[3]. Ensuring the efficiency and availability of this equipment is important for maintaining production levels and operational stability. However, a frequent challenge lies in organizing and standardizing maintenance records, which often lack consistency and reliability. In this context, performance indicators such as Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and Availability constitute

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valuable tools for evaluating equipment performance and supporting decision-making in industrial operations [4]-[7].

Although these indicators are widely applied in industrial maintenance contexts, their use in the analysis of large-scale industrial wood chippers based on real and longitudinal operational data remains limited [7]-[10]. Existing studies primarily focus on generic forestry equipment or small-scale experimental systems, which do not fully represent the operational complexity of industrial environments, where downtime can have a substantial economic impact. This gap is particularly relevant because even modest improvements in availability and reductions in MTTR may result in significant productivity gains and cost savings in a highly competitive sector that is sensitive to supply chain disruptions [11]-[14].

Previous studies reinforce the relevance of this approach. Kováč et al. [15], in an analysis of forwarder reliability, demonstrated that the systematic assessment of failures and repair times enables process optimization and the identification of significant reliability differences between similar equipment, highlighting the economic benefits of predictive maintenance supported by real operational data. Diniz et al. [16] reported that structured maintenance systems, including World Class Manufacturing (WCM), Total Productive Maintenance (TPM), and Reliability-Centered Maintenance (RCM), combined with continuous training and effective inventory management, contribute to improved availability and reduced MTTR. Shilovsky et al. [9] emphasized the importance of agile supply chains and cost-effective maintenance systems to increase competitiveness and reduce operational costs, identifying maintainability as a critical factor. Orošnjak and Šević [17] also highlighted the limited adoption of Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM), emphasizing the need for applied studies that relate classical reliability indicators to maintenance strategies adapted to real industrial conditions. Similarly, Linhares et al. [8] and Fiedler et al. [18] demonstrated that rigorous analysis of maintenance and operational histories is essential for failure mapping, evaluation of maintenance interventions, and decision-making aimed at maximizing productivity and operational sustainability.

Therefore, this study seeks to address this gap through the systematic application of classical performance indicators to the analysis of two industrial wood chippers based on twelve months of operational and maintenance data. The analysis aims to identify critical failure patterns, evaluate the effectiveness of current maintenance practices, and propose targeted operational and maintenance improvements. By integrating performance indicators with failure prioritization tools, this study provides practical contributions to improving productivity and sustainability in industrial forestry operations while supporting cost reduction and increased sector competitiveness.

This paper is organized as follows. Section 2 presents the literature review and theoretical framework, including the operation of wood chippers in industrial applications, reliability and maintenance performance indicators, statistical analysis methods, and the limitations of classical indicators. Section 3 describes the materials and methods, including operational characterization, maintenance record structure, calculation of classical reliability indicators, Weibull distribution modeling, Kaplan–Meier estimation, failure mode analysis, operational impact assessment, computational implementation, and methodological limitations. Section 4 presents and discusses the results, including the annual operational behavior of the equipment, the temporal evolution of reliability indicators for each wood chipper, the comparison between the two wood chippers, the detailed analysis of failure modes, and the economic impact of the proposed maintenance actions. Finally, Section 5 summarizes the main conclusions and outlines directions for future research.

2. Background

This section presents the foundational concepts underpinning the study, emphasizing the role of industrial wood chippers in large-scale forestry operations and the critical maintenance performance indicators, MTBF, MTTR, and Availability, which are essential for understanding the technical, operational, and economic challenges of these systems. It further discusses the principles of reliability analysis and the statistical methods employed in asset evaluation, including the Weibull distribution and the Kaplan–Meier estimator. These approaches enable detailed assessment of system degradation and temporal behavior, supporting the optimization of productivity, operational efficiency, and sustainability in industrial forestry contexts.

2.1 Wood Chippers in Industrial Operations

Industrial wood chippers represent critical assets within the forestry sector's value chain, performing the primary conversion of logs and woody residues

into sized biomass suitable for subsequent industrial processes, including the production of pulp, wood-based panels, pellets, and bioenergy. These machines are typically positioned at the interface between forest supply and industrial processing, directly influencing plant productivity, final product particle size, and operating costs [4], [10]. In large industrial facilities, wood chippers frequently operate continuously, twenty-four hours a day, enduring intense mechanical stress, high abrasiveness of raw material, and repetitive cyclic loads. Their design is based on high inertia rotary systems powered by high-capacity electric motors operating at low speed and high torque, ensuring consistent chip quality and high throughput. Mobile versions are also available, providing flexibility for field processing, although they are less commonly used in fixed industrial plants [4], [10].

Wood chippers are primarily constructed in two types, disc and drum [4], [10]. Disc models employ a rotating disc with multiple knives, typically ranging from two to twenty depending on capacity and desired chip size, cutting logs at an angle to produce uniform chips. These machines are valued for their cutting precision, yet require frequent maintenance, including sharpening or replacing knives, to prevent excessive wear and imbalances [4], [19]-[21]. Drum models receive material via conveyor or gravity feed, directing it toward a rotating drum equipped with tangentially mounted knives. This configuration is suitable for larger diameter logs and heterogeneous raw materials, but is more vulnerable to damage from foreign objects, demanding careful feed rate control and regular rotor inspection [4], [19]-[21].

The mechanical distinctions between disc and drum chippers affect not only the efficiency and uniformity of the produced chips but also the nature of failures, maintenance requirements, and operational downtime. Disc chippers typically exhibit localized wear and frequent imbalances, whereas drum chippers experience more uniform wear, overload damage, and degradation of counteracting knives. This necessitates targeted maintenance strategies, including regular inspections, blade sharpening or replacement schedules, and vibration monitoring [7], [19]-[21]. Preventive maintenance is essential for maintaining high availability and controlling operating costs. Neglecting routine tasks such as blade sharpening, lubrication, or vibration checks can lead to increased downtime, higher operational expenses, and lower energy efficiency. Well-maintained wood chippers, in contrast, reduce energy consumption, extend component life, improve chip quality, and contribute to both profitability and environmental sustainability [4], [11], [13], [20], [22], [23].

Considering the strategic importance of wood chippers in industrial operations, evaluating their reliability and performance using indicators such as MTBF, MTTR, and availability provides a robust quantitative foundation for maintenance planning and process optimization [4], [10]. Despite the relevance of this equipment, there remains limited literature on the long-term, comparative application of these indicators in large-scale industrial wood chippers. This study aims to address this gap by analyzing two machines in continuous industrial operation, identifying failure patterns, and proposing improvements with the potential to enhance productivity and reduce costs.

2.2 Maintenance Reliability and Performance Indicators

The analysis of repairable industrial systems requires an integrated approach that simultaneously considers the probabilistic behavior of failures and the organizational capacity for functional restoration. Within the context of reliability engineering, the operational performance of a technical asset can be understood as the result of the dynamic interaction between three fundamental dimensions: reliability, maintainability, and availability [24], [25].

Reliability expresses the probability that a system performs its required function under specified operating conditions during a defined time interval. Formally, it can be represented by the survival function $R(t)=P(T>t)$, where T represents the random variable corresponding to time to failure [24], [25].

Maintainability refers to the probability that a system can be restored to an operational condition within a specified time interval after a failure occurs. This dimension is directly associated with the statistical distribution of repair times [24], [25].

Availability represents the probability that a system is operational at a given moment, integrating the combined effects of reliability and maintainability. In continuous production systems, such as industrial wood chippers, even small variations in availability may result in significant annual production losses [24], [25].

2.2.1 Maintenance Performance Indicators: MTBF, MTTR, Availability

Performance indicators, also referred to as Key Performance Indicators in maintenance, consist of numerical measures defined for specific processes

that organizations intend to monitor, establish targets for, and evaluate over time. These indicators are implemented to support management in the pursuit of maintenance excellence. Standards also define maintenance performance as the outcome of efficiently managing resources to maintain an asset in a condition that enables it to perform its required function [26]-[28].

Improving the overall performance of a company or a specific piece of equipment requires identifying how maintenance activities can be managed to enhance profitability and market competitiveness. Once the most appropriate approach is identified, suitable adjustments or modifications can be implemented accordingly. At the production system or assembly line level, maintenance objectives may be associated with specific performance factors, including availability, among others [27]-[29].

Efficient and effective maintenance management depends on a set of indicators capable of providing meaningful information regarding the most relevant aspects of maintenance activities. It should also be considered that an indicator applied in one company may not necessarily be suitable for another, depending on the operational context and organizational structure [30], [31]. Although these indicators are widely applied in industrial maintenance, they remain underexplored in studies specifically focused on large-scale industrial wood chippers. Most existing studies address these indicators in the context of generic forestry equipment or small-scale experimental conditions, which do not fully represent the operational complexity, raw material variability, and economic constraints associated with continuous industrial production. Their application in the present study to two industrial wood chippers operating over an extended real-world period seeks to contribute to filling this gap through a longitudinal and comparative assessment of equipment performance and reliability [1], [10], [12], [15], [22], [32], [33].

In summary, it is important that professionals responsible for maintenance and production activities have access to specific performance indicators that allow the analysis of operational behavior and trends, the identification of potential improvements, and the determination of which equipment has the greatest impact on overall plant availability. Such analysis supports evaluation, planning, and decision-making processes aimed at improving the overall production system. The following are some of the most relevant maintenance indicators [28], [34]-[36]:

MTBF represents the frequency of interventions on equipment during a specific period. It is considered a reliability indicator, representing the ability of a given piece of equipment to perform its required functions without failure under established operating conditions. MTBF is obtained by dividing the sum of operating times during a given period by the number of breakdowns occurring in the same period. Where, T_{fi} represents the operating time during the period and $N_{Breakdowns}$ represents the number of breakdowns during the period [35]-[37]:

$$MTBF = \frac{\sum T_{fi}}{N_{Breakdowns}} \quad (1)$$

MTTR represents the ability of equipment to be restored to operational condition so that it can resume or continue performing its required function when maintenance is carried out according to established specifications. Where, T_{ri} represents the repair time during the period and $N_{Breakdowns}$ represents the number of breakdowns during the period [35]-[37]:

$$MTTR = \frac{\sum T_{ri}}{N_{Breakdowns}} \quad (2)$$

Availability represents the probability that a system, piece of equipment, or component is capable of performing its required function. It can be mathematically expressed as the ratio between MTBF and the sum of MTBF and MTTR, as shown in Eq. (3) [35]-[37]:

$$Availability = \frac{MTBF}{MTBF + MTTR} \quad (3)$$

Although MTBF, MTTR, and Availability are widely used in industrial maintenance studies, their application in detailed, long-term, and comparative evaluations of industrial wood chippers remains limited in the literature. The lack of specific real-world operational data restricts the understanding of how these indicators can support maintenance strategies in continuous large-scale industrial operations [10], [32], [35]-[37].

2.2.2 Statistical Analysis: Dispersion and Confidence Intervals

The MTBF and MTTR indicators represent sample estimates and are therefore subject to statistical variability. In monthly analyses, the number of observed failures is frequently lower than 30, making it necessary to consider the uncertainty associated with these estimates. The 95% confidence intervals were calculated using the Student's *t*- distribution, as presented in Eq. (4) [38]:

$$IC_{95\%} = \bar{x} \pm t_{(0.975;n-1)} \cdot \frac{s}{\sqrt{n}} \quad (4)$$

where [38]:

- $\bar{x}$ is the sample mean; s is the sample standard deviation;
- n is the number of observations;
- $t_{(0.975;n-1)}$ is the critical value of the t-distribution with n-1degrees of freedom.

The analysis of confidence intervals allows the robustness of the estimates to be evaluated, facilitates the identification of periods with greater operational instability, and enables statistically consistent comparisons between different periods [38].

Narrow confidence intervals indicate a stable and predictable failure regime, whereas wider intervals suggest greater heterogeneity or the coexistence of multiple failure mechanisms.

2.2.3 Limitations of Classical Indicators

Despite their operational relevance, classical indicators such as MTBF and MTTR present structural limitations. These indicators are aggregate measures and do not explicitly describe the temporal evolution of the failure rate. They also implicitly assume statistical homogeneity, do not allow direct inference regarding wear regimes, and do not provide a direct quantitative basis for risk-based predictive maintenance [10], [34], [37], [39].

These limitations justify the use of probabilistic time-to-failure models, namely the Weibull distribution and the Kaplan–Meier estimator, which allow explicit characterization of degradation regimes and estimation of the reliability function over operational time [40]-[42].

3. Materials and Methods

Section 3 describes the methodological framework adopted for the reliability analysis of two industrial wood chippers. The section includes the operational context of the equipment, the structure of the maintenance records, and the procedures used to calculate classical reliability indicators such as MTBF, MTTR, and operational availability. Parametric modeling based on the Weibull distribution and non-parametric survival estimation using the Kaplan–Meier method are also presented. In addition, the section describes the classification of failure modes and the assessment of their operational impact. Finally, the computational implementation of the analysis and the methodological limitations associated with the available data are discussed.

3.1 Study framework and operational characterization

This study focused on the reliability analysis of two stationary rotary drum wood chippers used in the production of wood chips for pulp. The equipment operates in an industrial unit located in the central region of Portugal under a continuous regime of three daily 8-hour shifts, seven days a week, corresponding to a nominal annual operation period of 8,760 hours.

The wood chippers predominantly process debarked Eucalyptus globulus and Pinus pinaster logs sourced from regional forest farms. The mechanical design of both machines is similar, based on a rotating drum equipped with replaceable blades subject to progressive wear due to the abrasiveness of the processed material. Operation is performed by operators with 5 to 10 years of experience, supported by an in-house team specialized in heavy mechanical maintenance. All corrective interventions were carried out internally, without the systematic use of external assistance.

Only unplanned corrective maintenance events occurring over 12 consecutive months were considered, while scheduled preventive maintenance activities were excluded in order to characterize the natural failure behavior of the equipment.

The preprocessing procedure included removal of incomplete entries, consolidation of merged events into single records, retention and separate classification of non-specified failures, sequential reconstruction of Time Between Failures (TBF) intervals exceeding 24 hours, and identification of right-censored observations at the end of the 12-month observation period. These right-censored observations were explicitly considered in the statistical analyses, including the non-parametric Kaplan–Meier survival estimation.

The recorded maintenance data included the type of failure, categorized according to a standardized taxonomy (i.e., Electrical failure, Mechanical failure, Operational difficulties, Jamming, and Blade replacement), idle time associated with each event (downtime), and TBF.

Downtime corresponded to the total duration of each intervention event, as reported in the company records, including personnel travel, parts delivery, waiting times, and equipment setup. These values were used in the calculation of downtime-based

MTTR and, where applicable, in adjusted estimates of technical MTTR. MTTR was calculated individually for each month, with standard deviation and 95% confidence intervals reflecting variability in downtime durations.

TBF was reconstructed sequentially for each failure event, regardless of failure type. Most TBF observations correspond to complete intervals between consecutive failures within the observation window. Right-censored intervals at the end of the study, as well as TBF intervals exceeding 24 hours reconstructed to span multiple days, were considered in the analysis, introducing slight uncertainty into MTBF estimation, which is typical of reliability analyses based on finite observation periods.

In addition to the monthly average, trend analysis was performed using linear regression and the Mann–Kendall test to verify stability or significant variation in the indicators throughout the year. The magnitude of possible biases in the MTTR estimate was assessed through the standard deviation and 95% confidence intervals, shown in Table A for Wood Chipper 1 and in Table B for Wood Chipper 2 (Appendix A).

Confidence intervals were calculated for MTBF and MTTR to account for variability, while availability was derived deterministically from these indicators. Therefore, uncertainty associated with availability is indirectly represented through the confidence intervals of the input variables.

To facilitate reproducibility, the complete table of failure events, including reconstructed stop time, failure type, downtime, and TBF, is available in Supplementary Material S1. Table 1 presents an excerpt from the database for both wood chippers, including stop time, TBF, description, and downtime.

This approach ensures a consistent and transparent characterization of equipment reliability, incorporating variability of repair durations, statistical uncertainty represented by standard deviations and 95% confidence intervals, the finite 12-month observation window, and a clear distinction between failure types and probable root causes, enabling Pareto analysis and prioritization of corrective actions.

The operational framework presented serves as the basis for the subsequent analysis of temporal evolution, statistical modeling using Weibull and Kaplan–Meier methods, and evaluation of availability and maintainability. Complete failure data for the 12-month study period are provided in Appendix A. To preserve confidentiality, exact event times were omitted, and the analyzed machines are identified only as Wood Chipper 1 and Wood Chipper 2.

3.2 Records and Data Structure

The records provided by the industrial unit consist of a monthly event table for two wood chippers, covering a consecutive 12-month period. Each record indicates the month, event number, failure type, downtime associated with each failure event (in hours), and the time elapsed since the last failure (TBF, in hours). While providing basic information about each occurrence, the data have limitations for detailed analysis: exact timestamps are not recorded, individual repair durations in minutes are unavailable, TBF values are rounded, and failure types are summarized in general categories such as "Mechanical failure," "Electrical failure," "Jamming," or "Blade replacement." These limitations require sequential reconstruction and careful interpretation of events to calculate reliability indicators such as MTBF, MTTR, and operational availability.

The data were manually extracted into separate spreadsheets for each wood chipper, organized chronologically by month, and subsequently converted into a single sequential list of failures covering the entire 12-month period. The recorded failure in-

Table 1. Example of TBF, downtime, and failure type for Wood Chippers 1 and 2.

Stop time	TBF (h)	Description	Downtime (h)
00:00	40.0	Electrical failure	1.0
16:00	53.1	Operational difficulties	1.0
21:06	35.9	Blade replacement	1.0
08:12	38.1	Blade replacement	1.0
22:18	36.8	Operational difficulties	1.2
10:28	35.8	Not specified	1.2
22:04	55.3	Electrical failure	1.3
05:22	29.0	Operational difficulties	1.3
10:16	65.1	Operational difficulties	1.3

tervals were assumed to correspond to net operating time (load time), excluding shutdown periods previously accounted for.

The Time Between Failures (TBF_i) was defined as the operational interval elapsed between failure $i-1$ and failure i, regardless of the failure type:

$$TBF_i = t_i - t_{i-1} \quad (5)$$

where t_i represents the occurrence time of failure i. Since absolute timestamps were not available, TBF values were inferred directly from the recorded intervals. Most TBF observations correspond to complete intervals between consecutive failures within the observation window. TBF intervals exceeding 24 hours were sequentially reconstructed to account for events spanning multiple days, and the interval between the last recorded failure and the end of the 12-month observation period constitutes a right-censored observation. This type of censoring is common in operational reliability studies and was explicitly considered in the statistical analyses, including non-parametric survival estimation using the Kaplan–Meier method. These factors introduce slight uncertainty into MTBF estimates, which is typical of analyses based on finite observation periods.

The final set of observations consisted of 173 failures for Wood Chipper 1 and 155 failures for Wood Chipper 2. For statistical modeling purposes, each TBF was treated as an independent observation, although minor dependence between failures may exist due to progressive component wear, which is a common assumption in reliability studies based on operational maintenance records.

3.3 Calculation of classic reliability indicators

The analysis of the two wood chippers was performed based on monthly data, considering both the individual monthly periods and the annual aggregate over 12 months. The data used included the TBF and the downtime associated with each failure event, recorded monthly for each piece of equipment.

For each wood chipper, the classical reliability indicators MTBF, MTTR, and operational availability were calculated based on the equations presented in Section 2.2 (Equations 1 to 3). Monthly MTBF was obtained by summing all recorded times between failures within each month and dividing by the total number of observed failures (Eq. 1). MTTR was calculated by summing the downtime associated with maintenance interventions and dividing by the same number of failures (Eq. 2), assuming relative homogeneity between interventions and including logistical and administrative components associated with the repair process. Availability was subsequently calculated according to Equation 3.

To reflect the statistical uncertainty associated with the monthly estimates, 95% confidence intervals were calculated using the Student's t-distribution (Eq. 4), considering the limited number of failures recorded per month and the absence of knowledge regarding the population standard deviation. Availability was derived deterministically from MTBF and MTTR; therefore, its uncertainty is indirectly represented through the confidence intervals associated with these input indicators.

Since the recorded MTTR includes not only effective repair duration, but also logistical and administrative delays such as resource mobilization, parts delivery, waiting times, and intervention organization, a sensitivity analysis was performed to evaluate the potential impact of these components on estimated operational availability.

For sensitivity analysis purposes, the arithmetic mean of the monthly MTBF values was adopted instead of the aggregated annual MTBF. This indicator provides a consolidated representation of equipment reliability while reducing additional variability associated with monthly analysis.

Next, the technical MTTR was estimated by removing the fraction of time attributed to logistical and administrative delays. The technical MTTR was calculated according to Equation 6:

$$\text{Technical MTTR} = \text{Total MTTR} \times \times (1 - \text{percentage of logistics}) \quad (6)$$

where the logistics percentage represents the fraction of the total MTTR considered as non-technical time.

Based on this adjusted MTTR value, estimated operational availability was recalculated using Equation 3.

MTBF was assumed to remain unaffected by the logistical scenarios considered, since logistical delays influence repair duration rather than the operating TBF.

To assess the sensitivity of the results, three distinct scenarios were considered. The first corresponds to the observed condition (0% logistics), in which the entire downtime-based MTTR is assumed to represent technical repair duration. The second considers a 20% logistics component, representing moderate logistical influence. The third considers a

50% logistics component, representing a conservative condition in which a substantial fraction of downtime is attributed to logistical delays.

This approach allowed evaluation of the extent to which logistical components included in MTTR may influence the estimation of operational availability and, consequently, the interpretation of reliability indicators.

For clarity, technical MTTR refers to the estimated repair duration excluding logistical and administrative delays, whereas downtime-based MTTR includes all operational and logistical components.

3.4 Parametric modeling – Weibull distribution

Parametric modeling was conducted separately for each wood chipper using the two-parameter Weibull model, which is appropriate for systems subject to progressive wear [41], [43]. The Weibull parameters were estimated independently for Wood Chipper 1 and Wood Chipper 2 to account for possible differences in operational behavior and failure patterns.

The Weibull distribution was selected for TBF modeling due to its flexibility and ability to represent different wear and failure regimes over time. In particular, the two-parameter Weibull model is widely applied in the reliability analysis of systems subject to progressive degradation, since its shape parameter allows the representation of aging-related failures ($\beta > 1$), random failures ($\beta \approx 1$), and early-life failures ($\beta < 1$). In the context of this study, the use of the Weibull distribution is justified by its suitability for describing the gradual degradation of wood chipper components over time, reflecting the mechanical wear and operational failure mechanisms observed during continuous equipment operation [41], [43], [44].

The adequacy of the Weibull fit was evaluated visually through probability plots and, where relevant, compared with the non-parametric Kaplan–Meier estimator.

3.4.1 Plotting order and position

The TBFs were ordered in ascending order: TBF(1) ≤ TBF(2)≤ … ≤TBF(n). The adjusted cumulative probability was estimated using Bernard's equation (7) [45]:

$$F_i = \frac{i - 0.3}{n + 0.4} \tag{7}$$

which reduces bias at the edges of the sample.

3.4.2 Linearization and regression

The following transformations were applied [45], [46]:

$$X_i = \ln\left(TBF_i\right) \tag{8}$$

$$Y_i = \ln\left[-\ln\left(1 - F_i\right)\right] \tag{9}$$

A simple linear regression was then fitted:

$$Y_i = \beta X_i + \alpha \tag{10}$$

where:

- β corresponds to the shape parameter;
- α to the independent term.

The scale parameter (η) was obtained by:

$$\eta = e^{-\alpha/\beta} \tag{11}$$

The coefficient of determination R^2 was used as a measure of goodness of fit.

3.4.3 Weibull Model Reliability Functions

Based on the estimated parameters, the following functions were determined. Reliability function [46]:

$$R(t) = e^{-(t/\eta)^{\beta}} \tag{12}$$

Cumulative failure function:

$$F(t) = 1 - R(t) \tag{13}$$

Failure rate function:

$$h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{14}$$

These functions allow characterization of the degradation regime over time and provide a quantitative basis for predictive maintenance planning.

3.5 Nonparametric estimation – Kaplan–Meier

For validation of the parametric model, the empirical survival function was estimated using the Kaplan–Meier method. In the present study, most TBF observations correspond to complete intervals between two consecutive failures. However, since the analysis is limited to a fixed 12-month period, the operational time elapsed between the last recorded failure and the end of the observation window may represent a potential right-censored interval and was

considered during interpretation of the reliability results. Survival was calculated iteratively [47], [48]:

$$\hat{S}(t) = \prod_{i:t_i \le t} \left(1 - \frac{d_i}{n_i}\right) \quad (15)$$

Where [47], [48]:

- d_i is the number of failures at time i (in this dataset, $d_i = 1$ for each event);
- n_i is the number of systems still operating immediately before time i.

This non-parametric estimation provides a benchmark for validation of the parametric Weibull model and allows assessment of the model fit, particularly in the central region of the observed TBF distribution.

The graphical comparison between $\hat{S}(t)$ and $R(t)$ allowed assessment of the adequacy of the Weibull model, particularly in the central region of the distribution.

3.6 Analysis of failure modes and operational impact

The failures recorded during the operational period were categorized into distinct technical classes: mechanical failures, electrical failures, jamming, blade replacement, operational difficulties, and Not specified failures. This classification allowed systematic structuring of the maintenance data, facilitating identification of recurring failure patterns and their operational implications.

Based on the monthly failure records and their classification, a cumulative Pareto analysis was performed. This approach allowed identification of the failure modes that contributed most significantly to the operational unavailability of the wood chippers studied. The Pareto diagram showed that a limited number of failure types were responsible for most of the downtime, highlighting priority areas for maintenance interventions and resource allocation.

Once the failure modes with the greatest operational impact had been identified, a complementary evaluation was conducted to determine whether preventive or predictive maintenance actions could be improved. This evaluation considered the technical characteristics of the equipment, the operating conditions associated with continuous industrial operation, and the typical degradation mechanisms of critical components.

To support this analysis, a structured failure taxonomy was developed linking each category to its probable root cause and corresponding maintenance actions. This taxonomy provides a systematic framework for interpretation of recorded failures, prioritization of corrective actions, and definition of mitigation strategies aimed at improving equipment reliability and availability.

3.7 Computational Implementation and Methodological Limitations

All statistical and reliability calculations were performed in Microsoft Excel®, ensuring transparency and reproducibility of the analytical procedure. Standard software functions were used, such as AVERAGE and STDEV.S for descriptive statistics, T.INV.2T for confidence interval calculation, and the "Data Analysis" tool for linear regression. Non-parametric reliability estimation using the Kaplan–Meier method was implemented using matrix formulas, while Weibull probability plots were manually constructed from the linear transformation of the data. No specialized statistical software was used.

The analysis was based on several simplifying assumptions adopted to model the available data. These assumptions include the approximate independence between consecutive failures, relative homogeneity of operating conditions throughout the 12-month observation period, and the absence of major structural modifications to the equipment during the study.

Additionally, the inherent limitations of the operational record structure, namely the absence of detailed temporal information for each event and the lack of detailed repair-duration records separating technical, logistical, and administrative components introduces residual uncertainty into the modeling and estimation of the reliability indicators.

4. Results and Discussion

Section 4 presents a detailed analysis of the study results, addressing the operational behavior of the two wood chippers over a twelve-month period. The initial analysis provides an overview of equipment performance, highlighting differences in reliability, failure regimes, and the temporal evolution of the indicators. Subsequently, the monthly variations of the main reliability indicators for each piece of equipment are analyzed, identifying periods of stability, degradation, and operational recovery. Finally, the comparison between the two wood chippers highlights differences in operational behavior, the influence of operating conditions, and the implications for maintenance and reliability management.

4.1 Overview of Annual Behavior

Over a period of 12 consecutive months (8,760 operating hours), 173 failures were recorded in Wood Chipper 1 and 155 failures in Wood Chipper 2. Both pieces of equipment operated under demanding industrial conditions, characterized by continuous mechanical stress, repetitive impacts, and high abrasiveness of the processed material.

The analyzed dataset was previously preprocessed and standardized according to the procedures described in Section 3, ensuring consistency in the reliability analysis.

Although operating in the same industrial context, the two wood chippers exhibited different behaviors in terms of reliability over time, TBF variability, severity of interventions, and stability of the failure regime.

In summary, the following patterns were observed: (i) Wood Chipper 1 showed a progressive operational evolution, with a clear transition toward an accumulated wear regime; (ii) Wood Chipper 2 exhibited more unstable behavior, alternating periods of high reliability with critical phases of abrupt degradation. This distinction constitutes an important operational finding.

4.2 Time Evolution of Reliability Indicators – Wood Chipper 1

Monthly analysis of the reliability indicators of Wood Chipper 1 identified different stages in its operational behavior over the twelve-month period. The combined evolution of MTBF, MTTR, and availability indicates changes in the failure regime, reflecting distinct degradation mechanisms and maintenance patterns (Table A).

Between January and April, Wood Chipper 1 exhibited a stable operational regime. MTBF ranged from 38.3 to 42.6 hours, while MTTR remained between 1.7 and 2.2 hours. Availability remained high, ranging from 95.0% to 96.1% (Figure 1). The relatively narrow confidence intervals observed during this period suggest limited variability in the intervals between failures and comparatively stable operational behavior. This pattern is associated with routine wear of consumable components, particularly the blades, whose replacement involves simple and rapid interventions. At this stage, no clear evidence of advanced structural degradation was observed from the reliability indicators (Table A).

Between May and September, Wood Chipper 1 showed a gradual change in operational behavior. MTBF increased significantly, rising from 59.8 hours in May to 79.0 hours in August and 86.8 hours in September. This improvement may be associated with corrective interventions, replacement of critical components, or improved operating conditions. Despite the increase in MTBF, downtime-based MTTR also increased in some months. In July, MTTR exceeded 5 hours, indicating that failures became less frequent overall but more complex and time-consuming to repair. This behavior suggests a transition from routine failures with rapid resolution to less frequent failures involving critical components or deeper degradation mechanisms (Table A).

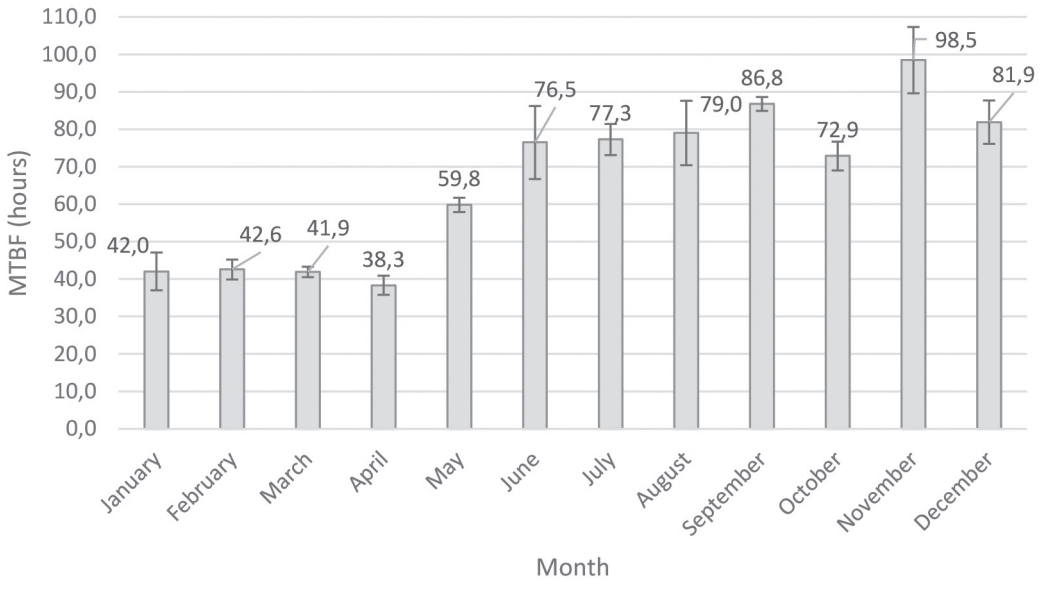


Figure 1. Monthly MTBF (hours) of Wood Chipper 1 with 95% confidence intervals.

Between October and December, Wood Chipper 1 exhibited behavior consistent with accumulated wear. MTBF remained high, reaching 98.5 hours in November, the highest value recorded during the analyzed period. However, downtime-based MTTR remained elevated compared to the beginning of the year, ranging from 4.4 to 5.6 hours (Figure 2). As a result, availability showed a slight reduction, varying between 93.5% and 95.7%. This pattern indicates that, despite the lower frequency of failures, the severity of the interventions increased, requiring more complex maintenance actions to restore operational conditions (Table A).

Over the full 12-month period, Wood Chipper 1 presented an aggregated annual MTBF of approximately 50.6 hours, calculated from the total operating time and the 173 recorded failures. When considering the simple average of the monthly MTBF values presented in Table A, the corresponding value was approximately 66.5 hours. These values are consistent with industrial equipment operating continuously under progressive mechanical wear. Availability remained generally high, ranging between 93.5% and 96.5%, indicating that maintenance interventions generally restored operational capacity, although repair duration increased in the final months (Table A).

The evolution of the indicators suggests three operational regimes for Wood Chipper 1. Initially, a stable regime associated with controlled wear and routine failures was observed. This was followed by a period of temporary improvement in reliability, characterized by longer intervals between failures. Finally, signs of accumulated structural wear emerged, reflected mainly in the increase in downtime-based MTTR (Table A).

The intervals between failures were fitted to the Weibull distribution, resulting in β equal to 3.56, η equal to 53.6 hours, and R^2 equal to 0.835 (Figure 3). The β value greater than 1 confirms a wear-dominated failure regime, characterized by a progressive increase in the failure rate over time. The absence of β values below 1 indicates the lack of infant failures, consistent with the stable behavior observed during the initial months.

The scale parameter η, equal to 53.6 hours, indicates that approximately 63.2% of the observed TBF intervals are expected to be shorter than 53.6 hours. Reliability decreases significantly after approximately 50 to 60 hours, indicating that continuous operation above this interval substantially increases the probability of failure. Comparison between the Weibull model and the Kaplan–Meier estimator shows satisfactory agreement in the central region of the distribution, with moderate divergences at the extremes, which may reflect the coexistence of multiple failure mechanisms partially represented by the two-parameter Weibull distribution (Figure 4).

The total accumulated downtime (TTR) was 415.7 hours. Three failure categories accounted for most of the downtime: Blade replacement (32.4%),

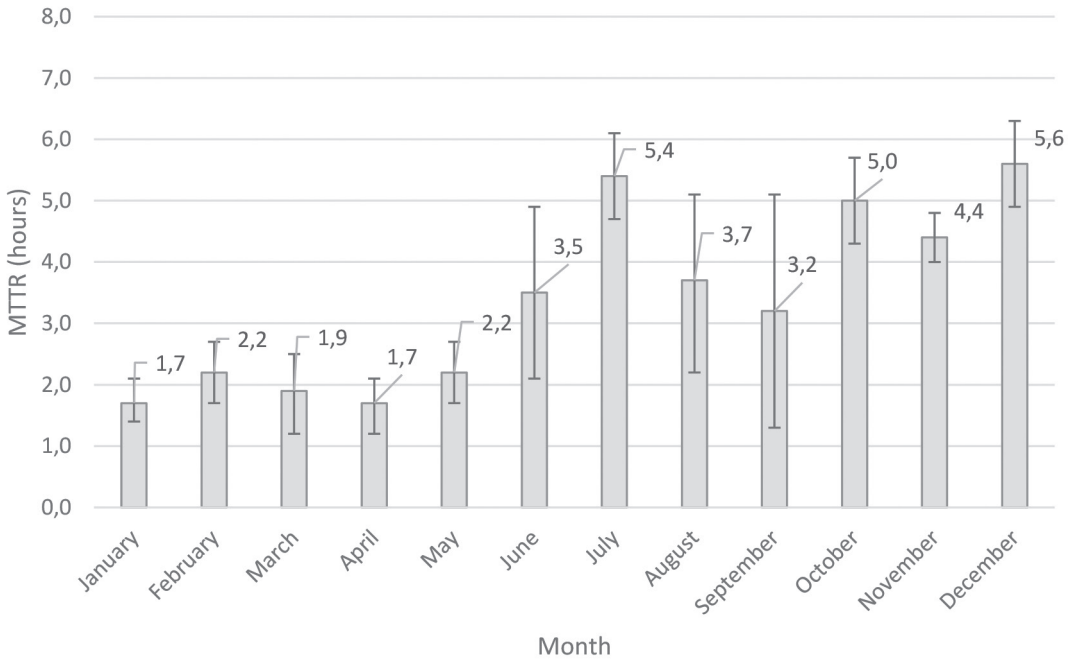


Figure 2. Monthly MTTR (hours) of Wood Chipper 1 with 95% confidence intervals.

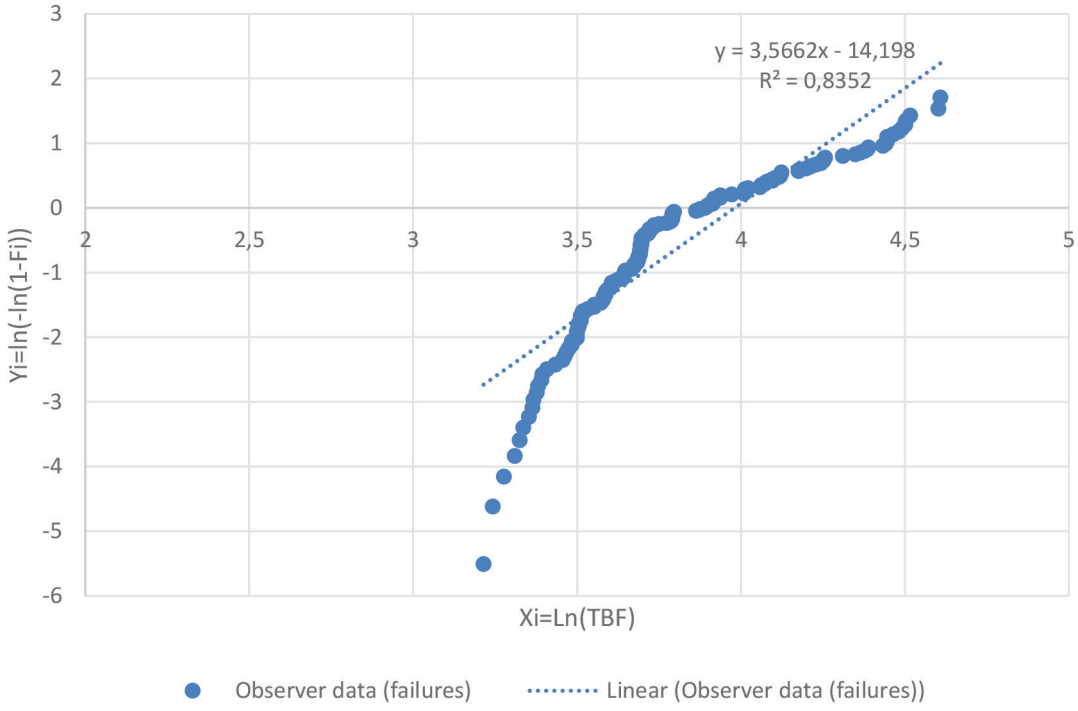


Figure 3. Weibull probability plot for Wood Chipper 1.

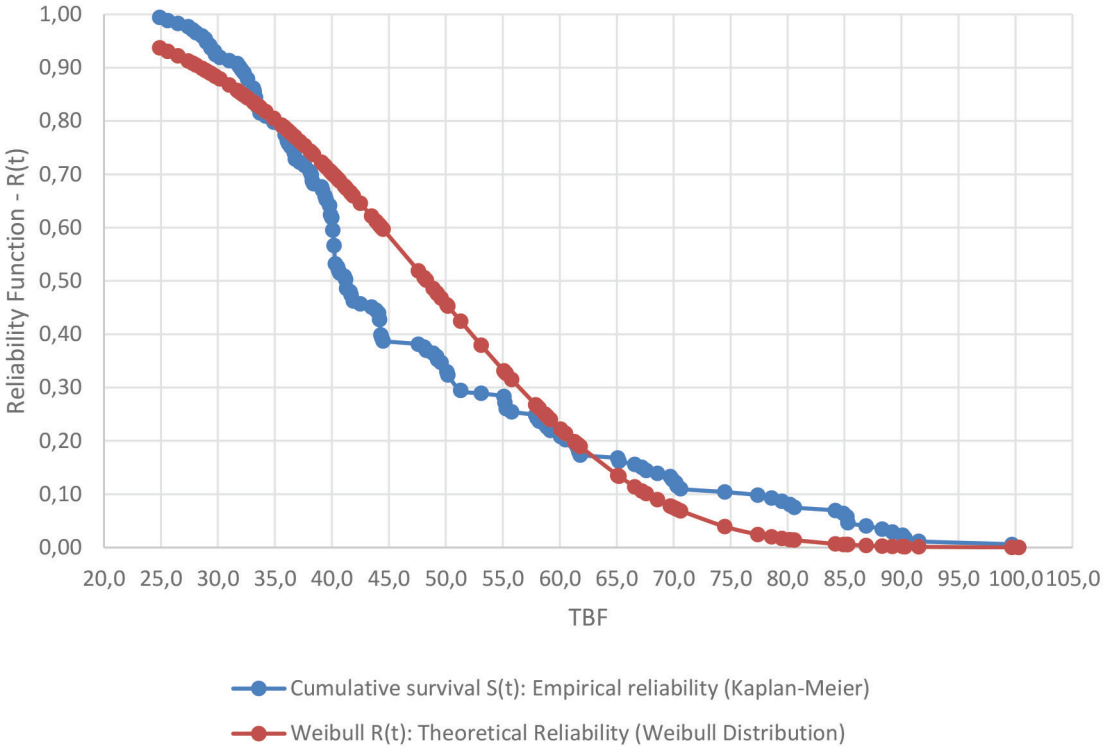


Figure 4. Comparison between the Kaplan–Meier survival curve and the Weibull model for the Wood Chipper 1.

Mechanical failure (24.7%), and Operational difficulties (18.0%), together representing 75.1% of total downtime (Figure 5).

Blade replacement represented the main cause of downtime in Wood Chipper 1, consistent with the wear-dominated failure regime identified through Weibull analysis. This pattern is typical of components subjected to abrasion and fatigue. Consequently, blade management directly influences operational availability and system productivity.

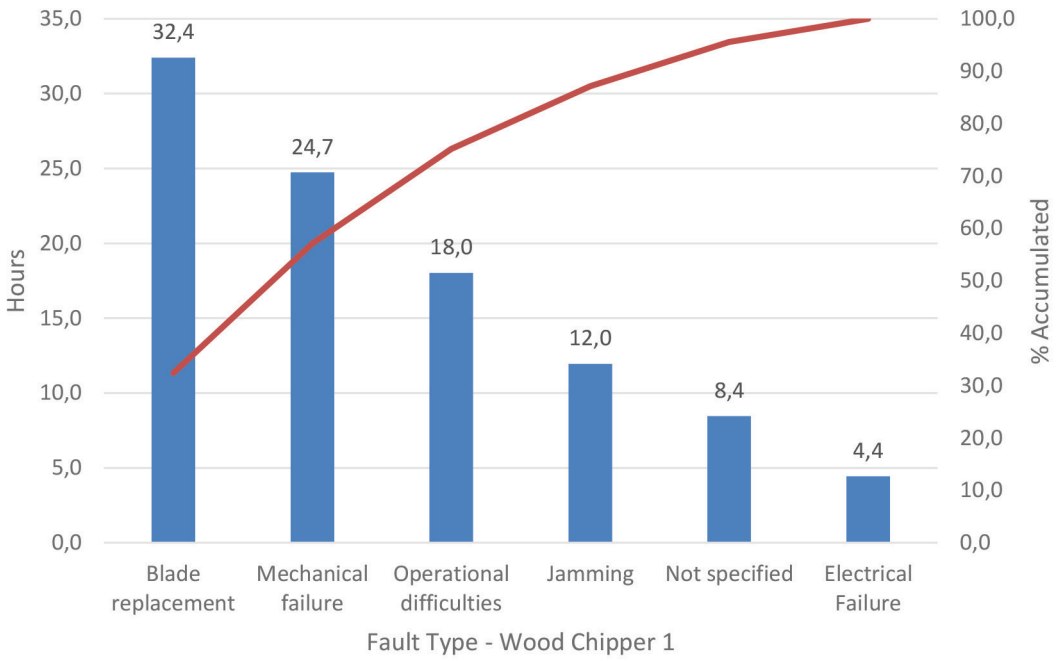


Figure 5. Analysis of various types of Wood Chipper 1 failures using the Pareto Diagram.

The following analysis refers specifically to the blade replacement failure mode in Wood Chipper 1. This subset includes 54 blade replacement events extracted from the complete dataset of 173 recorded failures. The subset was independently reprocessed and fitted to a dedicated two-parameter Weibull model. Therefore, the Weibull parameters presented in Figure 6 were obtained exclusively from this subset and should not be interpreted as representative of the complete failure dataset. For the complete dataset, the Weibull model resulted in β close to 3.56 and η close to 53.6 hours, whereas the blade replacement subset resulted in β close to 3.35, η close to 52.8 hours, and R^2 close to 0.804.

Analysis of the blade replacement subset through the cumulative probability of failure F(t) and reliability R(t) functions showed high reliability during the initial operating period. Up to 20 hours, reliability remained above 96%, while the cumulative probability of failure remained below 4%. At 30 hours, R(t) was 86.0% and F(t) 13.9%; at 35 hours, reliability decreased to 77.7%. From 40 hours onward, degradation became more pronounced, with reliability decreasing to nearly 67% and cumulative probability of failure exceeding 32%. At 47.5 hours, the cumulative probability of failure reached 50%, corresponding to the median blade lifetime.

The failure rate function h(t), obtained from the Weibull model, confirms this trend. During the initial operating period, the failure rate remained very low; at 10 hours, h(t) was 0.0013. The failure rate gradually increased to 0.0168 at 30 hours and 0.0330 at 40 hours. From 50 hours onward, a more pronounced increase was observed, with h(t) reaching 0.0559 and exceeding 0.1233 near 70 hours. This monotonic increase is consistent with the Weibull shape parameter obtained for the blade replacement subset (β = 3.35), characteristic of progressive wear mechanisms, confirming that blade behavior is dominated by wear-related degradation (Figure 6).

Based on these results, a critical degradation zone was identified approximately between 35 and 40 operating hours. Reliability-based maintenance criteria recommend interventions before reliability decreases below approximately 70% to 80%. Therefore, preventive blade replacement within this interval may reduce unexpected failures, minimize unplanned downtime, and improve the operational availability of Wood Chipper 1 (Figure 7).

4.3 Time Evolution of Reliability Indicators – Wood Chipper 2

Analysis of the reliability indicators of Wood Chipper 2 over twelve months reveals a more unstable operational behavior than that observed in Wood Chipper 1, both in TBF and availability (Table B). During this period, 155 failures were recorded, with times between failures ranging from approximately 20 to 105 hours, showing high variability and sensitivity to operating conditions and maintenance practices.

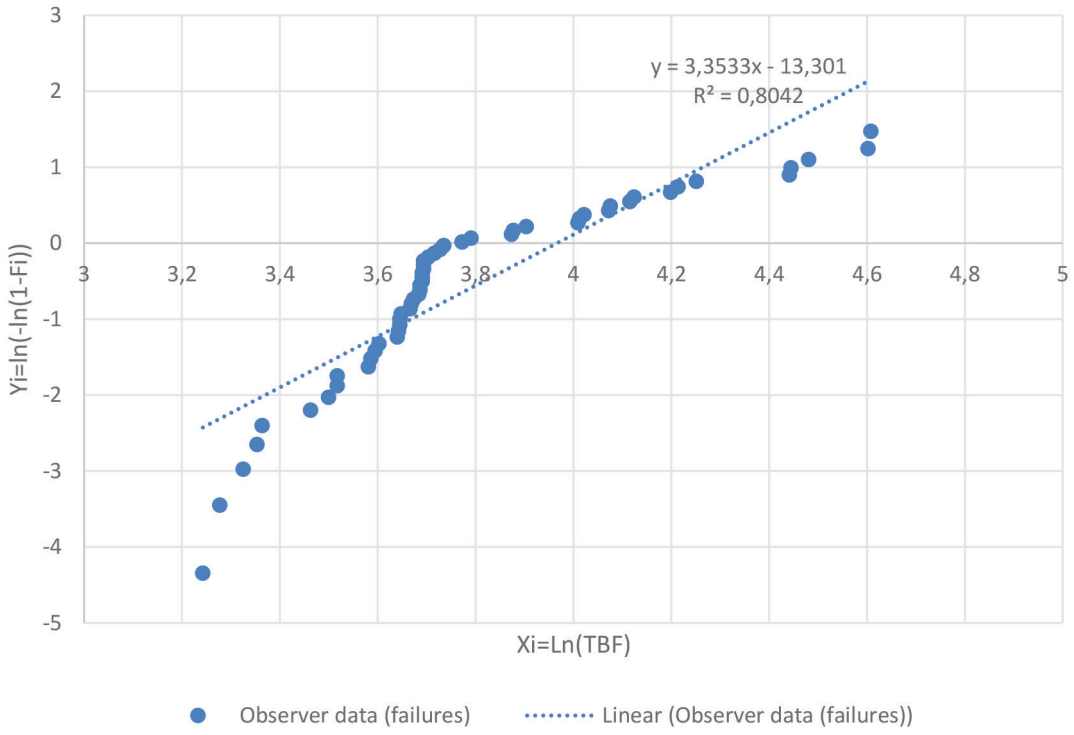


Figure 6. Weibull probability plot fitted exclusively to blade replacement failures in Wood Chipper 1.

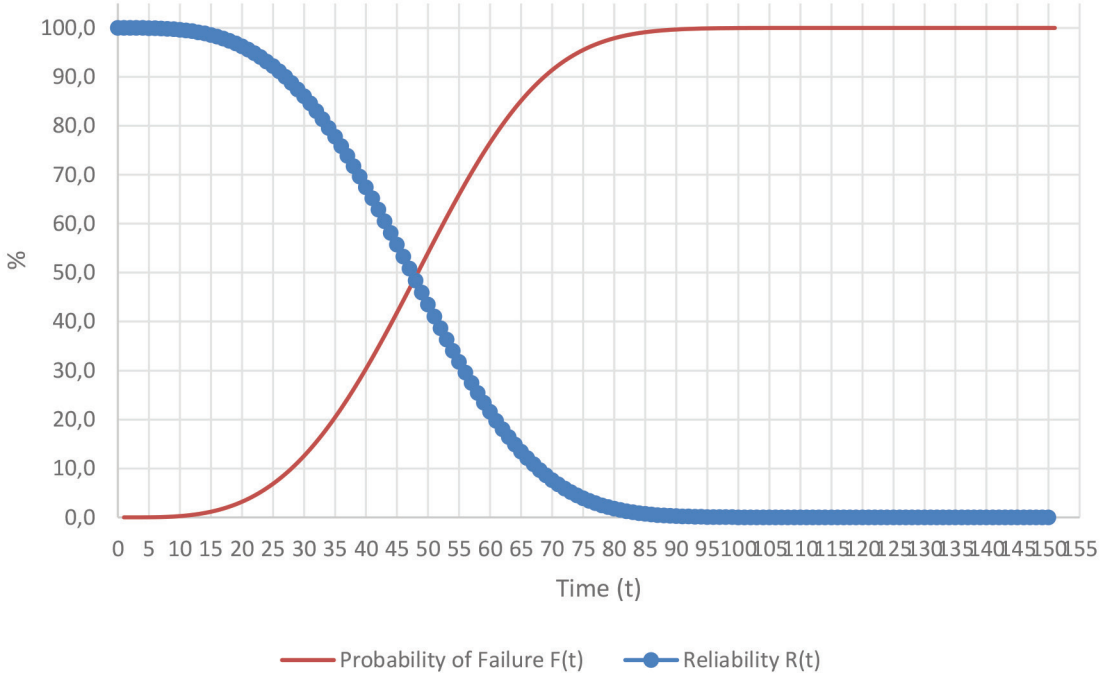


Figure 7. Cumulative failure functions F(t) and reliability R(t) of the Wood Chipper 1.

The combined evolution of MTBF, MTTR, and availability showed different operational phases, with episodes of degradation and periods of recovery. Overall, Wood Chipper 2 presented greater variability in the indicators, suggesting the influence of external factors, such as the stability of the raw material supply and the occurrence of blockages.

At the beginning of the period, in January, a relatively stable regime was observed, with an MTBF of 50.6 hours (Figure 8), a downtime-based MTTR of 2.6 hours, and availability of 95.1% (Figure 9). In February, operational performance deteriorated: MTBF decreased to 29.9 hours, and the intervals between failures became more regular, indicating highly recurrent

occurrences associated with adverse operating conditions or temporary structural problems (Table B).

Between March and September, reliability indicators showed an overall recovery, although with monthly fluctuations. MTBF exceeded 70 hours in several months and surpassed 100 hours in July (Figure 8). At certain times, downtime-based MTTR also increased, such as in March, when the average repair duration reached approximately 4.7 hours, suggesting more complex failures (Figure 9). Availability remained generally high, ranging from approximately 93.0% to 97.0%. July represented the period of best operational performance, with an MTBF of approximately 103 hours, low statistical dispersion, and availability around 97.0%. This result indicates that Wood Chipper 2 has high structural potential when operated under appropriate conditions, and that the failure regime depends not only on equipment limitations, but also on the effectiveness of operating conditions and maintenance interventions (Table B).

Over the 12-month period, Wood Chipper 2 presented an aggregated annual MTBF of 56.5 hours, calculated from total operating time and the 155 recorded failures. When considering the simple

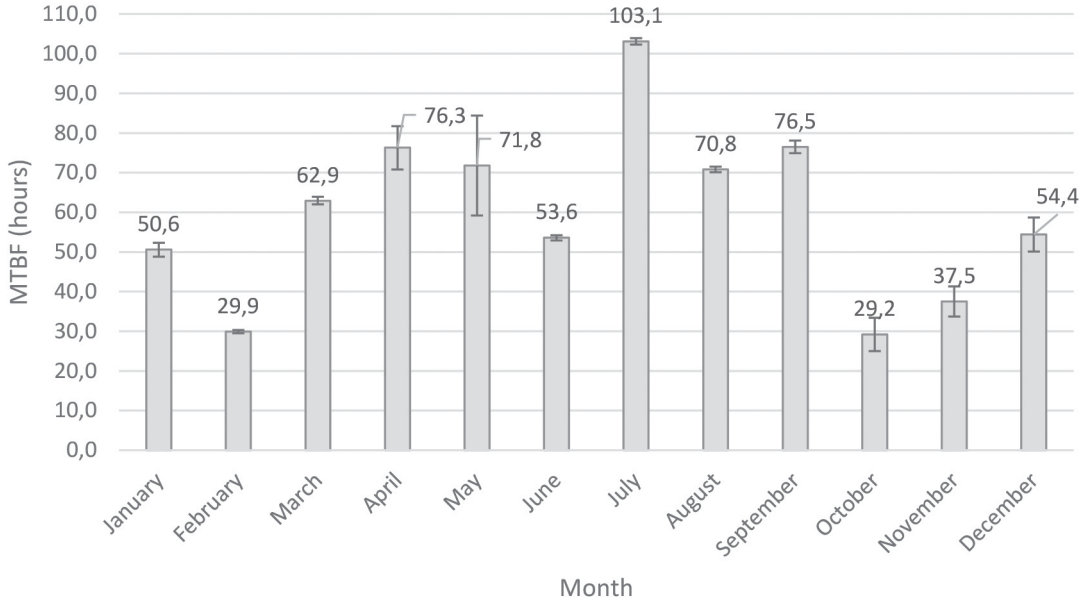


Figure 8. Monthly MTBF (hours) of Wood Chipper 2 with 95% confidence intervals.

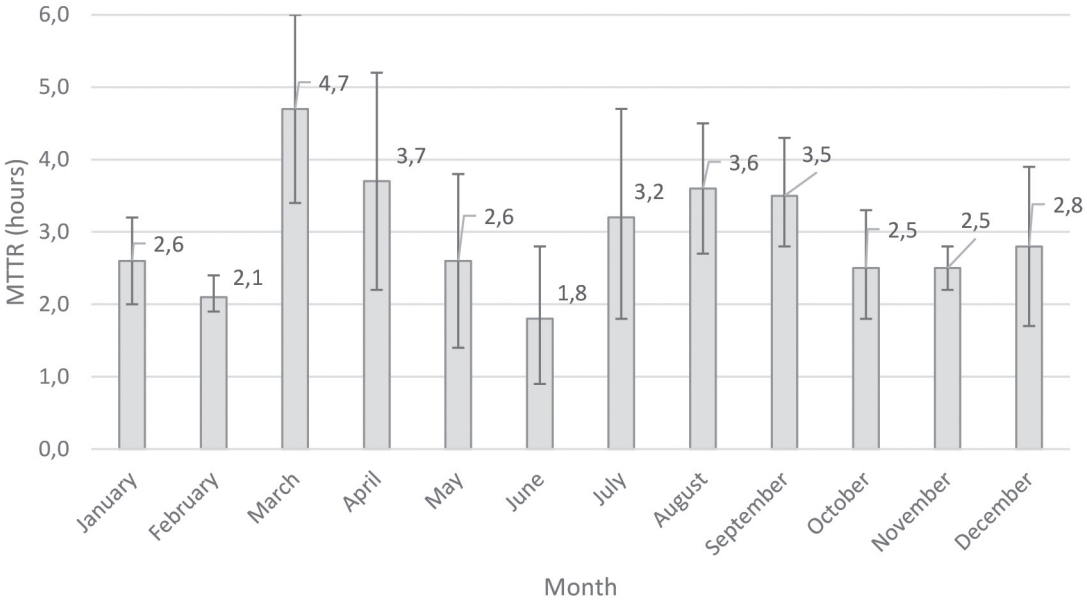


Figure 9. Monthly MTTR (hours) of Wood Chipper 2 with 95% confidence intervals.

average of the monthly MTBF values presented in Table B, the corresponding value was 59.7 hours. The aggregated annual downtime-based MTTR was 2.9 hours, while the simple monthly average was 3.0 hours. Average availability was 94.9%.

Following a favorable period, Wood Chipper 2 exhibited renewed degradation in October, with MTBF decreasing to 29.2 hours and availability to 92.0%, a pattern similar to that observed in February and reflecting adverse operational factors, seasonal effects, accumulated degradation, or an increased occurrence of jamming events (Table B). In November and December, a moderate recovery was observed: MTBF ranged from 37.5 to 54.4 hours, downtime-based MTTR ranged from 2.5 to 2.8 hours, and availability ranged from 93.7% to 95.1%, indicating partial stabilization without reaching the peak performance observed in July (Table B).

The annual behavior of Wood Chipper 2 can be summarized in four phases: a relatively stable regime in January, abrupt degradation in February, recovery with a peak in July, and renewed degradation in October followed by moderate stabilization. This pattern demonstrates good structural capacity, although with clear sensitivity to operating conditions and maintenance management (Table B).

Fitting the intervals between failures to the Weibull distribution resulted in β approximately equal to 2.98, η approximately equal to 60.2 hours, and R^2 approximately equal to 0.905 (Figure 10). The β value greater than 1 confirms a wear-dominated failure regime, characterized by an increasing failure rate over time, although slightly lower than that observed in Wood Chipper 1, while still reflecting the influence of operational factors.

The scale parameter η, equal to 60.2 hours, indicates that approximately 63.2% of the observed TBF intervals are expected to be shorter than 60.2 hours. Reliability decreased substantially after approximately 50 to 60 hours, with a more pronounced loss beyond the scale parameter η, suggesting that continuous operation above this interval significantly increases the probability of failure. The comparison between the Weibull model and the Kaplan–Meier estimator showed satisfactory agreement up to approximately 40 hours, with moderate divergences in the intermediate region and more pronounced deviations at the edges of the distribution, which may reflect limitations of the two-parameter Weibull representation. This behavior indicates that the Weibull model adequately represents the central failure regime, although it may partially simplify the complexity of the system (Figure 11).

The total accumulated repair time (TTR) for Wood Chipper 2 was 445.7 hours, slightly higher than that observed in Wood Chipper 1. The three main causes of unavailability were Jamming (28.5%), Blade Replacement (26.5%), and Mechanical Failure (19.7%), together accounting for 74.7% of the total downtime (Figure 12).

The predominance of Jamming highlights the influence of operational factors, such as instability in

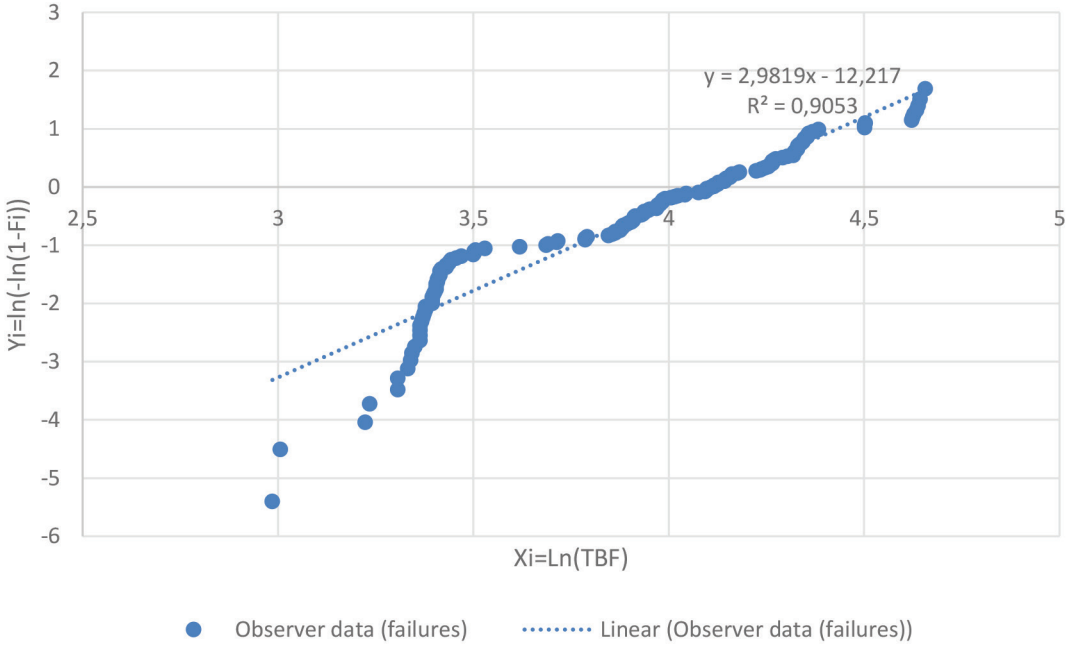


Figure 10. Weibull probability plot for Wood Chipper 2.

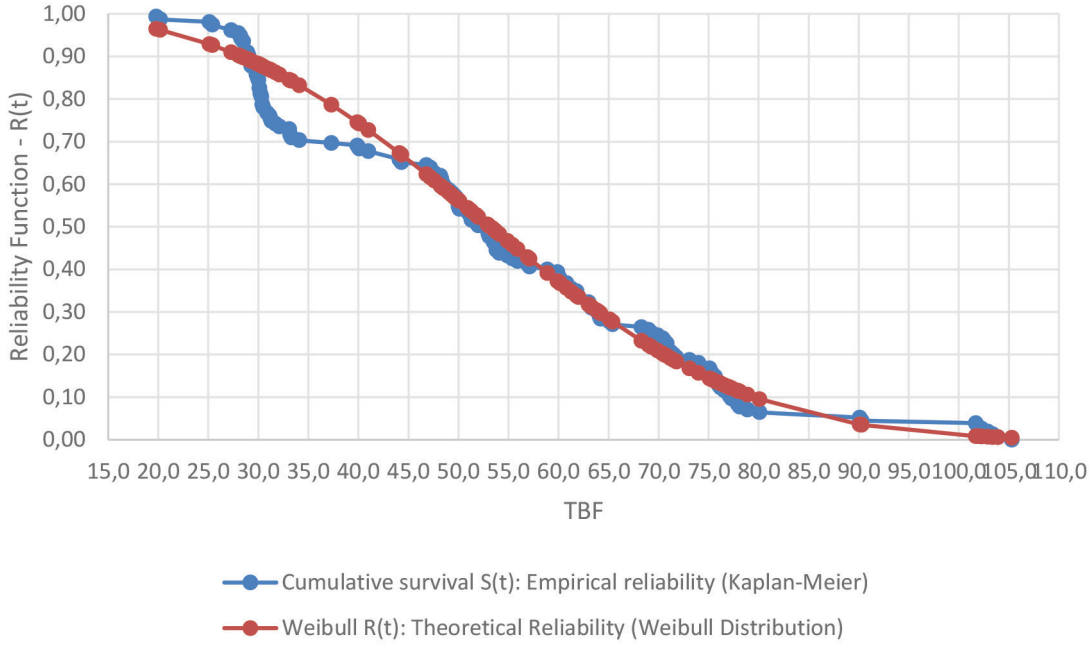


Figure 11. Comparison between the Kaplan–Meier survival curve and the Weibull model for the Wood Chipper 2.

feeding and heterogeneity of the raw material. Unlike Wood Chipper 1, where downtime was mainly associated with predictable blade interventions, Wood Chipper 2 exhibited more reactive operational events, increasing the variability of MTBF, MTTR, and availability. Equipment performance therefore depends strongly on the stability of the production process. Optimizing feeding conditions, standardizing procedures, improving raw material storage, and reducing setup and cleaning times may reduce downtime and improve overall reliability.

The following analysis refers specifically to the blade replacement failure mode in Wood Chipper 2. This subset includes 37 blade replacement events extracted from the complete dataset of 155 recorded failures. The subset was independently reprocessed and fitted to a dedicated two-parameter Weibull model. Therefore, the Weibull parameters presented in Figure 13 were obtained exclusively from this subset and should not be interpreted as the parameters of the complete failure dataset. For the complete dataset, the Weibull model resulted in β approximately equal to 2.98 and η approximately equal to 60.2 hours, whereas the blade replacement subset resulted in β approximately equal to 2.98, η approximately equal to 63.7 hours, and R^2 approximately equal to 0.937.

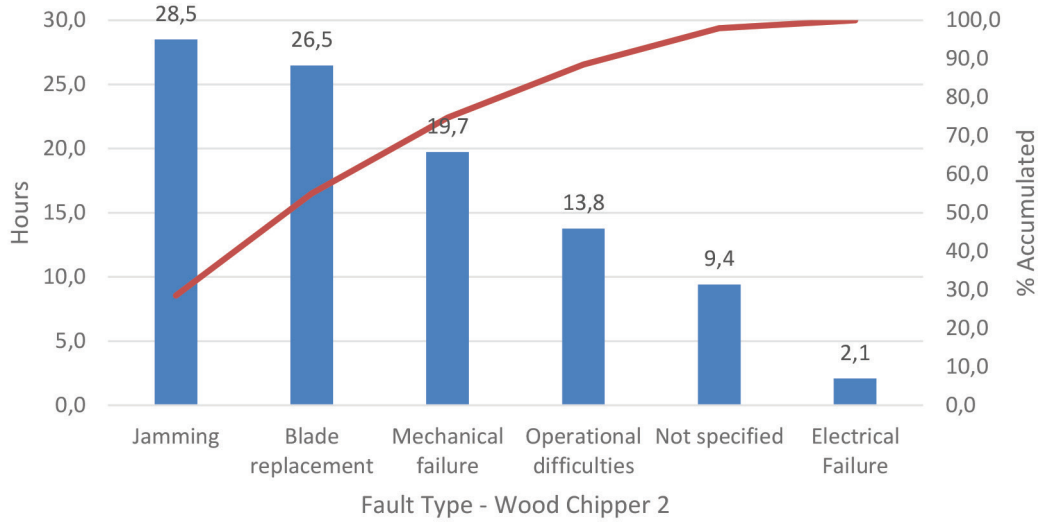


Figure 12. Analysis of various types of Wood Chipper 2 failures using the Pareto Diagram.

Analysis of the blade replacement subset showed high reliability during the initial operating periods: up to approximately 20 hours, R(t) remained above 96%, while the cumulative probability of failure F(t) remained below 3.1%.

With increasing operating time, progressive degradation was observed: at 30 hours, R(t) was 89.9% and F(t) 10.1%; at 35 hours, R(t) decreased to 84.5%. After 40 hours, degradation accelerated, with R(t) declining to 77.9% and F(t) exceeding 22.1%. At 50 hours, R(t) reached 61.5%, indicating that 38.5% of the blade replacement intervals were shorter than this value. These results support defining the preventive replacement interval around 40 to 45 operating hours.

Reliability-based maintenance criteria recommend preventive interventions before reliability decreases to approximately 70% to 80%. Preventive blade replacement should therefore be scheduled within this interval. The Weibull model fitted to the blade replacement subset reinforces the presence of progressive wear after an initial stable period. Beyond this interval, the loss of cutting capacity increases resistance to feeding and may increase the probability of system jams (Figure 13).

Thus, jams should not necessarily be interpreted as isolated events, since they may also be associated with progressive blade wear, reduced cutting efficiency, and increased feeding resistance. The integrated analysis of the results indicates that preventive blade replacement between 40 and 45 hours of operation is recommended not only to reduce the frequency of jams, but also to limit their possible evolution into more severe mechanical failures, which represent the third largest cause of accumulated downtime. In this way, proactive management of the blade life cycle plays an important role in preserving equipment integrity and improving the operational continuity of Wood Chipper 2 (Figure 14).

4.4 Comparison Between Equipment

A comparison between the two wood chippers reveals clear differences in failure patterns, reliability, and operational sensitivity. Wood Chipper 1 exhibited a relatively stable operating regime, with predictable failures mainly associated with blade wear. In contrast, Wood Chipper 2 showed greater variability, influenced by external factors such as irregular raw material feeding and the occurrence of jamming events.

Regarding reliability, Wood Chipper 1 presented a Weibull distribution with β greater than 3, indicating a predominance of failures associated with accelerated wear, lower variability, and more predictable degradation. Wood Chipper 2 presented β approximately equal to 2.98, also associated with wear-related failures, although with greater sensitivity to operating conditions, resulting in a more heterogeneous failure regime characterized by abrupt degradation episodes in February and October and peak performance in July.

Operational indicators reinforce these differences. Wood Chipper 1 showed relatively stable MTBF values and more predictable maintenance behavior,

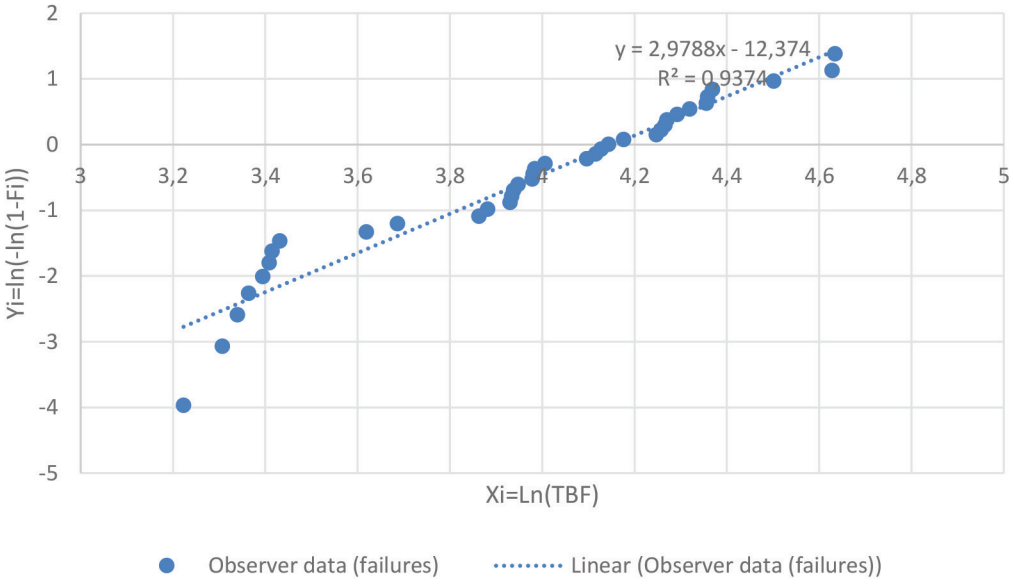


Figure 13. Weibull probability plot fitted exclusively to blade replacement failures in Wood Chipper 2.

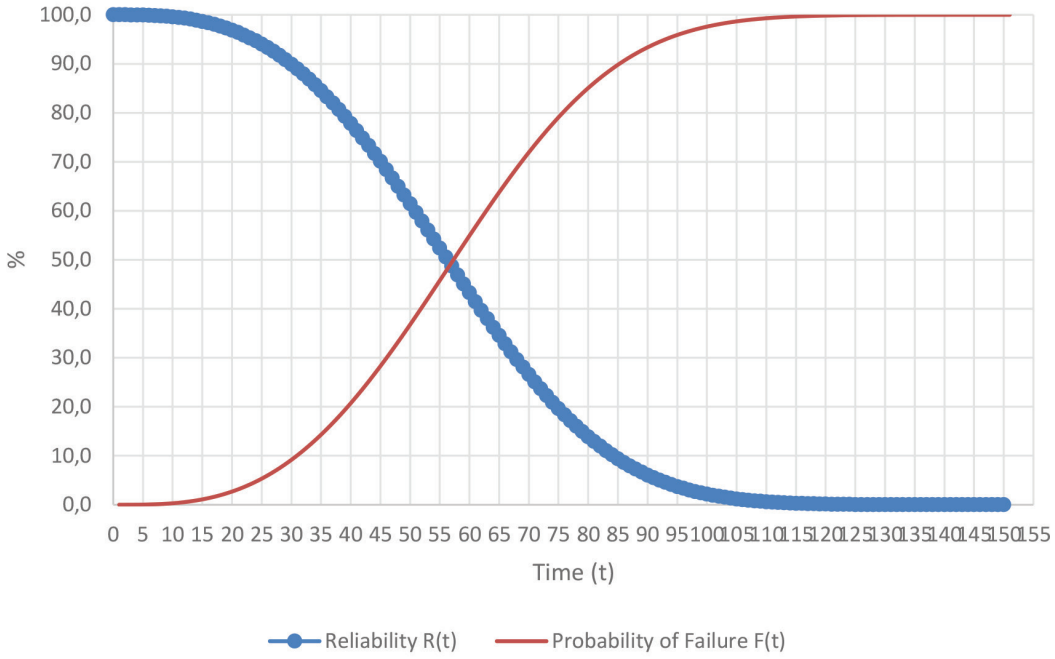


Figure 14. Cumulative failure functions F(t) and reliability R(t) of the Wood Chipper 2.

with availability ranging from approximately 93.5% to 96.5%. Wood Chipper 2 exhibited greater variability, with monthly MTBF values ranging from approximately 29.2 to 103.1 hours, MTTR ranging from approximately 1.8 to 4.7 hours, and availability fluctuating between 92.0% and 97.0% (Figure 15). This behavior reflects the interaction between blade wear and unplanned failures, particularly jamming events.

The analysis of monthly availability showed no significant degradation trend for either equipment. Linear regression confirmed operational stability: for Wood Chipper 1, $y = -0.1341x + 96.128$, $R^2 = 0.1902$; for Wood Chipper 2, $y = -0.0229x + 95.033$, $R^2 = 0.0029$. The low R^2 values and negative coefficients indicate that availability remained practically constant throughout the analyzed period, with no statistically significant linear trend ($p > 0.05$) (Figure 15). Confidence intervals were not calculated for availability because availability was derived deterministically from monthly MTBF and downtime-based MTTR values; therefore, uncertainty is indirectly represented through the confidence intervals associated with these two input indicators.

Considering that MTTR includes logistical and administrative times, a sensitivity analysis was performed to estimate the impact of these factors on operational availability. For sensitivity analysis purposes, the arithmetic mean of the monthly MTBF values was adopted instead of the aggregated annual MTBF in order to preserve the monthly operational variability observed throughout the year and to avoid overweighting periods with higher operating exposure. This resulted in representative MTBF values of 66.5 hours for Wood Chipper 1 and 59.7 hours for Wood Chipper 2. The estimated technical MTTR was obtained by removing the fraction attributed to logistical delays according to Equation 6. For example, when 20% of MTTR corresponds to logistical delays, the technical MTTR corresponds to 80% of the total observed MTTR. Operational availability was subsequently recalculated using Equation 3, considering that logistical delays affect repair duration but do not influence MTBF.

Three MTTR scenarios were analyzed. In the baseline scenario, using the observed downtime-based MTTR values, downtime-based MTTR was 3.4 hours for Wood Chipper 1 and 3.0 hours for Wood Chipper 2, resulting in estimated availability of 95.2% for both. In the intermediate scenario, assuming that 20% of MTTR corresponded to logistical delays, estimated technical MTTR decreased to 2.7 and 2.4 hours, respectively, increasing availability to 96.1%. In the conservative scenario, assuming a 50% contribution from logistical delays, estimated technical MTTR decreased to 1.7 and 1.5 hours, increasing estimated availability to 97.5% (Table 2).

Even under the conservative scenario, availability increased by approximately 2.3% for both wood chippers, demonstrating that the reliability indicators and failure-mode prioritization remained consistent. The relative importance of the main failure modes identified in the Pareto analysis remained unchanged, with

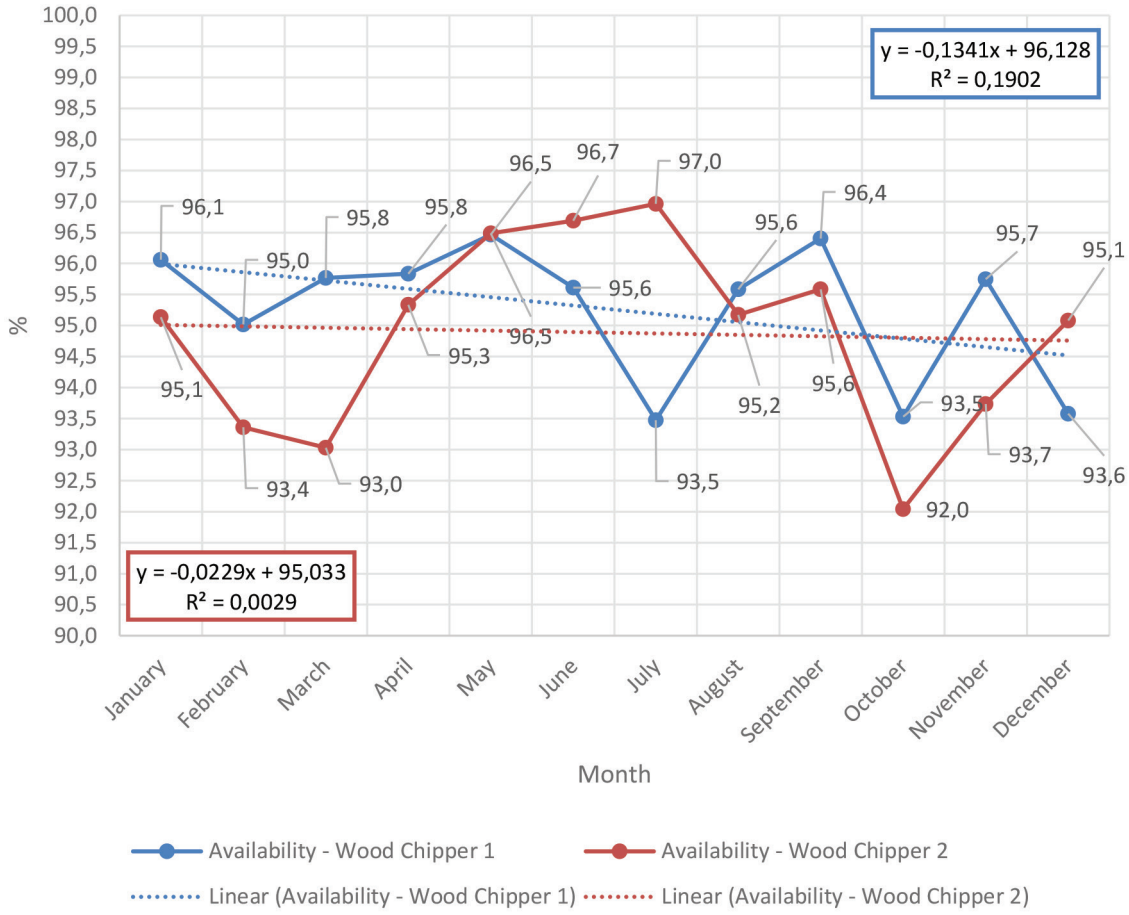


Figure 15. Monthly operational availability of wood chippers 1 and 2 over a 12-month period, with linear trend lines.

Table 2. Arithmetic mean of monthly MTBF values, technical MTTR, and estimated availability under different logistics delay scenarios.

Logistics Scenario	Wood Chipper	Arithmetic mean of monthly MTBF values (h)	Technical MTTR (h)	Estimated Availability (%)
0% (Current)	Wood Chipper 1	66.5	3.4	95.2
	Wood Chipper 2	59.7	3.0	95.2
20% Logistics	Wood Chipper 1	66.5	2.7	96.1
	Wood Chipper 2	59.7	2.4	96.1
50% Logistics	Wood Chipper 1	66.5	1.7	97.5
	Wood Chipper 2	59.7	1.5	97.5

blade replacement and jamming-related events continuing to represent the principal causes of downtime.

The analysis of failure modes further highlights the differences between the two machines. In Wood Chipper 1, downtime was predominantly associated with blade replacement events, allowing implementation of preventive maintenance strategies focused on wear control. In Wood Chipper 2, three failure modes explained 74.7% of total downtime: Jamming (28.5%), Blade Replacement (26.5%), and Mechanical Failure (19.7%). This distribution indicates greater dependence on operating conditions and a higher need for corrective interventions.

The difference in operational behavior between the two wood chippers is associated with operational conditions. Wood Chipper 2 receives primary feed directly, which is more heterogeneous and presents a higher probability of impurities or irregular logs, frequently processing larger or more difficult batches. Wood Chipper 1, in contrast, operates with pre-selected or partially processed material, reducing mechanical stress and contributing to more predictable failures.

Variability between operators and shifts also contributes to the heterogeneous behavior observed in

Wood Chipper 2. Higher personnel turnover and non-uniform training practices may result in inconsistent operation, variable intervention times, and greater susceptibility to unplanned failures.

This combination of factors explains the operational regime observed in Wood Chipper 2, characterized by periods of high performance, such as the peak observed in July, and abrupt degradation episodes in February and October. Wood Chipper 1 maintained more predictable operation and lower sensitivity to raw material variability.

From a maintenance perspective, Wood Chipper 1 benefits primarily from preventive strategies based on blade wear management. Wood Chipper 2 requires a broader operational approach, combining preventive blade replacement intervals between approximately 40 and 45 operating hours with operational measures aimed at optimizing feeding conditions and reducing blockages.

Despite its greater variability, Wood Chipper 2 demonstrated high structural potential, particularly during the peak performance observed in July. Its reliability remains strongly influenced by operational factors and by the interaction between blade wear and jamming events. Consequently, performance improvement depends not only on preventive maintenance strategies, but also on standardization of operator training, monitoring of wood quality, and, where necessary, adjustments to the production line configuration to reduce external operational impacts and promote a more stable operating regime.

4.5 Analysis of failure modes

During the 12-month operating period, corresponding to more than 8,760 hours per piece of equipment, failures in the wood chippers were classified according to a standardized technical scheme based on maintenance record descriptions, affected components, and corrective interventions. Each occurrence was assigned to a functional failure category to ensure consistency and reproducibility in the reliability analysis.

The cumulative Pareto analysis confirms the 80/20 principle, showing that a limited number of failure modes account for most of the downtime. The results indicate that the three main categories represented 75.2% of the total downtime in Wood Chipper 1 (415.7 hours) and 74.7% in Wood Chipper 2 (445.7 hours), as illustrated in the Pareto diagrams.

Table 3 presents the complete failure taxonomy, including operational definition, probable root cause, preventive actions based on fixed maintenance intervals, and predictive or operational mitigation actions. This structure allows direct correlation between the most recurrent failure modes and maintenance interventions capable of effectively reducing downtime.

Table 3. Taxonomy of Failures and Maintenance Actions for Wood Chippers.

Failure Category	Definition	Probable Root Cause	Preventive Action	Predictive or Operational Action
Blade replacement	Loss of cutting ability or blade chipping	Abrasive wear caused by eucalyptus and pine fibres	Scheduled replacement according to equipment-specific intervals: 35–40 h for Wood Chipper 1 and 40–45 h for Wood Chipper 2	Monitoring of blade wear and immediate replacement when necessary
Mechanical Failure	Failure of bearings, belts, or transmission elements	Accumulated fatigue and high torque under continuous operation	Periodic lubrication and scheduled visual inspections	CBM vibration sensors with spectral analysis
Jamming	Obstruction of the cutting drum or conveyor	Feedstock heterogeneity and irregular feeding	Pre-selection of wood and feed-rate standardization	Flow monitoring with overload alarms
Electrical Failure	Defects in motors, wiring, or sensors	Overheating or loosening of electrical connections	Periodic inspections and cleaning of electrical panels	Thermography and electric current signal analysis
Operational Difficulties	Minor downtime resolved by operators	Operational variability or improper configuration	Standardized procedures and operator training	Systematic recording of occurrences and root-cause analysis
Safety Stop	Activation of automatic safety interlocks	Sensor sensitivity to dust or particles	Periodic cleaning and recalibration	Monitoring of sensor status with deviation alarms

The results indicate that blade replacement accounted for 32.4% of total downtime in Wood Chipper 1 and 26.5% in Wood Chipper 2, followed by mechanical failures with 24.7% and 19.7%, respectively, and jamming events with 12.0% and 28.5%. These failure modes reflect typical operating conditions associated with continuous woody biomass processing, where raw material variability strongly influences equipment performance. The processed wood consisted mainly of eucalyptus and pine, whose density, moisture content, and presence of mineral contaminants directly affect blade wear and the probability of feed-system blockage.

The detailed analysis of the failure modes establishes a relationship between operational symptoms and probable root causes. In blade replacement events, the predominant cause was abrasive wear and loss of sharpness caused by continuous friction with high-density eucalyptus fibres. The proposed mitigation strategy involves optimization of the sharpening schedule and systematic blade-condition monitoring, promoting a transition from corrective to condition-based maintenance.

Regarding jamming events, variability in moisture content and raw material geometry was identified as a major contributing factor. The recommended operational strategy includes improving screening procedures at the wood chipper inlet, ensuring more stable material flow, and implementing overload alarms capable of enabling intervention before complete equipment shutdown.

For mechanical failures, the main degradation mechanism is associated with accumulated fatigue in components subjected to high torque, particularly bearings and belts. The implementation of CBM, especially vibration analysis, allows earlier identification of degradation processes and contributes to increasing MTBF through scheduled preventive interventions.

To complement the failure analysis, predictive maintenance technologies applicable to the critical components of the wood chippers were evaluated according to their detection principles and expected impact on reliability.

To complement the analysis of the CBM technologies presented in Table 4, it is important to consider their practical implementation in industrial wood chippers. Vibration sensors, for example, should be installed on main bearings and strategically selected rotating shafts to capture representative degradation signals while minimizing interference from secondary drum vibrations. The high concentration of dust and wood debris in the operating environment creates additional challenges, requiring mechanical protection of the sensors, periodic calibration, and continuous signal verification to ensure reliable data acquisition.

These considerations are important to ensure that the collected data can be effectively used to support predictive maintenance actions and reduce equipment downtime. In practical applications, vibration and current-signal monitoring should preferably be performed continuously or at short predefined intervals during operation, whereas thermographic inspections may be conducted periodically during planned maintenance stops.

The expected lead time for detection of progressive mechanical degradation is generally longer than that associated with sudden blockage events. This difference reflects the practical limitations of monitoring systems operating under highly dusty environments and variable feeding conditions, while also supporting more realistic predictive maintenance planning for industrial wood chippers.

4.6 Economic Impact and Operational Optimization of the Recommended Actions

The reliability indicators were recalculated based on the expanded 12-month operational dataset, resulting in a mean MTBF over the analyzed period of 66.5 hours for Wood Chipper 1 and 59.7 hours for Wood Chipper 2.

Table 4. Recommended Predictive Maintenance Technologies by Component.

CBM technique	Monitored Component	Detection Principle	Expected Impact on Reliability
Vibration Analysis	Main bearings and rotating shafts	Increased RMS vibration values and harmonics associated with wear	Early degradation detection with MTBF increase between 5% and 12%
Acoustic Emission	Cutting drum and blades	High-frequency signals associated with microfractures	Detection of blade chipping before functional failure
Current Signal Analysis	High-power motors	Variations in the current spectrum associated with overload or unbalance	Reduction of MTTR by 10% to 20% in jamming situations
Thermography	Electrical panels and motors	Identification of hotspots above 60 °C	Reduced probability of unexpected electrical failures

Operational availability was calculated using the classical relationship between reliability indicators, defined as the ratio between MTBF and the sum of MTBF and downtime-based MTTR, following the definitions presented in Section 2.2.1.

Technical MTTR refers exclusively to effective maintenance intervention time, excluding logistical and administrative delays, whereas total MTTR includes all observed interruption periods. Technical MTTR was estimated by isolating effective repair duration from logistical and organizational components associated with resource mobilization, waiting time, and parts availability. To evaluate the potential influence of these factors, three sensitivity scenarios were analyzed.

In the baseline scenario, assuming that the entire downtime-based MTTR corresponded to effective repair duration, MTTR values of 3.4 hours were obtained for Wood Chipper 1 and 3.0 hours for Wood Chipper 2, corresponding to an average operational availability of 95.2%. In the intermediate scenario, assuming that 20% of total downtime corresponded to logistical delays, the estimated technical MTTR decreased to 2.7 and 2.4 hours, respectively, increasing availability to 96.1%. In the conservative scenario, assuming that 50% of total downtime was associated with logistical or organizational factors, the estimated technical MTTR decreased to 1.7 hours for Wood Chipper 1 and 1.5 hours for Wood Chipper 2, resulting in estimated availability close to 97.5%.

Although confidence intervals were not calculated directly for availability, the associated uncertainty is indirectly represented through the confidence intervals of the MTBF and MTTR indicators used in its calculation.

Table 5 presents quantified improvement scenarios for the three main categories identified through Pareto analysis, considering an aggregate average MTBF of approximately 63.1 hours and a reference technical MTTR of approximately 2.0 hours, corresponding initially to operational availability of approximately 96.9%.

The annual economic recovery presented in each row of Table 5 was obtained by multiplying the additional operational hours gained through increased availability by a conservative opportunity cost of 50 euros per hour of productive downtime. Considering the complete set of proposed interventions, the portfolio of actions requires a total estimated investment of 9,500 euros and generates an estimated annual recovery of approximately 34,450 euros, corresponding to an overall increase of approximately 3.9% in the operational availability of the analyzed equipment.

4.7 Final Considerations of the Results

The operational performance of wood chippers and other biomass processing machines depends strongly on raw material preparation, preventive maintenance, and efficient failure management. Studies [49], [50] indicate that standardizing log size and geometry is important for reducing technical interruptions and increasing productivity. Spinelli et al. [3] emphasize that larger and more uniform logs allow better utilization of motor power, whereas small or irregular pieces prolong feeding time and reduce efficiency. Similarly, Mihelič et al. [51] observe that raw material heterogeneity decreases the mass collected per load, increasing processing time and contributing to higher rates of mechanical failures. Kunickaya et al. [52] advocate for the "intellectualization" of log sorting, allowing the detection of non-standard pieces and supporting more efficient equipment use.

MTTR and machine availability are closely linked to the competence of the maintenance team, the quality of technical diagnosis, and spare-parts

Table 5. Quantified Improvement Scenarios with Cost Details.

Priority Action	Intervention Base	Expected MTTR Reduction (h)	Final Availability (%)	Hours Earned per Year (h)	Investment (€)	Annual Recovered Value (€)	Return Period (months)
Blade Management	Training of 10 people	2.0 to 1.4	97.8	236	2,000	11,800	Less than 3
Jam Control	Normalization of the feedstock	2.0 to 1.5	97.7	170	1,000	8,500	Less than 2
CBM Vibration Sensors	Installation on main bearings	2.0 to 1.5	97.7	198	5,000	9,900	About 6
Technical Training	Standardization of shifts	2.0 to 1.7	96.6	85	1,500	4,250	Less than 4

management [27], [53]. Piechnicki et al. [54] highlight that team training and the adoption of autonomous maintenance significantly reduce repair duration, while Diniz et al. [55] show that the creation of on-site critical spare-parts warehouses allowed greater agility in responding to failures. Spinelli et al. [32] observe that CBM is effective in increasing MTBF and reducing recurring failures, provided that it is associated with accurate diagnostics and continuous monitoring of blade wear. The literature also indicates that operational failures frequently result from feeding contaminated or irregularly sized logs. Mihelič et al. [51] confirm that metals and stones cause severe damage, while Kuptz and Hartmann [56] highlight that heterogeneous logs can cause blockages in conveyors and silos. Diniz et al. [55] add that impurities, such as dust, affect hydraulic systems by increasing oil viscosity and hindering machine movements, thereby reducing productivity.

The use of blade inspection and protection methods is important for extending equipment service life. Dananjaya et al. [57] detail processes for the prior elimination of contaminants, such as nails and metallic materials, while Spinelli et al. [58] reinforce that worn blades can reduce productivity by half and substantially increase fuel consumption. Kunickaya et al. [52] propose automated monitoring systems that allow wear identification and maintenance at the appropriate time, avoiding catastrophic failures. The application of statistical analyses, such as Weibull and Kaplan–Meier methods, is indicated to evaluate machine reliability and predict the service life of critical components, supporting strategic maintenance decisions [6], [59]-[65].

Investment in operational training, predictive maintenance, and robust diagnostics is repeatedly cited as an important factor in reducing MTTR and increasing MTBF. Piechnicki et al. [54] include "autonomous maintenance activities" in their RCM model to allow operators to contribute directly to reducing failures, while Diniz et al. [16] show that training mechanics and operators significantly increased availability and operational continuity. Spinelli et al. [32] highlight that inexperienced operators increase maintenance costs and failure frequency, reinforcing the importance of systematic training. The use of analytical tools, such as the Pareto Diagram, has also proven effective in prioritizing critical failures and optimizing maintenance flow [6], [66]-[68].

Continuous review of preventive maintenance schedules and strategic management of spare parts are important for ensuring operational sustainability. Mendes et al. [6], Garg et al. [66], Martins et al. [67] and Spinelli et al. [32] argue that continuous improvement of these plans increases equipment availability, while Acharya et al. [62], Musa et al. [68] and Wardani et al. [63] emphasize operational training as an instrument for inspecting, diagnosing, cleaning and lubricating equipment, ensuring greater reliability and continuous production. In addition, failure mode mapping, including blade replacement, mechanical failures and clogging, reinforces the importance of preventive and predictive strategies [6], [21], [59], [62], [63], [68], [69]. Spinelli et al. [32] demonstrate that blade handling accounts for up to 80% of the total maintenance cost of wood chippers, and Kuptz and Hartmann [56] indicate that non-standard particles cause blockages in conveyors and silos. In this context, feed standardization and contaminant elimination emerge as important measures to reduce failures and optimize performance [51], [57], [58].

The maturity of maintenance processes represents a significant competitive advantage in sectors such as timber and mining. Piechnicki et al. [54] state that mature production systems allow more precise decisions at all operational levels, affecting reliability, costs, and quality indicators. Diniz et al. [16] highlight that the WCM model promotes the transition from reactive to strategic preventive maintenance, increasing mechanical availability and ensuring the economic sustainability of operations. Dananjaya et al. [57] add that the integration of waste management and maintenance contributes to environmental sustainability, while De Zabala et al. [70] reinforce that the strategic orchestration of resources is essential to overcome challenges in an automated and globalized industrial environment.

The results obtained in this study demonstrate that the analyzed wood chippers presented high reliability and availability indicators, with MTBF values ranging from 38 to 105 hours, downtime-based MTTR between 1.7 and 5.6 hours, and availability between 92% and 97%. These results are in agreement with Mihelič et al. [51], who observed very high mechanical availabilities for new industrial wood chippers, ranging from 94.1% to 99.3%, and with Stolarski et al. [71], who consider 95% as a reference for technical availability for Albach and Bruks units. The MTBF values found, especially the peaks of 105 hours, suggest periods of operation with better quality raw material or more robust preventive maintenance, corroborating Diniz et al. [16], who reported MTBF between 24.67 and 45.90 hours and state that values within this range are adequate for adverse operating conditions. Similarly,

the MTTR values obtained are in line with the study by [16], who recorded values between 2.14 and 4.24 hours, and with [54], who indicate times of 1.17 to 1.55 hours after improvements in the maintenance process.

The analysis of failure regimes using the Weibull distribution, with β values close to 2.98 and 3.56, indicates progressive wear, typical of components subjected to continuous stress such as blades and hydraulic systems, in accordance with Spinelli et al. [32], who highlight that the frequency and severity of failures increase with accumulated wear. Blade wear was considered particularly relevant, being variable and difficult to predict based solely on time, as observed by Kunickaya et al. [52], who emphasize that the wear limit generates clear signs of the need for maintenance.

The distinct operational phases, especially for Wood Chipper 2, show periods of stability, abrupt degradation, and recovery, demonstrating strong operational sensitivity. This sensitivity is explained by the presence of contaminants such as metals or stones, which cause severe and abrupt damage, as reported by Mihelič et al. [51], and by the technological complexity of modern machines, whose exposed hydraulic systems increase the risk of failures, according to Diniz et al. [55]. Spinelli and Visser [72] also argue that higher productivity operations make equipment more sensitive to logistical failures or variations in raw materials, justifying the abrupt degradation observed in Wood Chipper 2.

Regarding the predominant failure modes, blade replacement was the main cause of downtime, accounting for 32.4% in Wood Chipper 1 and 26.5% in Wood Chipper 2. This predominance of blades is consistent with Spinelli et al. [32], who indicate that blade handling represents 80% of the total maintenance cost of wood chippers, and with Kunickaya et al. [52] and Eliasson et al. [73], who reinforce the importance of regular blade replacement. Mechanical failures, representing 24.7% and 19.7%, are aligned with Diniz et al. [16], who highlight hydraulic hose ruptures and clearance adjustments as recurring issues, while Spinelli and Visser [72] indicate that mechanical delays represent, on average, 8% of the scheduled time. As for jamming events, more frequent in Wood Chipper 2 (28.5%), they can be attributed to the heterogeneity of the raw material and the irregular size of the processed pieces, according to Kuptz and Hartmann [56] and Mihelič et al. [51], who demonstrated the influence of material flow instability and contaminants on the increase in blockages.

The influence of material and operation is also evident. The heterogeneity of the raw material, including Eucalyptus grandis, Pinus taeda, and contaminants, directly impacts blade wear and jams, corroborating Diniz et al. [16], Kuptz and Hartmann [56], and Mihelič et al. [51]. The position in the production line, with Wood Chipper 2 receiving raw material and Wood Chipper 1 receiving pre-processed material, explains differences in efficiency, flow, and productivity, according to Kunickaya et al. [52], Kormanek [74], and Mihelič et al. [51]. The variation between operators and shifts also influences MTTR and failure patterns, as highlighted by Spinelli et al. [58], Piechnicki et al. [54], and Diniz et al. [16], demonstrating the importance of operator competence and training to maximize MTBF and reduce downtime.

The implementation of preventive and predictive maintenance proved effective. Recommended intervals for blade replacement of 35 to 50 hours are consistent with Diniz et al. [16] and Grigorev et al. [75], while Spinelli et al. [32] highlight the practice of regular sharpening as a preventive method. The use of CBM, including vibration analysis, acoustic emission, current analysis, and thermography, contributed to a 5 to 12% increase in MTBF and a 10 to 20% reduction in MTTR, validating the results of Spinelli et al. [32] and Piechnicki et al. [54], with support from Wessels and Sauter [76] in anomaly detection. The integration of maintenance with operation, through operator training, standardization of feeding, and teamwork, reinforces the conclusions of Diniz et al. [55], Kunickaya et al. [52] and Piechnicki et al. [54], showing that these measures increase the efficiency and reliability of wood chippers.

Finally, the economic impact demonstrated that the €9,500 investment in improvements, resulting in an annual recovery of €34,450 and an increase in availability of 3.9%, is in line with the studies by Piechnicki et al. [54], Diniz et al. [55], and Bagagiolo et al. [77]. The economies of scale and productive efficiency, mentioned by Muganyi & Mbohwa [78] and Diniz et al. [16], validate the viability of the WCM model and the economic sustainability of the implemented measures, reinforcing the importance of the maturity of the maintenance system and technological innovation, as highlighted by Piechnicki et al. [54] and Dananjaya et al. [57]. These results demonstrate that the integration of technical, operational, and human aspects is important for maximizing availability, reducing failures, and ensuring financial efficiency in wood chipper operations.

5. Conclusions

Maintenance has evolved significantly within business structures, assuming a decisive role in the overall performance of organizations, with the forestry and wood processing sector representing a clear example of this reality. In this context, the efficiency and availability of assets such as wood chippers are essential to guarantee productivity and continuity of operations. This study analyzed the availability and reliability behavior of two industrial wood chippers, identifying opportunities for improvement in operational procedures, operator training, and maintenance management. The results showed that equipment failures remain one of the main causes of productivity losses and reduced operational availability.

The proper operation of wood chippers depends on strong involvement from the maintenance team, with interventions performed according to consistent technical standards. At the same time, operators must be trained and qualified to perform routine visual and auditory inspections, strengthening the human-machine interface and contributing to increased equipment availability. Raw material receiving, handling, storage, and processing should also be carefully controlled, since external factors such as material heterogeneity directly affect the operational performance of wood chippers.

The evaluation of twelve months of operational data allowed the performance of each wood chipper to be characterized and the most frequent failure modes to be identified, namely mechanical failures, blade replacement, electrical failures, jamming, and operational difficulties. The analyses were conducted using a carefully preprocessed dataset, including the removal of incomplete entries, the consolidation of merged events, and the treatment of unspecified or ambiguous records, as described in Section 3.1. Statistical modeling using the Weibull distribution allowed the failure regimes to be characterized, showing that both machines operate under progressive wear conditions, with failure rate increasing with operating time. This behavior was confirmed by β shape parameter values of approximately 3.56 for Wood Chipper 1 and 2.98 for Wood Chipper 2. These results support the adoption of preventive and condition-based maintenance strategies, allowing interventions to be planned before failures become more severe.

The results indicate that the wood chippers presented high reliability and availability levels, with operational availability ranging between 92% and 97%. The MTTR analysis distinguished between estimated technical repair time and downtime-based MTTR, which includes logistical and administrative delays, allowing a more complete assessment of operational availability. Differences were observed between the two machines. Wood Chipper 1 showed a more predictable and stable wear trajectory, while Wood Chipper 2 presented greater variability and instability, strongly influenced by external operational factors, especially jamming events associated with heterogeneous raw material feeding. Among the failure modes identified, blade replacement represented approximately 32.4% of downtime in Wood Chipper 1, while jamming represented 28.5% of total unavailability in Wood Chipper 2.

The study also showed that predictive maintenance strategies, including vibration analysis, acoustic emission, current-signal analysis, and thermography, may contribute to increasing MTBF by approximately 5% to 12% and reducing MTTR by approximately 10% to 20%. These approaches may support earlier detection of anomalies and allow maintenance actions to be performed before failures become more severe. Under the conservative economic scenario, the proposed interventions require an estimated investment of €9,500 and generate an estimated annual recovery of €34,450, corresponding to an increase in availability of approximately 3.9%. These results demonstrate the economic viability of structured maintenance strategies and reinforce the importance of combining technical monitoring, operator training, and maintenance team involvement.

Finally, this study reinforces the importance of structured maintenance for operational and environmental sustainability, since more efficient equipment tends to consume less energy, generate less waste, and reduce the environmental impacts associated with failures. Future work should consider the implementation of Total Productive Maintenance practices, particularly Autonomous Maintenance and Operator Education and Training, with subsequent expansion to other stages of forestry operations. The integration of real-time monitoring systems, using vibration sensors, acoustic emission, current-signal analysis, or thermography, may improve early failure detection, increase operational continuity, and promote more sustainable practices in the forestry production chain. Future research may further investigate the relationship between machine wear and mechanical delays, explore artificial intelligence applications in raw material sorting, optimize work cycles and energy consumption, and include ergonomic and safety assessments for operators, consolidating an integrated and sustainable approach to wood chipper maintenance.

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Appendix A. Monthly MTBF, downtime-based MTTR, confidence intervals, and availability for the wood chippers.

Table A. Monthly MTBF and downtime-based MTTR values with 95% confidence intervals and estimated availability for Wood Chipper 1.

Month	MTBF (h)	95% CI MTBF	Downtime-based MTTR (h)	95% CI MTTR	Availability (%)
January	42.0	37.0–47.1	1.7	1.4–2.1	96.1
February	42.6	39.9–45.2	2.2	1.7–2.7	95.0
March	41.9	40.5–43.3	1.9	1.2–2.5	95.8
April	38.3	35.8–40.9	1.7	1.2–2.1	95.8
May	59.8	57.9–61.7	2.2	1.7–2.7	96.5
June	76.5	66.7–86.2	3.5	2.1–4.9	95.6
July	77.3	73.1–81.4	5.4	4.7–6.1	93.5
August	79.0	70.4–87.6	3.7	2.2–5.1	95.6
September	86.8	84.9–88.6	3.2	1.3–5.1	96.4
October	72.9	69.0–76.7	5.0	4.3–5.7	93.5
November	98.5	89.6–107.3	4.4	4.0–4.8	95.7
December	81.9	76.1–87.7	5.6	4.9–6.3	93.6

Table B. Monthly MTBF and downtime-based MTTR values with 95% confidence intervals and estimated availability for Wood Chipper 2.

Month	MTBF (h)	95% CI MTBF	Downtime-based MTTR (h)	95% CI MTTR	Availability (%)
January	50.6	48.8–52.3	2.6	2.0–3.2	95.1
February	29.9	29.5–30.3	2.1	1.9–2.4	93.4
March	62.9	62.0–63.9	4.7	3.4–6.0	93.0
April	76.3	70.8–81.7	3.7	2.2–5.2	95.3
May	71.8	59.2–84.4	2.6	1.4–3.8	96.5
June	53.6	52.9–54.2	1.8	0.9–2.8	96.7
July	103.1	102.3–103.9	3.2	1.8–4.7	97.0
August	70.8	70.1–71.5	3.6	2.7–4.5	95.2
September	76.5	74.9–78.1	3.5	2.8–4.3	95.6
October	29.2	25.0–33.4	2.5	1.8–3.3	92.0
November	37.5	33.7–41.3	2.5	2.2–2.8	93.7
December	54.4	50.1–58.7	2.8	1.7–3.9	95.1