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Effective Maintenance Planning for Improving the Reliability of Underground Mining Equipment—A Case Study

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Abstract: The Load Haul Dumper (LHD) is essential machinery utilized for moving ore in the underground mining industry, in order to fulfil production targets. In this connection, the efficiency of the equipment should be maintained at an ideal standard, to be accomplished by reducing unexpected failure of components or subsystems in this intricate system. Downtime analysis helped identify faulty components and subsystems, which require the development of complementary maintenance plans to facilitate the replacement or fixing of parts. Proper practices of maintenance management improve the performance of the equipment. In this research, the efficiency of the LHD machine was assessed through reliability methods. Initially, the assumption of independent and identical distribution (IID) for the data sets was validated using trend and serial correlation analyses. The statistical tests indicated that the data sets adhered to the IID assumption. Therefore, a renewal process method was utilized for additional examination. The Kolmogorov-Smirnov (K-S) test was utilized to identify the most suitable distribution for the data sets. The theoretical probability distributions were estimated parametrically using the Maximum Likelihood Estimate (MLE) approach. The dependability of each separate subsystem was determined using the optimal fit distribution. Based on the reliability outcomes, preventive maintenance (PM) time plans were created to reach the targeted 90% reliability. Different maintenance strategies, in addition, were suggested to the maintenance team to extend the lifespan of the machine.

Keywords: Preventive maintenance (PM); Reliability; Key performance indicators (KPI); Breakdown; Load Haul Dumper (LHD)

1 Introduction

The productivity and effectiveness of any industry largely rely on the proficient use of both personnel and machinery. Equipment malfunctions and unexpected maintenance significantly lead to production losses and unnecessary investments in novel equipment [1, 2]. Efficient maintenance management is a crucial factor in achieving the continually rising production goals in terms of both quality and quantity [3]. A considerable amount of capital can be lost without a robust maintenance strategy, and there is significant potential to reduce this loss through informed maintenance choices [4]. An unanticipated failure can incur repair costs that are substantially higher than those associated with scheduled maintenance or repairs [5, 6]. Even more critical is the production loss linked to major equipment failure. One approach to lessen the effects of such failure is to enhance the reliability of the machinery. In the business realm, ensuring that equipment operates with a high degree of reliability is a vital component [7]. In underground mining operations, machinery such as Load Haul Dumpers (LHDs) plays a key role in the production strategy. In recent years, the underground metal mines in India have their output fallen short of the expected targets. The primary reason for the decline in production rates within the sector is the inadequate availability of machinery [8]. Improved availability facilitates optimal utilization, thus enhancing the production rate of capital-intensive goods [9]. To increase the availability rate of any equipment, it is crucial to reduce its downtime hours [10]. This can be accomplished by thoroughly assessing the efficiency of the machinery.

Assessing reliability is essential for measuring the effectiveness of any system or device [11, 12]. The effectiveness of equipment largely depends on the dependability of its utilization, the surrounding conditions, the quality of maintenance, the operational practices, and the expertise of the operators [13]. These forecasts are beneficial for structuring suitable maintenance and production plans, performing reliability evaluations, and detecting issues in the production system for the risk assessment process [14, 15].

Reliability assessment is one of the primary methods to validate anticipated results that consistently support the intangible factors like customer loyalty and brand reputation [16–18]. A phase of inactivity usually results in considerable and major losses. Such losses can occur due to specific faulty parts or components; therefore, it is essential to establish a robust strategy for repairing, replacing, and altering configurations associated with those parts or components [19, 20]. The reliability of a repairable system can be enhanced by applying suitable maintenance strategies [21].

Reliability-based analysis of a shovel and dumpers is the theoretical probability distribution such as Weibull distributions (one parameter (1P), two parameters (2P), and three parameters (3P) distributions) to fit the failure data (time between failure (TBF) and time to repair (TTR)) in any surface miTBFne [22, 23]. This analysis in the mining industry assists in pinpointing preventive maintenance (PM) schedules for production machinery. This leads to a decrease in the total maintenance expenses [24]. Employing statistical reliability techniques provides additional understanding of the maintenance attributes of machinery [25]. The present research has been carried out to evaluate failure, determine the main reasons for failure and their occurrences, identify key subassemblies, and create models for predicting sub-system reliability.

2 Methodology

The significance of each specific subassembly or subsystem is assessed by examining time between failure (TBF) data [26, 27]. Data on failure for all four LHD machines has been collected over a designated period from the maintenance logs of an industry, to confirm that each LHD remains operational. The collected data sets were analysed for independent and identical distribution (IID) traits to determine the existence or lack of trends and correlations in the information. The data was regarded as IID when there were no signs of trends or relationships among the data points [28]. The data sets were then employed to assess the goodness of fit allocation via Kolmogorov-Smirnov (K-S) analysis [29]. The suitable distribution models are essential for forecasting the dependability of every single component or subcomponent. The procedure for reliability analysis of a crucial subassembly is depicted in a flow chart (Figure 1) as shown [30]:

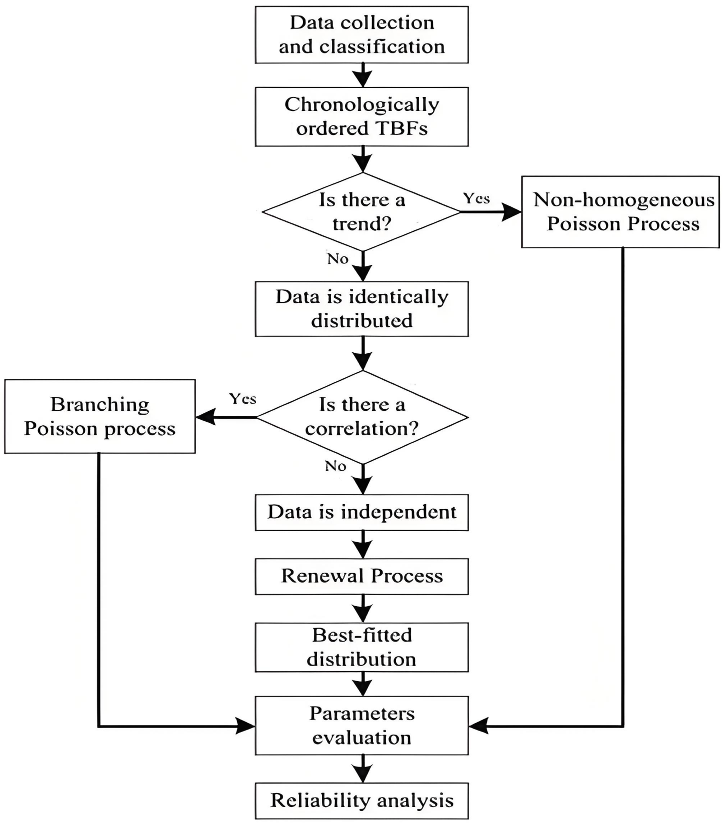


Figure 1. Reliability analysis [2]

3 Case Study

The current study has been conducted in one of the leading production industries known as Hindustan Zinc Limited, which significantly contributes to the gross domestic product (GDP) of the Indian economy. A diverse range of large-scale equipment is employed in the industry to extract ore and minerals from underground sources. In addition to Blast Hole Drills, the industry utilizes versatile machines such as Bucket Wheel Excavators, Dragline Excavators, Mining trucks, and LHDs for the loading, transportation, and dumping of loose materials in underground environments. This analysis focused on the performance of Sandvik LHD machines, specifically the LH21, LH22, LH24, and LH25 models (Sandvik LH517 model). Generally, the specifications differ from one model to another, with significant variations in capacities ranging from 1 to 25 tonnes and bucket sizes from 0.8 to 10.0 m^3. For example, the Sandvik LH517 has a tramming capacity of 17,200 kg and a bucket size of 7.0 m^3, whereas the LH410 provides a tramming capacity of 10,000 kg with a standard bucket of 4.0 m^3. Other models, such as the Sandvik LH208L, featuring a capacity of 7.7 tonnes and a bucket height of 3.3 m, are tailored for low-profile operations [25]. Serving as the primary method for transporting ore from mined areas to the main crushing site, LHDs are regarded as mid-level mechanized systems utilized in underground mining operations. Figure 2 is a photo of a LHD machine.

Figure 2. LHD machine being maintained at a workshop

Before performing the intended analysis of the data sets, it is crucial to classify each item of the equipment into a defined number of subassemblies [16]. These categories together with their modes of failure were created, based on the reasoning documented in the maintenance logs kept by the maintenance team. This analysis categorized the selected Sandvik LH517 model LHD machines into seven different subsystems (Table 1).

Table 1. Subsystem classification of LHD

Subsystem	Modes of Failure	Code
Engine	Engine, exhaust system, engine cooling system	SSE
Brake	Leakage of braking fluid, stocking of brake	SSBr
Tire/Wheel	Tire puncher, hose puncture/leakage	SSTy
Hydraulic	Lubrication system, cylinder, pump failure	SSH
Electrical	Cable breakage, air conditioning, fire protection	SSEl
Transmission	Steering system, transmission, torque converter, drive line	SSTr
Mechanical	Axle, steering system, bucket attachment system, dump box, frame and cabin	SSM

The information about the historical failure of various LHDs in Table 2 was collected throughout one fiscal year (i.e., from April 2016 to March 2017). The gathered information is displayed as spreadsheets featuring maintenance records compiled by the maintenance team, along with the digital versions of the maintenance data saved on a computer. This data includes the count of failures/failure rate (FF), the TBF and the TTR. Data collected from field visits is shown in Table 3, and the failure rate of each subsystem is represented in Figure 3.

Table 2. Metrics of various LHDs in one financial year

Machine ID	Scheduled Working Hours	Scheduled Service Hours	Hours of Breakdown	Idle Hours
LH21	8,784	170	3,410	1,586
LH22	8,784	309	2,298	2,100
LH24	8,784	317	1,972	2,460
LH25	8,784	270	2,043	1,704

Table 3. Data, collected from the field visits, about various LHDs

Machine	ID	SSE	SSBr	SSTy	SSH	SSEl	SSTr	SSM
	FF	40	30	50	35	38	36	52
LH21 (Hrs)	TBF	168	220	125	197	178	195	108
	TTR	47	62	47	49	49	57	57
	FF	36	24	37	26	25	30	41
LH22 (Hrs)	TBF	184	263	151	242	250	205	127
	TTR	66	90	78	84	89	77	80
	FF	38	23	39	25	38	25	37
LH24 (Hrs)	TBF	160	271	145	248	160	239	136
	TTR	70	108	80	101	70	110	100
	FF	27	22	30	20	24	22	36
LH25 (Hrs)	TBF	231	300	206	328	278	295	172
	TTR	83	85	77	95	75	91	64

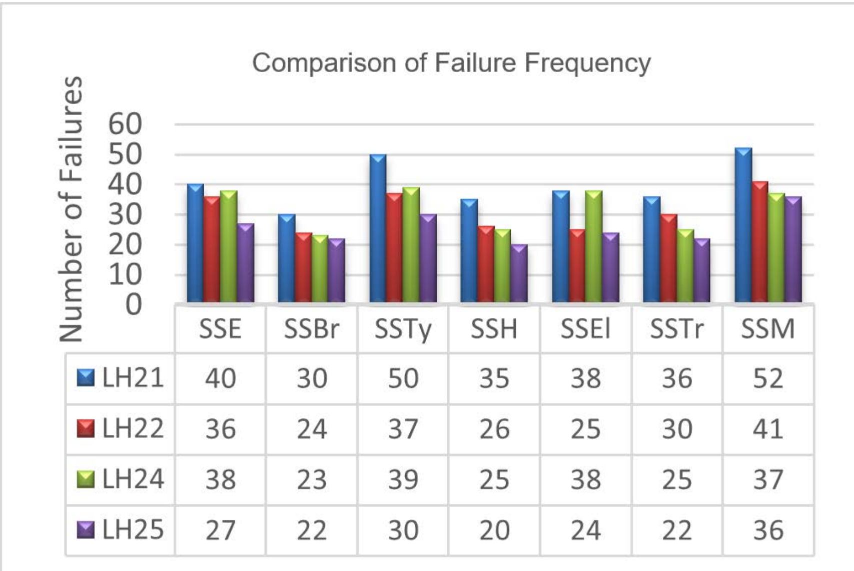


Figure 3. Failure frequency of various subsystems

4 Results and Discussion

4.1 Key Performance Indicators (KPI)

As regards post-data collection from field visits, evaluating the performance of equipment is essential. This evaluation can be performed by computing the KPI, such as availability percentage (AP) and utilization percentage (UP). The availability percentage refers to the duration that the machine can operate to execute its assigned task at its working face. The AP of a machine can likewise be defined as the proportion of available machine hours to the planned working hours. The management of a mine is exclusively accountable for deciding the planned working hours. These hours are considered the complete allotted hours for a certain timeframe of equipment usage. If there are extra hours of work outside the assigned shift, these can be part of the planned working hours. Any unproductive time lasting 15 minutes or less can be ignored. The AP and UP are computed from Eqs. (1) and (2).

$$\text{Availability Percentage} = \frac{\text{Machine Available Hours}}{\text{Scheduled Working Hours}} \times 100 \quad (1)$$

$$\text{Utilization Percentage} = \frac{\text{Machine Working Hours}}{\text{Scheduled Working Hours}} \times 100 \quad (2)$$

UP is defined as the proportion of actual machine operating hours or used hours to the planned working hours. The number of UP changes in accordance with the value of the denominator. Based on observations, the available machine hours are regularly fewer than the scheduled shift hours. Table 4 shows the computed values of AP and UP whereas Figure 4 demonstrates their differences.

Table 4. AP and UP of various LHDs investigated during the field visits

Scheduled Available Hours	Machine Available Hours	Machine Working Hours	Availability (%)	Utilization (%)
8,614	5,204	3,618	59.24	41.18
8,475	6,177	4,077	70.32	46.41
8,467	6,495	4,035	73.94	45.93
8,514	6,471	4,767	73.66	54.26

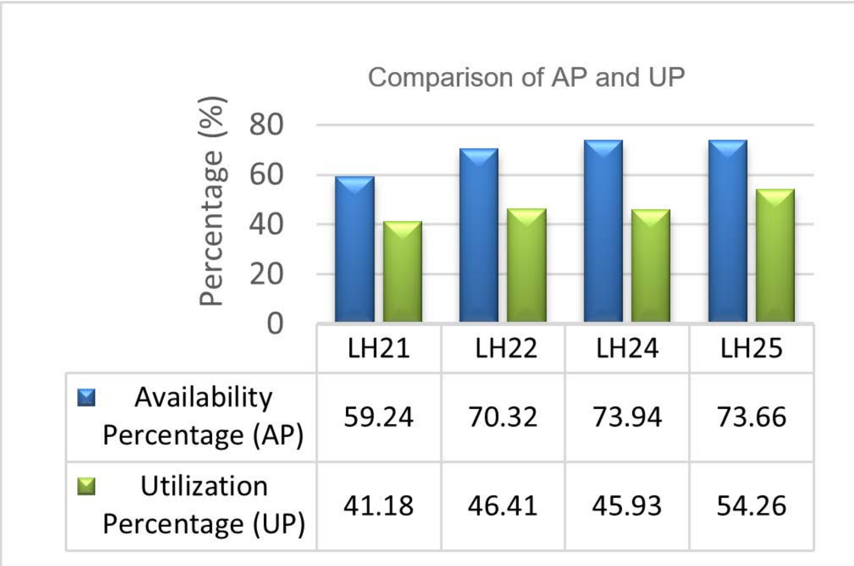
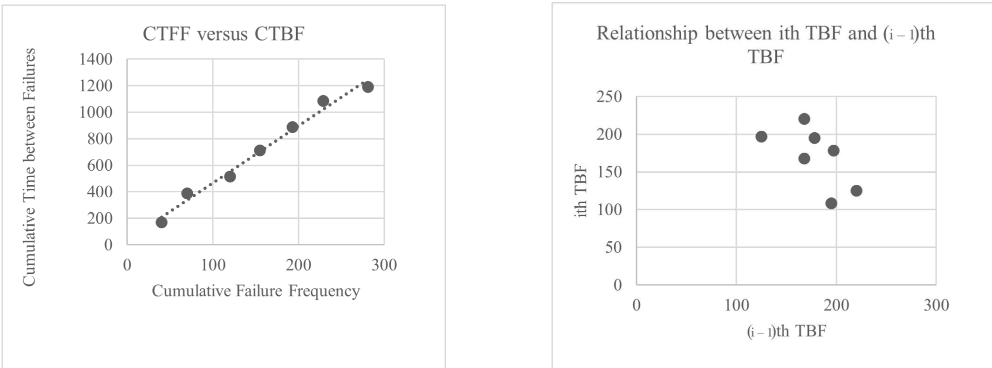


Figure 4. Differences between AP and UP

4.2 Trend and Serial Correlation Tests

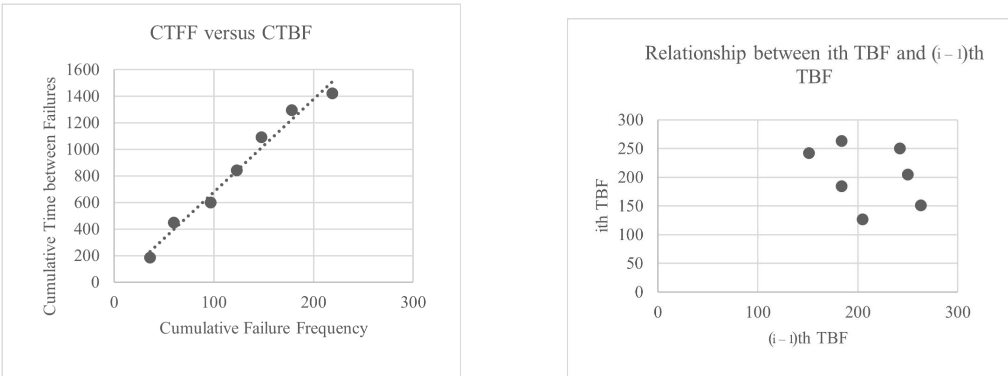
The trend test serves to identify the patterns of failure trends within an entire machine or a specific sub-system. This test entails plotting the cumulative number of failures against the cumulative time elapsed between failures. In the current study, the trend test was conducted graphically to ascertain whether the data exhibited a trend, or the failure rate for each sub-system was on the rise, decline, or remained stable. The configuration of the trend plot will indicate whether a piece of equipment is undergoing a reduction in failure rate (improvement) or an escalation in failure rate (deterioration). A non-linear plot signifies the presence of a discernible trend. An upward trend line, characterized by a consistently increasing slope, represents a rise in the failure rate, while a downward trend line, marked by a consistently decreasing slope, signifies a decline in the failure rate [26]. The existence of a trend suggests a correlation. Besides, a serial correlation test was performed to examine the relationship between two variables. The scatter plots depicting the two variables (ith TBF and (i − 1)th TBF) illustrate the correlation between them.

These assessments are conducted to analyze the breakdown of each individual sub-system in order to ascertain the presence of characteristics related to independent and identical distribution (IID). The trend reflected by the gathered data can be evaluated by constructing a graph to illustrate the cumulative frequencies of failures (CTFF) in relation to the cumulative time between failures (CTBF). In conducting a trend analysis, if the data points are arranged in a linear format, it signifies that the examined data sets do not exhibit any trend [26]. In addition, a serial correlation test was executed to investigate the relationship between the ith value of TBF and the (i − 1)th value of TBF. Scatter plots representing the data sets for the ith value of TBF and the (i − 1)th value of TBF reveal the correlation between these two values [30]. The graphs from Figure 5 to 8 demonstrated that the data points were interconnected in a linear fashion throughout the trend examination in the analysis. Consequently, no discernible pattern was detected in the collected data sets. Regarding the serial correlation test, the points appeared to be randomly distributed, indicating the absence of correlation. The results of these assessments implied that the data sets for all subsystems were determined to be trendless, and the points were evenly distributed. Therefore, the IID assumption for the data sets was upheld for each subsystem.



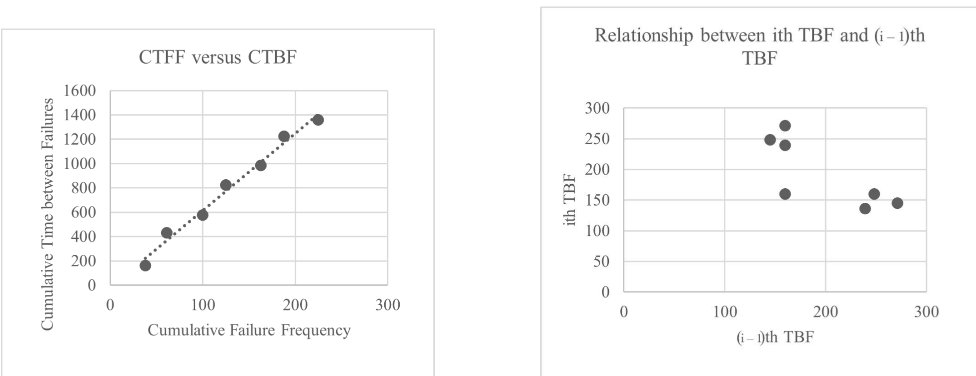
(a) (b)

Figure 5. (a) Trend test plot of LH21; (b) Serial correlation test plot of LH21.



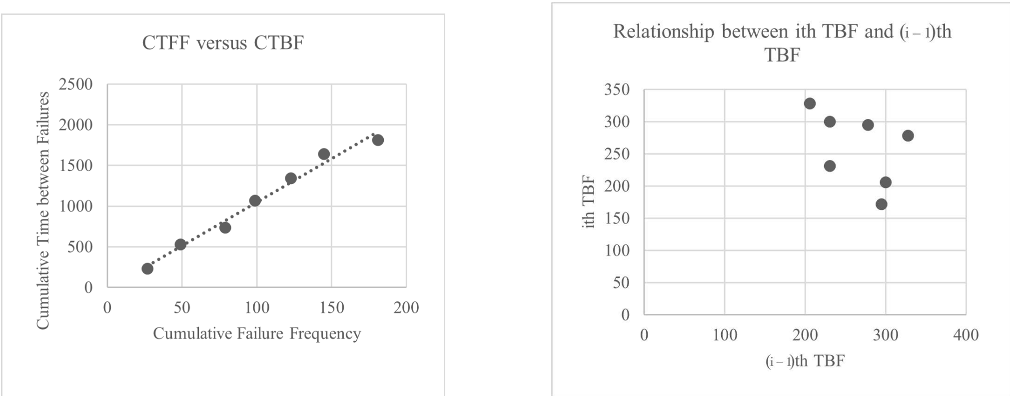
(a) (b)

Figure 6. (a) Trend test plot of LH22; (b) Serial correlation test plot of LH22.



(a) (b)

Figure 7. (a) Trend test plot of LH24; (b) Serial correlation test plot of LH24.



(a) (b)

Figure 8. (a) Trend test plot of LH25; (b) Serial correlation test plot of LH25.

4.3 Goodness of Fit/Best Fit Distribution

After validating the IID assumption, it is essential to carry out probability distribution of the data sets. This procedure is clarified by examining the best fit/goodness of fit distribution. This study performed the analysis utilizing the 'Isograph Reliability Workbench 13.0' software. During the analysis, a variety of parameters were assessed, such as exponential, 1-parameter Weibull, 2-parameter Weibull, and 3-parameter Weibull. Of these, the goodness of fit was found to be most accurately represented by the 2-parameter Weibull and 3-parameter Weibull distributions for different subassemblies (see Table 5). The assessment of the goodness of fit for the data sets was conducted using the Kolmogorov-Smirnov (K-S) test. A reduced significance level (ε) in the K-S test signifies a superior fit. The parametric estimation of theoretical probability distributions was conducted utilizing the Maximum Likelihood Estimate (MLE) technique. Table 6 provides the details of the parameters of Scale η, Shape β and Location γ for the optimal distribution function using MLE.

Table 5. K-S test results of LHDs

Machine ID	K-S Statistics Dmax				Best Fit Model
	Expo.	Weibull 1-P	Weibull 2-P	Weibull 3-P	
LH21	0.2262	0.2034	0.0627	0.2262	Weibull 2-P
LH22	0.2189	0.1963	0.0477	0.0470	Weibull 3-P
LH24	0.2167	0.1937	0.0992	0.0751	Weibull 3-P
LH25	0.2315	0.2083	0.0543	0.0543	Weibull 3-P

Table 6. Results of MLE with the best fitted distribution model

Machine ID	Best Fit Model	ML Parameters of the Best Fit		
		Scale η	Shape β	Location γ
LH21	Weibull 2-P	187.7	4.048	0
LH22	Weibull 3-P	325.4	5.964	-99.69
LH24	Weibull 3-P	71.05	0.9036	129.4
LH25	Weibull 3-P	284.2	4.571	-1.419

4.4 Reliability and Maintainability Analysis

Owing to the trend lessness observed in the data sets, a renewal process has been employed to evaluate the reliability of each separate sub-system. Utilizing the optimal model, the software generated outcomes for the reliability percentage (R) (see Figure 9 to 12) and the unreliability percentage (F), recorded in Table 7. Furthermore, the average time between failures (MTBF) and the average time to repair (MTTR) were calculated to evaluate the metrics of maintainability (Eq. (3)) and failure rate (Eq. (4)), as displayed in Table 8. The MTBF for each LHD machine can be calculated by dividing CTBF by the overall number of failures. Likewise, MTTR was determined by dividing CTTR by the overall number of failures. These computations rely on the most suitable distributions. In this examination, the data sets followed Weibull distributions. The maintainability equation for Weibull distribution is expressed as follows:

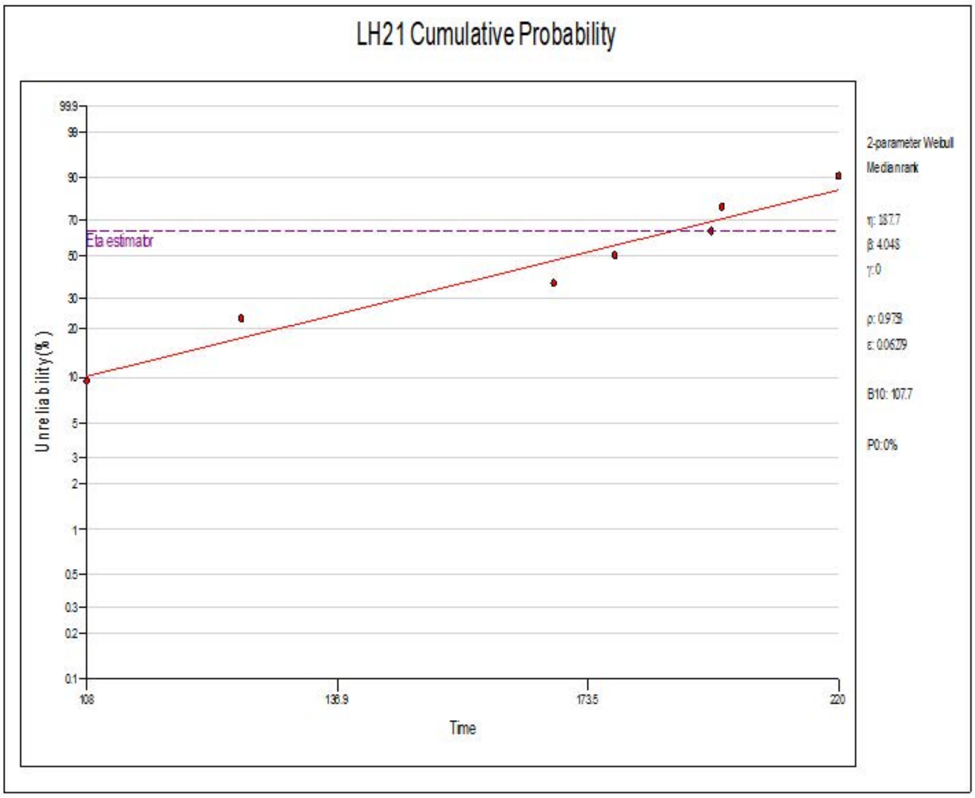


Figure 9. Cumulative probability curve of LH21

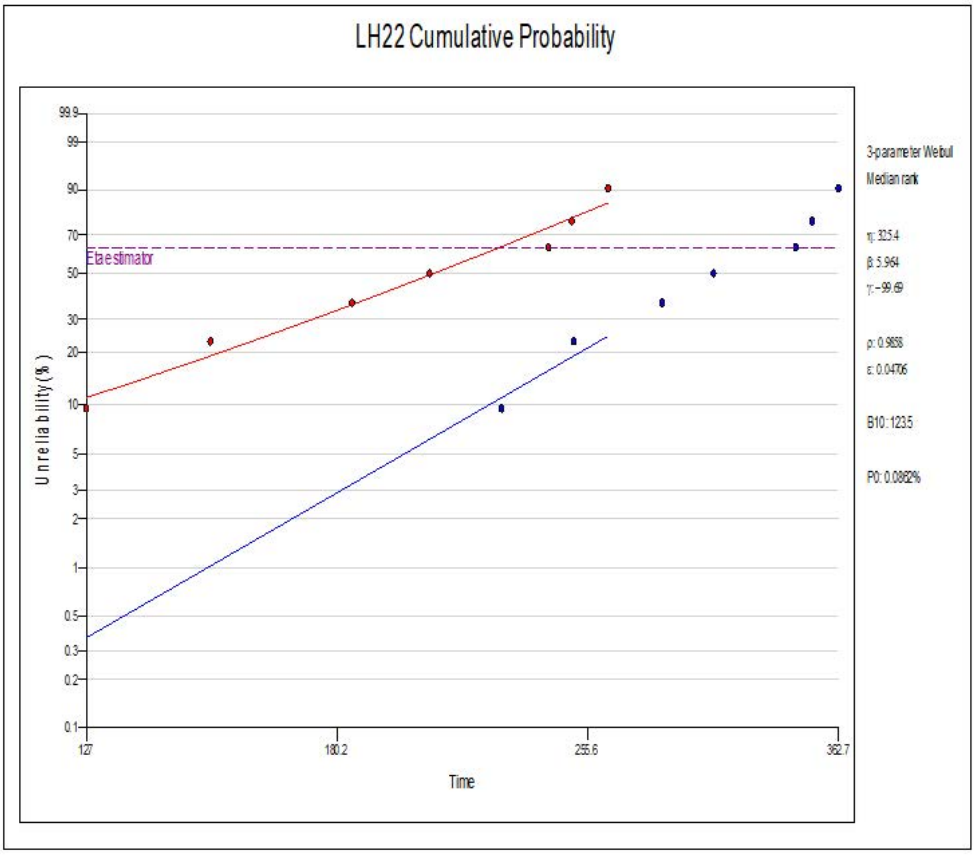


Figure 10. Cumulative probability curve of LH22

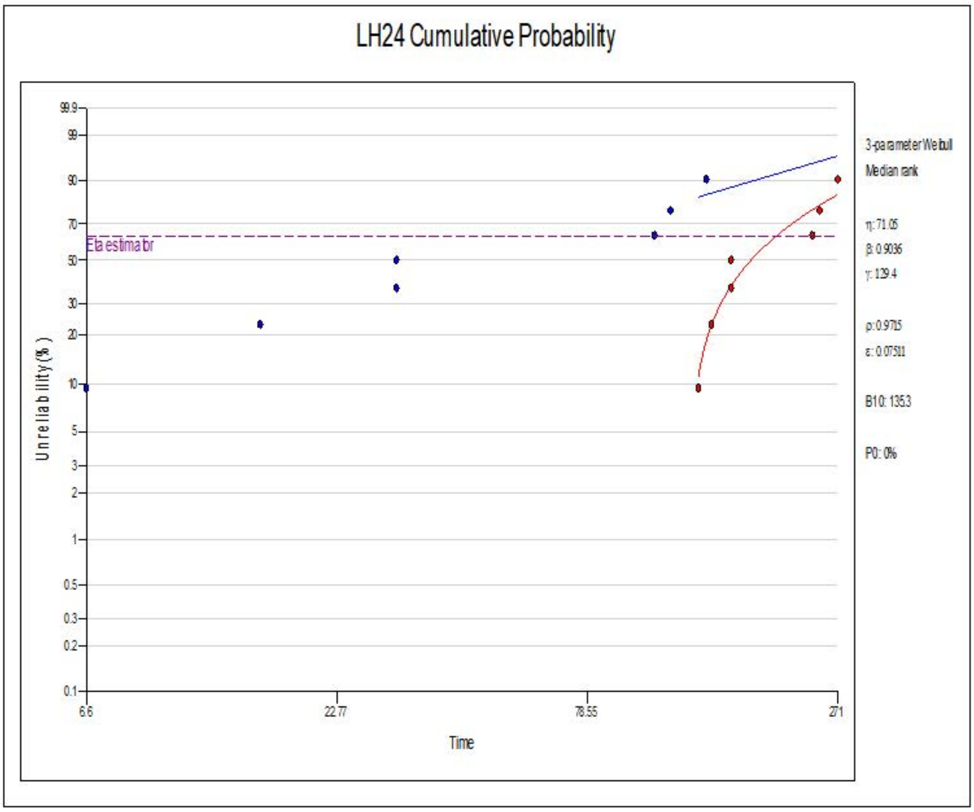


Figure 11. Cumulative probability curve of LH24

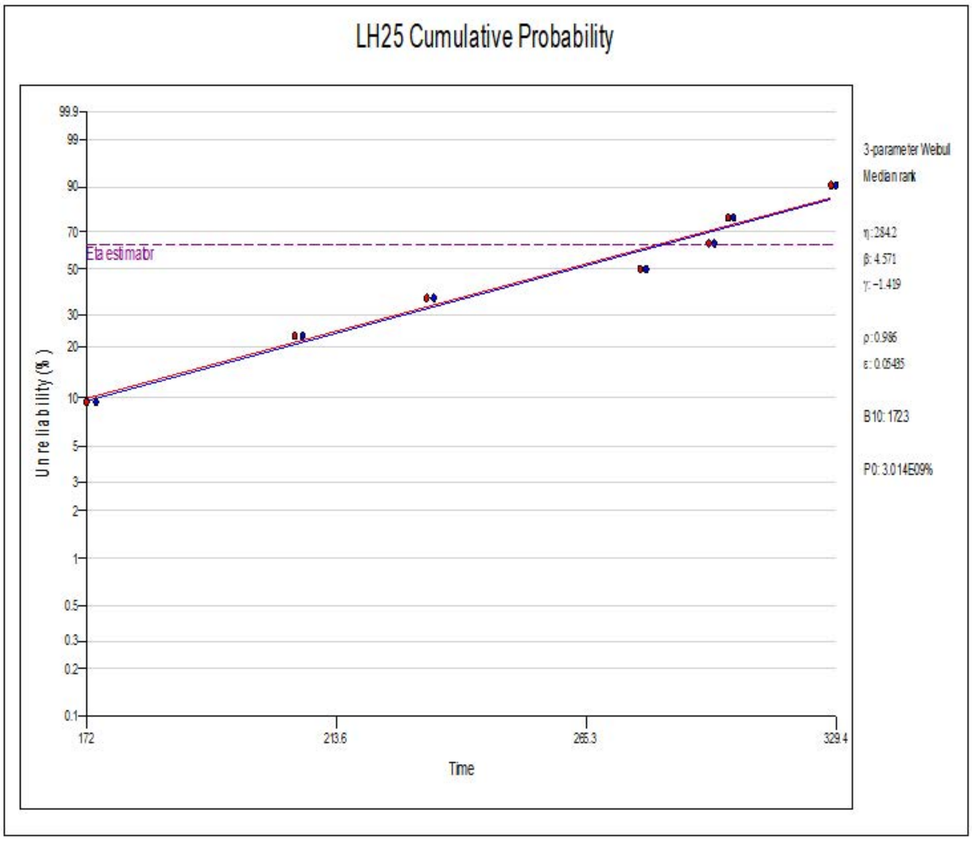


Figure 12. Cumulative probability curve of LH25

$$\text{Maintainability} = 1 - e^{-\left(\frac{MITR}{\eta}\right)^{\beta}} \tag{3}$$

$$\text{Failure rate } (\lambda) = \frac{1}{\text{MTBF}} \tag{4}$$

Table 7. Percentages of reliability and unreliability of each sub-system

Machine ID	Parameter	SSE	SSBr	SSBo	SSTy	SSH	SSEl	SSTr	SSM
	F (%)	36.4	90.5	22.9	77.0	50.0	63.5	9.4	36.4
LH21	R (%)	63.5	9.4	77.0	22.9	50.0	36.4	90.5	63.5
	TBF	168	220	125	197	178	195	108	168
	F (%)	36.4	90.5	22.9	63.5	77.0	50.0	9.4	36.49
LH22	R (%)	63.5	9.4	77.0	36.4	22.9	50.0	90.5	63.51
	TBF	184	263	151	242	250	205	127	184
	F (%)	36.4	90.5	22.9	77.0	50.0	63.5	9.4	36.49
LH24	R (%)	63.5	9.4	77.0	22.9	50.0	36.4	90.5	63.51
	TBF	160	271	145	248	160	239	136	160
	F (%)	36.4	77.0	22.9	90.5	50.0	63.5	9.4	36.49
LH25	R (%)	63.5	22.9	77.0	9.4	50.0	36.4	90.5	63.51
	TBF	231	300	206	328	278	295	172	231

Table 8. Results of availability and maintainability

Machine ID	TFF	MTBF (Hrs)	MTTR (Hrs)	Failure Rate	Maintainability
LH21	281	4.23	1.30	0.2364	99.99%
LH22	219	6.49	2.57	0.1540	100.00%
LH24	225	6.04	2.84	0.1655	94.69%
LH25	181	10.00	3.14	0.1	99.99%

4.5 Reliability Based Preventive Maintenance (PM) Time Schedules

Preventive maintenance (PM) involves measures implemented to keep components in a designated state via efficient assessment and prompt failure identification [17]. In this research, PM time schedules were computed according to the expected reliability levels (Table 9). The determined PM time schedules (Eq. (5)) showed that with a 90% reliability requirement for LH21, maintenance needs occurred every 108.6 hours. Similarly, for LH22, LH24, and LH25, the maintenance periods were 127.14 hours, 138.25 hours and 168.56 hours respectively.

$$R(t) = e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \times 100 \tag{5}$$

Table 9. PM time schedules of LHD machines

Expected Reliability	PM Time Schedules (Hrs)			
	LH21	LH22	LH24	LH25
0.90	108.62	127.14	138.25	168.56

5 Conclusions

Preventive maintenance is an ongoing process that must be addressed with priority. Regularly servicing equipment through tune-ups can extend its operational lifespan. Moreover, such maintenance practices can avert costly emergency repairs, reduce operational interruptions, and lead to significant long-term savings despite upfront costs involved. It enables the early identification of minor concerns that can be addressed affordably before they develop into serious and costly breakdowns. The strategic implementation of inventory control measures guarantees the availability of suitable spare parts for routine maintenance and common failures, thus reducing equipment downtime during proactive maintenance and repairs. This analysis concluded that preventive maintenance resulted in:

- A decrease in energy and maintenance expenditures of up to 30%;
- A reduction in machinery failures ranging from 35% to 45%; and

• A decrease in downtime of as much as 75%.

The data sets acquired from the four LHD machines were analyzed to evaluate their reliability. The reliability calculations demonstrated that the reliability figures for the Breaking sub-system (SSBr) at 9.46%, the Tyre sub-system (SSTy) at 22.97%, and the Mechanical sub-system (SSM) at 36.49% were notably low. It was determined that SSBr, SSTy, and SSM are the most critical sub-systems in terms of reliability. Insufficient and ineffective maintenance, along with operational practices, lead to unforeseen failures. These problems negatively impact the overall dependability of each machine or piece of equipment.

Forecasting reliability-based preventive maintenance (PM) time intervals will yield vital insights for executing scheduled maintenance. Timely completion of planned maintenance is indispensable for achieving the anticipated lifespan of a machine. When the desired reliability is set at 90%, PM may be performed every 108.62 hours for LH21, 127.14 hours for LH22, and 138.25 hours for LH24. This study observed that various operational and environmental factors necessitate distinct maintenance strategies for different LHD machines. To facilitate effective maintenance planning and organization, it is imperative to evaluate the reliability of each machine or equipment individually.

Author Contributions

Investigation, B.J., G.R.M., and A.K.T.; data collection and analysis, B.J., G.R.M., and A.K.T.; writing—original draft preparation, B.J.; writing—review and editing, B.J., G.R.M., and A.K.T. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflict of interest.

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