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Technical Note

Estimation of reliability-based maintenance time intervals of Load-Haul-Dumper in an underground coal mine

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Abstract
Reliability estimation plays a significant role in the performance assessment of mining equipment, and aids in designing efficient and effective preventive maintenance strategies. Continuous and random/irregular occurrence of failures in a system could be the main cause for performance drop of machinery. The accomplishment of a projected level of production is possible only by an efficient operation of the equipment. In order to improve the equipment life, a critical analysis of failure/breakdown occurrences is required to be carried out, and appropriate remedial measures need to be designed and implemented to enhance reliability. This paper presents a reliability analysis of Load-Haul-Dumper (LHD) in an underground coal mine. The goodness-of-fit distribution of each LHD was made through the Cramer-Von-Mises statistic test. The parameters involved were estimated using both the maximum likelihood analytical estimation process and the graphical process. Further, an attempt was made to reduce the total cost of operation by estimating the reliability-based preventive maintenance time intervals.

Keywords: *LHD, Reliability, Cramer-Von-Mises, Goodness-of-Fit, Preventive Maintenance.*

1. Introduction

Estimation of reliability plays an important role in the performance evolution of a mining system or equipment. The performance of mining equipment depends on the reliability of the machine used, operating background, maintenance effectiveness, operation procedure, technical skill of the operators, etc. Reliability forecasts are necessary for every type of machinery, similar to maintenance planning, production planning, reliability assessment, fault detection in the production system of mine, and risk evaluation. The reliability of a repairable system can be enhanced by applying proper maintenance strategies. This analysis can contribute to the identification of optimum preventive maintenance (PM) intervals for mining equipment, and thus in the reduction of overall maintenance costs. The application of statistical-based reliability methods provides a further insight into the maintenance characteristics of equipment [1].

One of the most extensively utilized lifetime distributions for reliability appliance is a Weibull distribution. It is an exceptionally adaptable and suitable option for factor estimation, and shows numerous sorts of failure rate activities. On the basis of shape parameter, β value, the Weibull distribution is a versatile distribution that can take characteristics of other kinds of distributions. In a Weibull approximation, two or three parameters are utilized for every solution, scale, shape, and location parameters. A mixture of strategies is available for assessing the values for these parameters; most of them are analytical, and a few numbers are graphical. Graphical strategies incorporate both the cumulative distribution function (CDF) plots and the failure rate (FR) plots, and probability density function (PDF) plots. These strategies are not exceptionally exact but they are moderately quick. The analytical strategies incorporate the most extreme probability approaches, least square strategy,

strategy of moments, etc. [2]. These strategies are considered as more precise and dependable compared to the graphical strategy. The Weibull distribution is the most commonly used technique among all the other approaches such as exponential distribution, lognormal distribution, and gamma distribution to estimate the parametric distributions in a reliability analysis. This approximation was named by the Swedish researcher Waloddi Weibull (1887-1979), who created it in 1937 and distributed it in 1951. This approximation is exceptionally adaptable and reliable in numerous realistic applications. The reliability of a system or sub-system can be estimated using two or three parameters (shape, scale, and location) [2]. The linear regression model is much popular to the engineers for estimating the hypothesis of experiments using correlation coefficient. In the same way, a comprehensive analysis of complete failure data for goodness-of-fit can be possible with a variety of distributions. The shape, scale, and location parameters are regularly used in data distributions to design and characterize the machines with different models. For modeling a best-fit analysis, three varieties of Weibull distribution approaches including the 1-parament Weibull, 2-parameter Weibull, and 3-parameter Weibull distributions are available. The consequent best-fit data is helpful to the maintenance engineers to make a strategic decision on identification of the critical component of the failure machine [3]. Therefore, the performance of each sub-system and component should be analyzed to determine how each sub-system and component affects the availability and reliability performance.

2. Theoretical probability distribution parameters

Reliability estimation is an essential part of a mining organization for the effective utilization of resources and to improve the health condition of the equipment [4]. In order to estimate the reliability of the equipment, it is necessary to determine the goodness-of-fit (best fit) of each machine. A wide variety of theoretical probability distribution parameters are being used to determine the best fit of machine. These could be termed as the exponential distribution, lognormal distribution, gamma distribution, 1-parameter Weibull, 2-parameter Weibull, and 3-parameter Weibull distribution functions [5]. In this distribution, the cumulative probability, failure rate, and probability density function (PDF) curves are changed by the influence of shape parameter (β), scale parameter (η), and location parameter (γ) variation. Shape parameter (β) is moreover known as the Weibull slope. Diverse qualities of the shape parameter require denoted impacts on the distribution behavior. In fact, a few values for the shape parameter cause the distribution equations to decrease. For example, when $\beta = 1$, PDF of 3-parameter Weibull decreases to that of the 2-parameter exponential distribution. The shape parameter (β) is a dimensionless number.

The most imperative perspectives of the shape parameter (β) for the 3-parameter Weibull distributions are as follow. $\beta < 1$ indicates that the rate of failure of a system or component decrease with respect to time; this condition can be treated as the early-life failure. Weibull distributions with β nearer to or equivalent to 1 have a constant rate of failure, also known as the useful life zone or arbitrary failure zone. Similarly, Weibull distributions with $\beta > 1$ have an increased failure rate with respect to time, denoted as the wear-out failure. A typical 'bathtub curve' plot clearly depicts the three segments of failure zones. The failure rate of blended Weibull distributions is possible to observe with the $\beta < 1$, $\beta = 1$, and $\beta > 1$ sub-populations. A sample of a typical bathtub curve is shown in Figure 1.

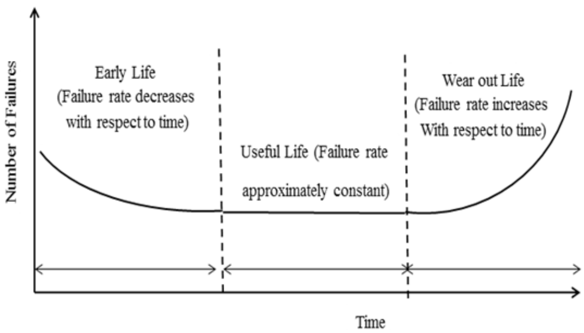

Figure 1. A typical bathtub curve.

3. Case study

The present case study was carried out in one of the underground coal mines of the Singareni Collieries Company Limited located in a southern region of India. The colliery is currently being operated in Seam 4 and Seam 6, employing the board and pillar methods. Coal extraction is done by drilling and blasting, and LHD is used as the main work horse for coal handling and transportation. LHDs are used to scoop the extracted coal, load it into the bucket, and dump it in the bottom of mine to undergo primary crushing before being hoisted to the surface out of the mine [6]. Figure 2 shows a typical LHD vehicle performing a loading operation.

Figure 2. A typical LHD vehicle performing a loading operation.

SCCL operates both the underground and open-cast mines. 80% of the production comes from the open-cast mine and 20% is from the underground mines. Technology has been a critical factor in the success of SCCL. For open-cast mines, it uses technologies like shovel dumpers, draglines, and in-pit crushing, while for underground mining, it uses technologies ranging from (Side-Discharge-Loader) SDLs & LHDs to highly mechanized longwall faces. An increase in the productivity and decrease in the utilization cost of SCCL can be largely attributed to the phasewise mechanization and also the adaptation of state-of-the-art technologies.

3.1. Reliability analysis

The term reliability is defined as the probability of a machine or its components to perform the specified task within a given interval of time before going into the failure mode. Failure of the machine is caused due to a wide variety of reasons. Before identifying the failures, the machine must be classified into a number of systems and sub-systems in order to categorize the occurred type of failures. These categorizations are based upon the maintenance records kept by maintenance personnel as well as the reasons described by these records [1]. In this investigation, the considered systems were named as E1-LHD1, E2-LHD2, E3-LHD3, E5-LHD5, and E6-LHD6. Sub-systems of LHDs were classified into eight numbers of varieties such as engine (SSE), braking system (SSBr), body (SSBo), tyre (SSTy), hydraulic system (SSH), electrical system (SSEl), transmission system, and mechanical system (SSM). The classification of sub-systems is presented in Table 1.

Table 1. Classification of sub-systems of an LHD.

Sub-system	Failure type	Code
Engine (E)	Piston-cylinder, radiator, O-ring failure	SSE
Brake (Br)	Oil leakage, brake jamming	SSBr
Body (Bo)	Bucket wear out, welding, cylinder	SSBo
Tyre/Wheel (Ty)	Tyre puncher, rim failure	SSTy
Hydraulic (H)	Leakages, lubrication suspension system	SSH
Electrical (El)	Cable reel, socket, signal light, sensor	SSE
Transmission (Tr)	Gear train wear out, lubrication	SSTr
Mechanical (M)	Structural failure, chassis damage	SSM

3.2. Data collection and classification

The very first step in a reliability analysis is data collection. A complete and accurate data is essential to perform the reliability analysis with a more effective manner. The failure and repair data presented in this paper relates to five numbers of LHDs with Emico Elicon make. The data was collected over a period of one financial year from Apr’ 2014 to Mar’ 2015 using hand-written forms prepared by maintenance personal in the form of maintenance cards, daily reports, and computerized recorded maintenance data base. These maintenance cards include the time to failure, failure frequency, and time to repairs of each sub-system. The collected data of failure and repair data of LHDs are shown in Table 2.

In the observed data, each sub-system has a different frequency of failures. A typical example of the frequency of failures of each individual sub-system is shown in Figure 3. Each sub-system can have both the repairable and non-repairable components. The repairable components would be repaired at the time of regular scheduled maintenance. Some of the failed components in the sub-systems are not possible to be repaired during the scheduled maintenance. These are considered as the non-repairable components, and can be replaced by a new set. These non-repairable component failures are treated as the censored failures, and the replacement time of these components is treated as the censored data [7].

Table 2. Failure and repair data of various sub-systems of LHD.

Machine ID	Parameter	SSE	SSBr	SSBo	SSTy	SSH	SSEl	SSTr	SSM
E1-LHD1	FF (No/.)	8	5	4	9	6	9	4	16
	TBF (Hrs)	477.8	766.6	959.7	421.4	639.5	416.2	962.2	135.0
	TTR (Hrs)	279.8	447.8	559.75	248.7	373.16	248.7	559.7	139.9
E2-LHD2	FF (No/.)	8	0	0	4	2	16	1	24
	TBF (Hrs)	442.1	3585	3585	890.5	1788	220.6	3583	65.79
	TTR (Hrs)	147.8	1135	1135	289.5	572	74.31	1137	130.8
E3-LHD3	FF (No/.)	8	7	5	10	5	12	6	12
	TBF (Hrs)	474.6	541.5	759.8	377.5	762.2	317.5	616.3	288.3
	TTR (Hrs)	399.3	457.2	638.4	321.7	636.2	265.0	529.6	294.3
E5-LHD5	FF (No/.)	6	5	4	10	6	19	4	24
	TBF (Hrs)	622.5	744	930.7	368.5	621.8	191	935	144.1
	TTR (Hrs)	542.8	654.4	817.2	330.7	543.5	171.6	813	147.2
E6-LHD6	FF (No/.)	7	5	5	10	6	19	5	30
	TBF (Hrs)	539.4	767.4	759.2	375.2	632.5	192.7	763.6	110.4
	TTR (Hrs)	370.7	516	515	261.9	429.3	142.5	510.6	101.9

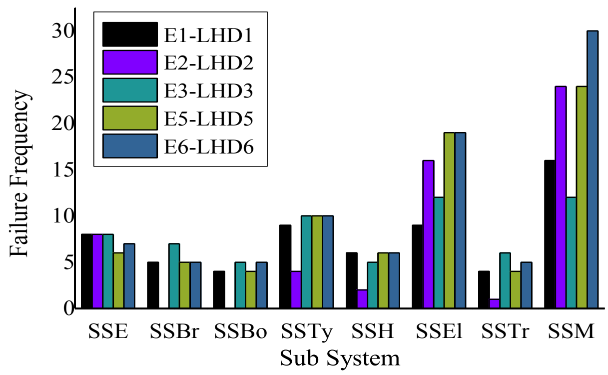

Figure 3. Failure frequencies of LHDs.

4. Results and discussion

4.1. Trend test and serial correlation test

The trend test is used to find out the trends in the failure patterns of an entire machine or an individual sub-system. A trend test involves plotting the cumulative failure number against the cumulative time between failures. The trend test for the present work was carried out graphically to check whether the data has a trend or the failure rate for each sub-system has been increasing, decreasing or constant. The shape of the trend plot will reveal if a piece of equipment is experiencing a decreasing failure rate (improving) or an increasing failure rate (deteriorating). A non-linear plot indicates that there is an existence of observable trend. An increase in the failure rate is depicted by a trend line with a constantly increasing slope, whereas a decrease in the failure rate is illustrated by a trend line with a constantly decreasing slope [1].

The presence of a trend indicates a correlation. A serial correlation test was also carried out to check the relationship between two variables. The scatter plots between the two variables (ith TBF and (i-1)th TBF) exhibits the correlation between the two variables. Figure 4(a) and Figure 4(b) to Figure 8(a) and Figure 8 (b) represent the trend test for CFF and CTBF or CTTR and correlation test, i.e. the scatter plot for the ith TBF and (i-1)th TBF similarly, and the ith TTR and (i-1)th TTR. In most of the cases, a trend was noticed as interpreted from the convexity of the curve. Similarly, the serial correlation test shows that the data is widely scattered, and thus there is a correlation existing between two consequent failures. This validates the assumptions of iid of TBF and TTR. The data sets have a trend, and a correlation exists between the failures. Hence, the in-homogeneous Poisson process (power law process) could be considered for finding out the goodness of fit functions, and the reliability parameters can be calculated through the analytical approach.

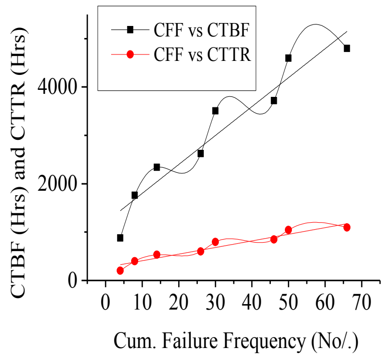

Figure 4 (a). Trend test of E1-LHD1.

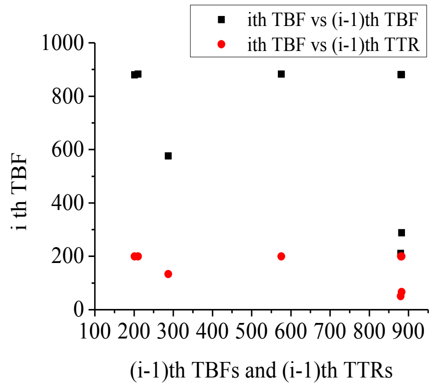

Figure 4 (b). Serial correlation test of E-LHD1.

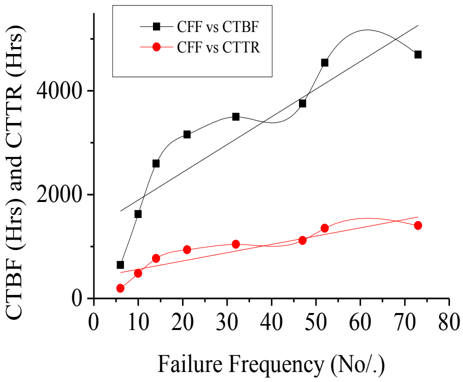

Figure 5 (a). Trend test of E2-LHD2.

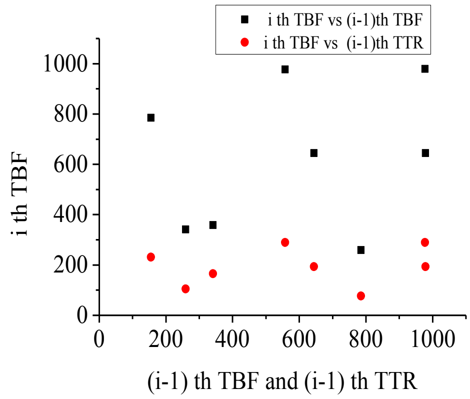

Figure 5 (b). Serial correlation test of E2-LHD2.

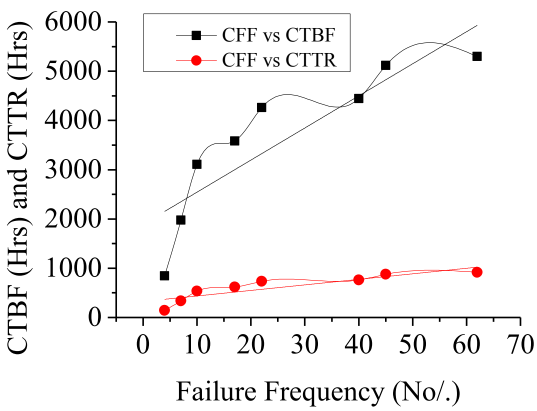

Figure 6 (a). Trend test of E3-LHD3.

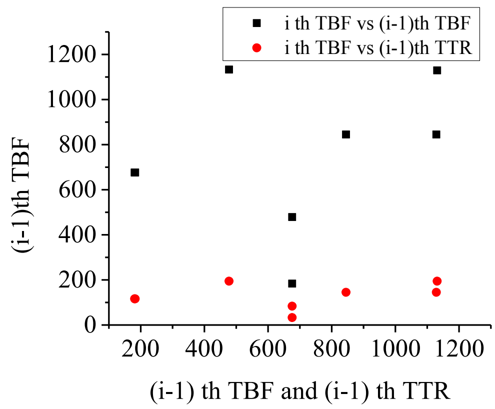

Figure 6 (b). Serial correlation test of E3-LHD3.

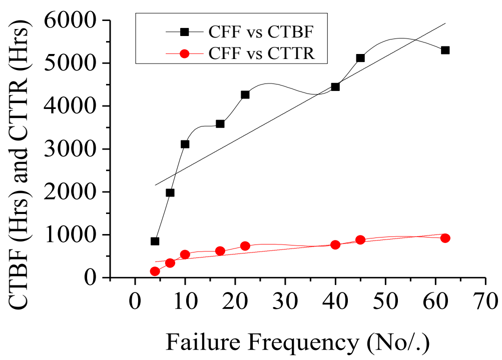

Figure 7 (a). Trend test of E5-LHD5.

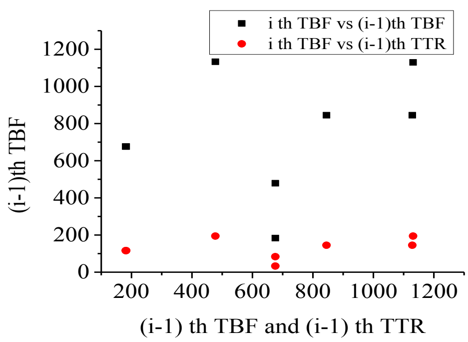

Figure 7 (b). Serial correlation test of E5-LHD5.

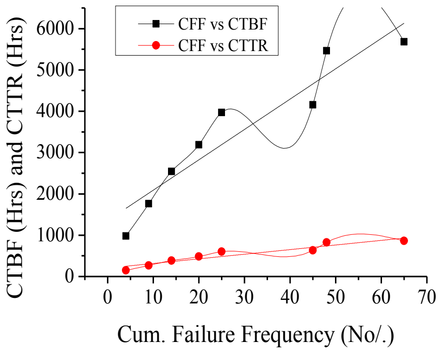

Figure 8 (a). Trend test of E6-LHD6.

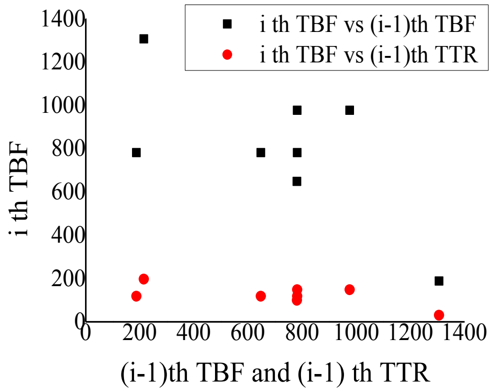

Figure 8 (b). Serial correlation test of E6-LHD6.

4.2. Statistic U-test (Chi-squared test)

Statistic U-test is a technique used to find out whether the null hypothesis is rejected or not at an expected level of significance.

This test was performed in this investigation to check whether the dataset has an independent and identically distributed (iid) nature or not with its corresponding dataset. The calculated values for the statistic-U-test are given in Table 3. From these values, it was identified that at a 5% level of significance, the null hypothesis was rejected. Thus the assumption that the datasets were iid in time contradicted for the sub-systems. The datasets were validated using the following expression [8]:

$$U = 2\sum_{i=1}^{n} \ln \frac{Tn}{Ti} \quad (1)$$

where Tn is the time to failure or time to repair at the nth level. The datasets were tested for null hypothesis rejection using the statistic U-test (Chi-squared test) with a 2(n-1) degree of freedom. If the null hypothesis is rejected in the Chi-squared test, and then the in-homogeneous Poisson process (power-law-process) is adopted for a best-fit analysis. If the null hypothesis is not rejected in the Chi-squared test, then the non-homogeneous Poisson process will be adopted for best-fit analysis.

Table 3. Results of Statistic U-test for LHDs.

Machine ID	Dataset	Degree of freedom	Calculated statistic U	Rejection of null hypothesis at 5% level of significance	Status
E1-LHD1	TBF	61	09.93	09.93<80.23	Rejected
	TTR	61	08.66	08.66<80.23	Rejected
E2-LHD2	TBF	55	21.93	21.93<73.31	Rejected
	TTR	55	17.97	17.97<73.31	Rejected
E3-LHD3	TBF	65	07.16	07.16<84.82	Rejected
	TTR	65	06.66	06.66<84.82	Rejected
E5-LHD5	TBF	78	10.87	10.87<99.62	Rejected
	TTR	78	10.44	10.44<99.62	Rejected
E6-LHD6	TBF	87	09.19	09.19<109.77	Rejected
	TTR	87	08.22	08.22<109.77	Rejected

4.3. Power-law-process model

The trend existed data was further analyzed to determine the accurate characteristics of the failure time distributions of sub-systems. LHDs are treated as in-homogeneous, and the PLP model is adopted to compute the results of each dataset.

PLP is a certain form of in-homogeneous Poisson process, which has proved to be a useful technique for evaluating the systems that are deteriorating or improving with time. The intensity, u(T), of the PLP form is given by:

$$u(T) = \frac{\eta}{\beta}\left\{\frac{T}{\beta}\right\}^{\eta-1} \quad (2)$$

where η and β are the scale and shape parameters, respectively, and T is the global or running time.

The parameters η and β in Equation (2) can be anticipated by the following expressions, recommended by Crow (1975) [9]:

$$\eta = \frac{n}{\sum_{i=1}^{n-1} \ln\left(\frac{Tn}{Ti}\right)}, \beta = \frac{Tn}{n^{\frac{1}{\eta}}} \quad (3)$$

$$\eta = \frac{n}{\sum_{i=1}^{n} \ln\left(\frac{T}{Ti}\right)}, \beta = \frac{T}{n^{\frac{1}{\eta}}} \quad (4)$$

where n denotes the metric of breakdown events and Ti is the total running time at the ith event. Equation (3) is to be used when the test is failure-truncated, i.e. the machine is identified to a pre-allocated number of breakdowns n. Equation (4) is suitable for time-truncation, i.e. when the machine is identified for a pre-allocated time *T(Tn < T)* [8].

The parameters η and β can also be estimated through graphical analysis by plotting the logarithm of the cumulative number of failures against the logarithm of the running time. The slope of the best-fitted line gives an estimate of η, and β can be observed at logarithm of the cumulative number of failures. This approach is based on the fact that for a PLP with an intensity function given by Equation (2), we have:

$$E\left[N(T)\right] = \left(\frac{T}{\beta}\right)^{\eta} \quad (5)$$

where N(T) denotes the cumulative number of failures at time T and E[N(T)] denotes the mean value of the measure. If E[N(T)] is predicted by the measured number of failures at time T, Equation (5) is written as:

$$\ln N(T) = \eta \ln T - \eta \ln\beta \quad (6)$$

4.4. Goodness-of-fit test

It is necessary to check whether the time between the consecutive failures of LHDs under deliberation can be illustrated by the PLP model. In this investigation, both the analytical and graphical approaches were used to test the goodness-of-fit in the PLP model.

4.4.1. Analytical approach

In this analysis, in order to check the assumption that PLP expresses the time between consecutive failures (TBF) of each individual sub-system, the Cramer-Von-Mises (COM) test was used. According to [9], the COM test statistic is:

$$C^2m = \frac{1}{(12M)} + \sum_{j=1}^{M} \left\{Zj^{\beta} - (Zj-1)/2M\right\}^2 \quad (7)$$

where M = n - 1 if the data is failure-truncated and M = n when the data is time-truncated. Similarly, Zj = (Tj/Tn) when the data is failure-truncated and Zj = (Tj/T) when the data is time-truncated with Tn < T.

If the statistic C^2m is greater than the selected critical value, then the hypothesis that the failure times follow a PLP will be rejected at the preferred significance level. If the statistic C^2m is less than this value, then the hypothesis that the failure times follow the PLP model will not be contradicted. From the computed values of COM statistics (Table 4), it can be understood that the assumption of TBFs follows the PLP, and is not contradicted at the 5% significance level.

Table 4. Computed values of COM test.

Machine No.	Sample size n	Cramer-Von-Misses test results C^2_M	Critical values at 5% Level of significance
E1-LHD1	32	0.1841	0.2181
E2-LHD2	29	0.2062	0.2181
E3-LHD3	34	0.2024	0.2182
E5-LHD5	40	0.1991	0.2186
E6-LHD6	45	0.2046	0.2191

4.4.2. Graphical approach

If the graph is plotted between ln N(Ti) and Ti, where Tj is the successive time to failure at the jth time and if a straight line is observed in a graph, then the PLP might be an appropriate model. This graphical technique gives a linear plot in most of the cases (from Figure 9 to Figure 13).

4.5. Estimation of scale parameter and shape parameter

After validation of the PLP assumption, the parameters of the PLP model were estimated by both analytically using the maximum likelihood estimate given by the expression in Equation (3) (Section 4.3) and also by the graphical method. For example, estimation of η and β by the graphical method for sub-systems of the LHDs is shown in Figure 9 to Figure 13. The estimate of η is to acquire from the slope of the best-fit line and that of β by reading the point where the rate of In N(T) is zero. The estimates of η and β in both the analytical and graphical approaches are given in Table 5.

Table 5. Estimates of scale and shape parameters in both analytical and graphical approaches.

Machine No.	Estimate of η and β by analytical method		Estimate of η and β by graphical method	
E1-LHD1	14.77	233.0	3.05	5.51
E2-LHD2	5.013	326.7	1.46	5.92
E3-LHD3	18.14	212.7	3.49	5.54
E5-LHD5	14.32	171.7	3.54	5.10
E6-LHD6	17.38	153.3	4.21	5.26

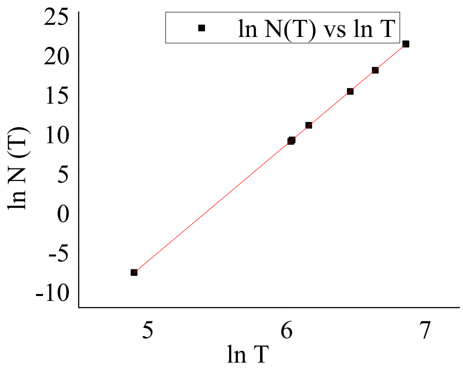

Figure 9. Graphical estimate of PLP for E1-LHD1.

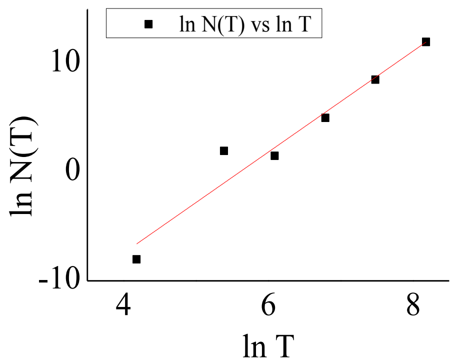

Figure 10. Graphical estimate of PLP for E2-LHD2.

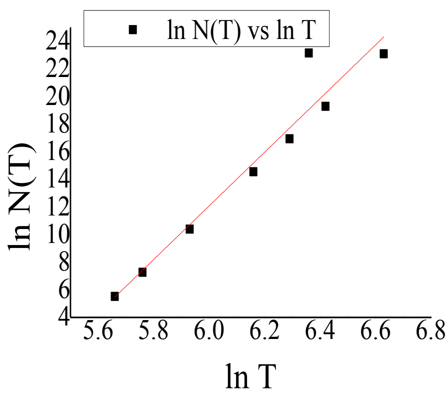

Figure 11. Graphical estimate of PLP for E3-LHD3.

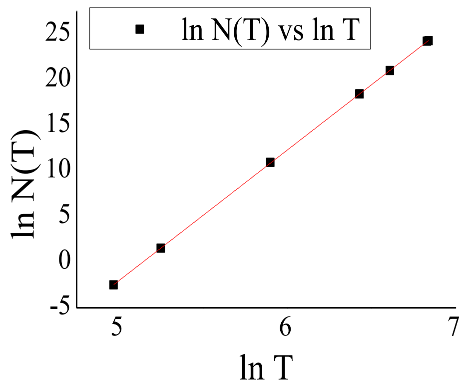

Figure 12. Graphical estimate of PLP for E5-LHD5.

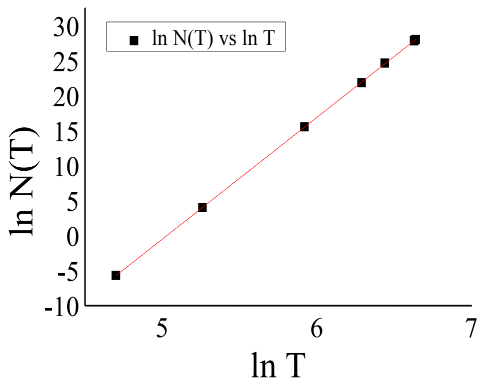

Figure 13. Graphical estimate of PLP for E6-LHD6.

4.6. Preventive maintenance (PM) time intervals

PM is defined as the set of activities performed in an attempt to hold the components for the desired condition [10].

The PM intervals are used to minimize the total operating cost and to maximize the availability of equipment. In most of the cases, it is assumed that the time to failure distribution has the rising failure rate (IFR) metrics and the cost of PM is less than the cost of failure substitution. Most of these models are analytical in the approach, and graphical methods are often ignored [8]. In this work, the analytical approach was used to estimate the PM time intervals, which will reduce the long-run cost per unit time of operation when the system is modeled by PLP.

Suppose that p is taken as the cost of an intended maintenance and k is the supplementary cost incurred in case the component fails during operation. Unintentional maintenance is nominal renovate, i.e. the system is repaired to the state just ahead of failure, and the failure record can be modeled by a PLP model with $\eta > 1$; it can be proved that the long run cost per unit time is:

$$P(T) = \frac{(p+q)\left(\frac{T}{\beta}\right)\eta + p}{T} \tag{8}$$

Expression (8) for P(T) has a minimum at To, where:

$$To = \beta\left(\frac{p}{(p+q)(\eta-1)}\right)\frac{1}{\eta} \tag{9}$$

Therefore, one possibility of estimating the optimal time interval is to use Equation (9).

Table 6. PM time intervals using analytical technique for different values of p/(p+ q).

Machine No.	p/(p+q)						
	2	**1**	**0.8**	**0.6**	**0.5**	**0.4**	**0.3**
E1-LHD1	204	195	192	189	186	183	181
E2-LHD2	284	247	236	228	215	206	198
E3-LHD3	189	181	179	177	175	172	171
E5-LHD5	150	143	141	139	136	134	132
E6-LHD6	135	130	128	127	125	123	122

5. Conclusions

A continuous operation of equipment with minor failures can only be possible by organizing the appropriate maintenance planning and implementation. The highest equipment availability and its effective utilization are the two important factors to improve the reliability. The assumptions of independent and identical distribution of TBFs of LHD sub-systems were not valid and deteriorated from the trend and serial correlation tests.

The PLP model was found to be very suitable for modeling the reliability and maintenance problems of repairable systems. The PLP assumption effectively describes the TBFs of each sub-system of LHDs, and were evaluated by both the analytical (Cramer-Von-Mises test, Table 4) and graphical approaches (from Figure 9 to Figure 13). From the values for scale parameter η and β shape parameter (Table 5) it can clearly be indicated that the failure intensities of sub-systems are increasing, and their maintenance policies should either be changed or further reinforcement should be made depending upon the requirement and cost analysis. The results obtained by the analytical methods are approximately in agreement with those obtained by the graphical method.

Computation of reliability-based PM schedules aids in designing and implementing a maintenance strategy that would potentially increase/enlarge the expected life of the machine. From the results (Table 6) of PM intervals, it was evident that most favorable PM intervals for the sub-systems of LHDs could easily be estimated by taking into account the preventive maintenance cost (p) and the additional cost incurred when the system fails during operation (p + q). The values for PM time intervals were reduced (from 204 h to 181 h) with respect to the cost of operation and an additional cost of system failure ratio variation (from 2.0 to 0.33, Table 6). In this work, the overall equipment performance of LHDs was not considered, and performance evaluation was based only on the availability and utilization calculations. Future research works should include the measurement of key performance indicators.

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