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Reliability investigation of diesel engines used in dumpers by the Bayesian approach

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Abstract

Mining is a global multibillion dollar industry. The growing complexity of mining equipment and systems often leads to failures. As a consequence, reliability, maintainability and availability of mining equipment has come to the forefront (Kunar *et al*., 2013). Dump trucks are used for transporting ore in open pit mines. The most critical subsystem of these trucks is the diesel engine. Failure of the engine stops the entire operation which results in loss of revenue from production. For reducing downtime, changes in maintenance policies is necessary (Sevasar, 2013). For changing maintenance strategies of the engine, assessment of reliability of its subsystems becomes vital. In this study, a reliability assessment of an engine and its subsystems is carried out. The engine is divided into different subsystems. Trend analysis of Time Between Failure (TBF) data collected for each subsystem is performed. The engine TBF data are treated into four types of probability distributions: Weibull, Exponential, Normal and Lognormal. The MLE method from Minitab software is used for estimating the parameters of distribution required to determine the reliability of the subsystems. Although the TBF data is collected for three years, the failure data of each engine subsystem contains sparse failure data. Hence, for analysis purpose, the collected data has been grouped for three of the same types of engines. To supplement the result, 100 failure data examples have been generated by the MCS technique. To estimate the reliability for each subsystem of a single engine without grouping the TBF data, the Bayesian method is used. Using reliability analysis, failure of components of engines is predicted in order to take up maintenance at the right time with an aim to reduce the maintenance cost.

Keywords: Bayesian Approach; Least square estimation (LSE); Maximum Likelihood Estimation (MLE); Monte-Carlo Simulation (MCS); Reliability Block Diagram (RBD).

1. Introduction

With the increase in mechanization in the mining industry, more efficient and reliable equipment is in demand (Kumar *et al*., 1989). An operational reliability investigation is appropriate for reducing maintenance costs and improving the performance of a system (Kuo, W *et al*., 2003).

Kumar *et al* (1996) evaluated the reliability of an automotive transmission system. They divided the transmission system into 12 subsystems and using Weibull distribution, they calculated parameters based on which suitable maintenance policies were suggested.

Barabady *et al*. (2008) conducted a case study on the reliability and availability of a crushing plant in the Jajarm Bauxite mine in Iran. The plant was divided into six subsystems. The parameters for each subsystem were estimated using reliability analysis software. The results of the analysis showed that the conveyer and screen were critical from a reliability viewpoint, whereas crushers and conveyers were critical from an availability standpoint.

A reliability block diagram and Markov chain method were used by Dhillon *et al.* (1997) for the reliability analysis of a transmission system for a general service type of vehicle. The shape parameters and reliability were determined using Weibull distribution.

Olwell *et al*. (2001) supplemented limited filed data with prior information using Weibull probability distribution. They analyzed 2,000 firings for a missile motor under field conditions using classical MLE and Bayesian methods. The authors concluded that there was less than a 10% chance that more than 1% of the missiles would fail after twenty years.

Guida *et al.* (2002) considered a Bayesian method for making inference on the reliability of a new upgraded version of automobile mechanical components. They used failure data from a previous version of the component and prior information about the effectiveness of the design modification introduced in the new version. In their study, a Weibull model is assumed as prior distribution to describe the behavior of failure data. The results show a posterior distribution which estimates reliability. This shows an appreciable increase than the already estimated reliability of the old version of the component.

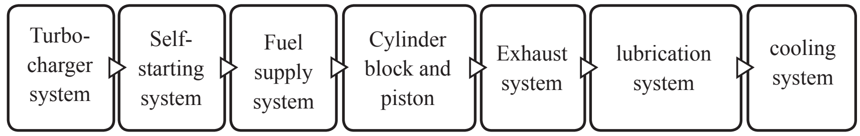

Fig. 1. The engine subsystems

Barnabas *et al.* (2012) investigated the failure rate analysis of IC engines. The interval between two failures was found by using the chi-square test. In addition, employing the Markov chain, the failure probabilities of all IC engine subsystems were determined. Finally, Behera *et al*. (2011) investigated the reliability in a load haul dump machine using Weibull, Exponential and Lognormal probability distribution plots.

It is evident that comprehensive studies on reliability analyses of automotive vehicles has been carried out. However, reliability analysis of diesel engines of heavy earth moving machinery used in surface mines has not been studied. Dumpers are one critical piece of equipment for the transportation of ore in open pit mines. Because of this, their availability is paramount. This availability depends on the reliability of the diesel engines used as the prime mover of the vehicle. Very few research studies exist on reliability analysis of dump truck engines. One reason may be the sparse failure data. This research gap motivated the authors to assess reliability of dumper engines by grouping the failure data. In this study, a reliability assessment of internal combustion engines used in dump trucks is considered. Previous research shows that the Bayesian approach can be used for reliability analysis when little failure data is available. Hence, we use the Bayesian approach to calculate TBI based on reliability for a new engine from the fleet. (The same engine is used in the other dumps trucks.) The Bayesian approach has been applied using the Bayesian-Weibull tool in Weibull++ software. The data from this study may prevent future failure of engine subsystems.

2. Engine subsystems

The reliability of a complex system that is repaired upon failure will often depend on the system's chronological age (Crow, 1975). A dumper engine is conceived as a repairable system comprised of subsystems connected in series. Thus, if one unit is down due to poor reliability, the whole system is stopped. This will lead to increased downtime. Various subsystems of the engines under study are shown in Figure 1. Even though the time between failure (TBF) data are collected for the past three years, the cylinder block and piston assembly subsystem and exhaust subsystem do not have more than one failure. Hence, the reliability analysis is not carried out on this subsystem as it will not lead to a significant conclusion. The subsystems which have more than three numbers of TBF data in three years have been considered in the analysis.

3. Data collection

The field TBF data for old and new engine subsystems were collected from the workshop maintenance record book of a leading open pit mine. The engines under study are 12-cylinder V-type turbocharged engines used in 85 ton dumpers with 983 HP. For reliability analysis, TBFs of different subsystems have been considered and are given in Table 1. Column 3 of Table 1 shows the field TBF data of subsystems for an old engine, and Column 4 shows field TBF data of subsystems for the new engine on which Bayesian approach is applied.

4. Methodology

4.1. Trend analysis

The dumper engine is divided into various subsystems. Before considering the failure data in probability distributions, it is necessary to test that the collected failure data has come from an independent and identical distribution (*iid*) (Uday Kumar *et al.*, 1992). Therefore, trend analysis and a test for serial correlation can be conducted with the failure data. A serial correlation test is necessary to confirm that the error of one data set belonging to a particular distribution is not carried to the next data. Therefore, the collected failure data for each subsystem are first tested for *iid* by conducting a trend test and test for serial correlation. To check the data for *iid*, a trend analysis of TBF data was considered, and the relationship between cumulative time between successive failure and the cumulative number of failures was calculated graphically for each subsystem of the engines. The linearity

Table 1. Time Between Failure (TBF) for engine subsystems.

Serial Number	Engine Subsystem	TBF (hours) (old engine)	TBF (hours) (new engine) Bayesian approach
1	Turbo charger system	2655, 633, 4112, 422, 600, 2036, 479, 77, 3585, 1673	13, 146, 646
2	Self-starting system	1246, 44, 856, 1595, 2328, 423, 185, 761, 1197, 616, 1920, 797, 550, 191, 917, 3950, 3913, 538	2744, 31, 130, 769
3	Fuel supply system	423, 240, 525, 36, 96, 442, 114, 77, 1349, 290, 225	84, 398, 216.
4	Lubrication system	2066, 2278, 1114, 1584, 757, 238, 991, 916, 855, 115, 103, 1367, 134	761,405,1823,1785
5	Cooling system	3827, 2356, 3856, 577, 1823, 1177, 680, 1424, 2149, 170, 108, 219, 934, 329, 3419	1184, 58, 274, 55

of the graph validates that collected data has no trend and is independent, thus confirming that the data are drawn from the same probability distribution.

In the next step, the test for serial correlation of the failure data is examined. The graph was drawn between $(i-1)^{th}$ TBF and i^{th} TBF. The scattered nature of the graph indicates no serial correlation, where *i* is the number of failures.

4.2. Maximum Likelihood Estimation (MLE) method

MLE is asymptotically unbiased with minimum variance and is one method used for parameter estimation. MLE provides a graphical (probability plots) and quantitative (goodness of fit) statistics. In this study, Reliability Life Data Analysis is carried out for the engine subsystems. The most commonly used and most widely applicable distributions for life data analysis are Weibull, Exponential, Normal, Lognormal and Bayesian-Weibull Analysis, so these are used for reliability analyses of the subsystems of the old engines. Bayesian-Weibull Analysis is employed for the reliability analysis of the new engine subsystems, as there is less TBF data for the new engine. Weibull, Exponential, Normal and Lognormal probability distributions were fitted to the TBF data for each subsystem. Among the four distributions, the best fit distribution for each engine subsystem was found by Anderson-Darling (A-D) goodness of fit test statistics value (Anderson, 2010). The probability distribution of engine subsystem having the lowest value of Anderson-Darling (A-D) statistics is the best fit distribution for that particular subsystem. Moreover, the probability distribution overview plot was drawn for estimating probability distribution parameters. It shows four graphs: a probability distribution plot, a Probability Density Function (PDF), a survival plot, and a hazard plot. The PDF describes the shape of the failure distribution data. The survival plot shows the relation between reliability and time. The hazard function provides a measure of the likelihood of failure as a function of time. It provides the instantaneous rate of failure. Finally, the probability distribution overview plot estimates the parameters utilized for the reliability estimation of engine subsystems using RBD.

4.3. Monte Carlo Simulation (MCS)

The TBF data of each engine subsystem contain small sample sizes. For analysis purposes, the collected data were grouped for the same three types of engines. To augment the results, 100 failure data have been generated by MCS technique. MCS is a process to run a simulation various times with a small number of data in order to obtain a particular distribution. The aim is to generate a large number of data for analysis (Aydogdu *et al*., 2010; Emad *et al.,* 2013). MCS observations are better than manual ones for predicting a particular distribution. The coefficient of determination (r^2 value) for best fit distribution for each subsystem obtained from the original data is compared. It is validated by determining r^2 values of the two methods using failure data of each subsystem. Finally, the reliability of each subsystem is used to determine the reliability of the whole engine using RBD.

4.4. Bayesian approach

The Bayesian approach can be used for small sample sizes of failure data. The approach allows researchers to draw inferences. The Bayesian method can incorporate prior informational data to supplement limited data. Prior information may be in the form of test results, predictions or engineering judgment (Jiqiang, 2011; Mense, 2012). In this study the prior information data are field data that estimate the reliability of the system. To estimate the reliability for a single engine of each subsystem, analyses were carried out using the Bayesian-Weibull tool in Weibull++ software.

4.5. Reliability Block Diagram (RBD)

A RBD is a graphical representation of the subsystems of a system. The diagram epitomizes the running state (i.e., success or failure) of the system in terms of the operating states of its components. For example, a simple series configuration indicates that all of the components must operate for the system to operate. A parallel configuration indicates that at least one of the components must operate, and so on. For engines, the work of each subsystem is related to the other. In other words, if one subsystem fails, the other subsystem will not work. This suggests a series relation between the subsystems of the engine system. Thus, if one unit is down due to failure, the whole system is unavailable, thereby reducing availability. The engine reliability is calculated by considering the product of its component reliability.

5. Results and discussions

5.1. Trend analysis

To see if there is any presence of structure in the TBF of the engine subsystems, the cumulative time between successive failures was plotted against the cumulative number of failures for each subsystem. The TBF test for independence was required by testing the failure data for serial correlation. To do this, the (i-1)th TBF was plotted against the ith TBF (Figs. 3, 5, 7, 9 and 11). The scattered nature of these graphs shows there is no serial correlation between the TBF data for turbocharger, self-starting, fuel supply, lubrication and cooling subsystems, respectively. The TBF data points in Figs. 2, 4, 6, 8, and 10 follow linearity, suggesting that there is no trend in TBF data related to the turbocharger, fuel supply, self-starting, lubrication and cooling subsystem failure data. As the TBF data is iid in a turbocharger, fuel supply, self-starting, lubrication and cooling subsystems, the MLE method is used for the reliability analysis with the help of Minitab Software.

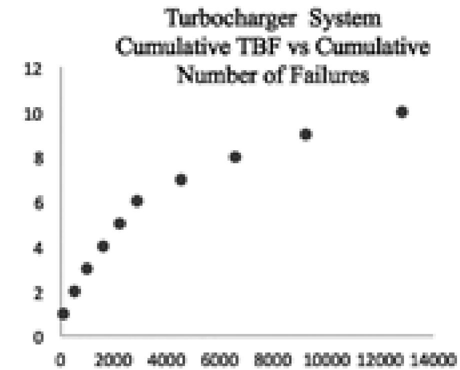

Fig. 2. Trend test for TBF of turbocharger system of engine

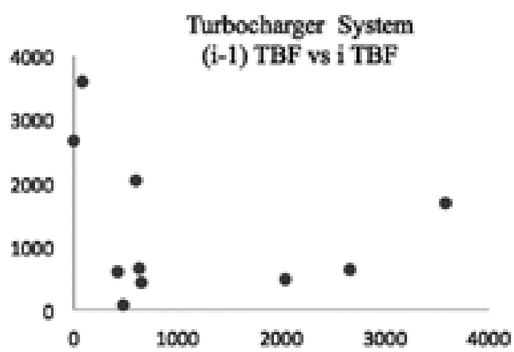

Fig. 3. Test of serial correlation for TBF of turbocharger system of engine

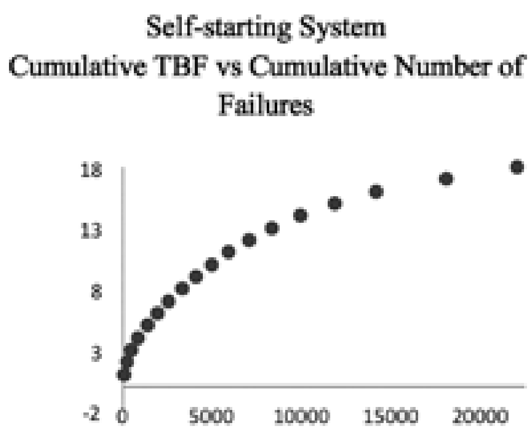

Fig. 4. Trend test for TBF of self-starting system of engine

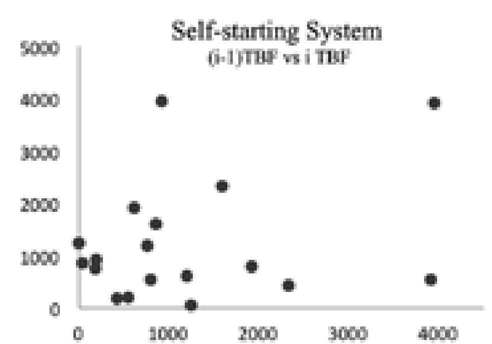

Fig. 5. Test of serial correlation for TBF of self-starting system of engine

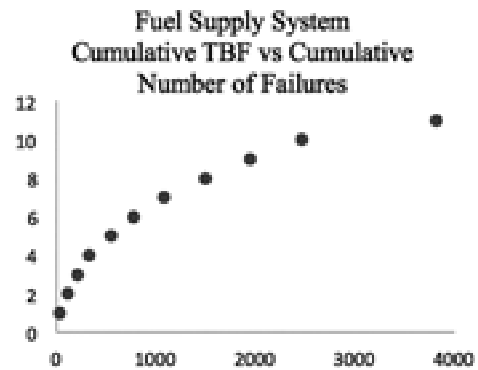

Fig. 6. Trend Test for Time between failures of fuel supply system of engine

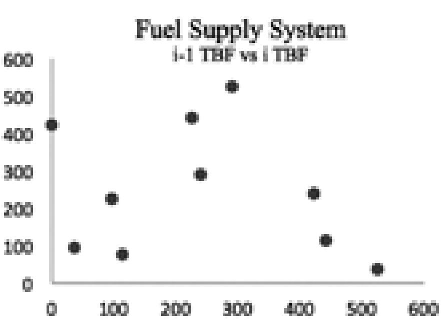

Fig. 7. Test of serial correlation for Time between failures of fuel supply system of engine

5.2. Data analysis

The different distributions (Exponential, Weibull, Normal and Lognormal) are fitted to the TBF data of turbocharger, fuel supply, self-starting, lubrication and cooling subsystems. Data are shown in Figures 12, 14, 16, 18, and 20, respectively. After plotting the data in Minitab software, the best fit distribution for each subsystem was found using the MLE method. The best fit was chosen by Anderson-Darling (A-D) goodness of fit test statistics, as shown in Table 2. The lowest value of A-D statistics ensures the best fit distribution.

The distribution parameters generated by the MLE method for the best fit distribution for each subsystem were used as assumed data to generate 100 failure data by MCS. The best fit distribution for each subsystem obtained from the original data was validated. Validation was carried out by comparing the coefficient of determination (r^2 value) determined from 100 failure data generated by the MCS method of the best fit distribution of each subsystem. The r^2 value for the original TBF data was calculated using the LSE technique. Table 3 shows that the lubrication system has the highest difference in r^2 value (3.93%), while the self-starting system has the lowest (0.2%). Further distribution overview plots were generated for engine subsystems.

Table 2. Goodness-of-fit test of engine subsystems.

System/Subsystems	Weibull	Lognormal	Exponential	Normal	Best Fit Model
Turbocharger system	1.601	1.603	1.617	1.902	Weibull
Self-Starting system	0.961	1.014	1.042	1.936	Weibull
Fuel supply system	1.367	1.318	1.396	2.066	Lognormal
Lubrication system	1.459	1.732	1.524	1.296	Normal
Cooling system	1.032	1.416	1.038	1.485	Weibull

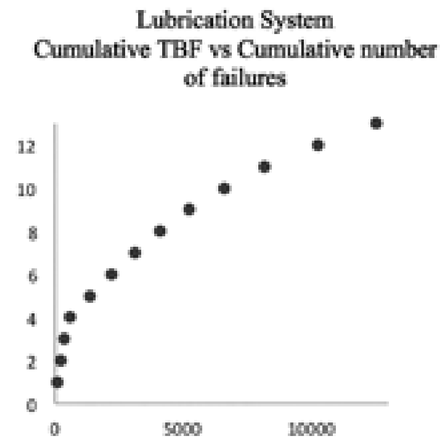

Fig. 8. Trend test for TBF of lubrication system of engine

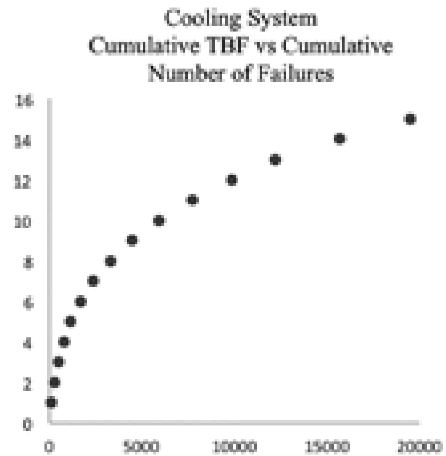

Fig. 10. Trend Test for TBF of cooling system of engine

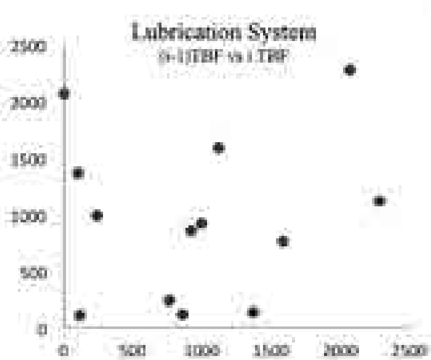

Fig. 9. Test of serial correlation for TBF of lubrication system of engine

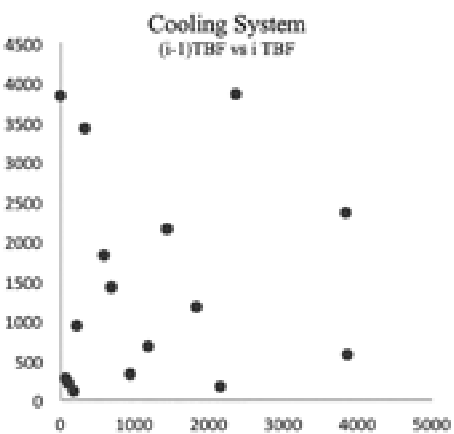

Fig. 11. Test of serial correlation for TBF of cooling system of engine

Based on the best fit distribution for each subsystem system (sorted by the value of the lowest A-D statistics), further distribution overview plots were created for turbocharger, fuel supply, self-starting, lubrication and cooling as shown in Fig.13, 15, 17, 19 and 21, respectively. Minitab software was used for this. The distribution overview graph has the same format for all subsystems. It shows four plots along with the table. The table shows the value of various distribution parameters such as mean, number of failure, coefficient of determination, etc. The different four plots in the overview graphs are survival plot, hazard plot, probability density function plot and the best fit distribution plot. The survival

Table 3. Coefficient of determination r2 value comparison for field TBF data and 100 TBF generated by mCS for engine subsystems.

Serial Number	Engine System	Best Fit Distribution	r^2 value for field data	r^2 value for Monte-Carlo	Difference in r2 (%)
1	Turbocharger system	Weibull	0.935	0.970	3.74
2	Self-Starting system	Weibull	0.970	0.972	0.21
3	Fuel supply system	Lognormal	0.976	0.988	1.23
4	Lubrication system	Normal	0.943	0.980	3.92
5	Cooling system	Weibull	0.990	0.970	2.02

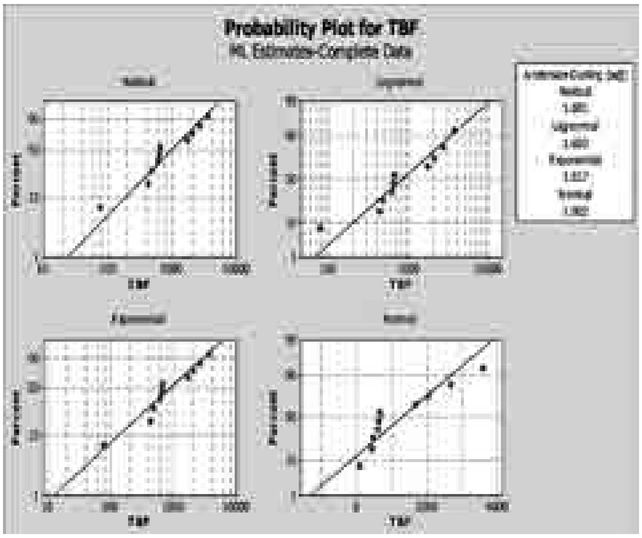

Fig. 12. Weibull, exponential, normal, lognormal distribution plot for turbocharger system

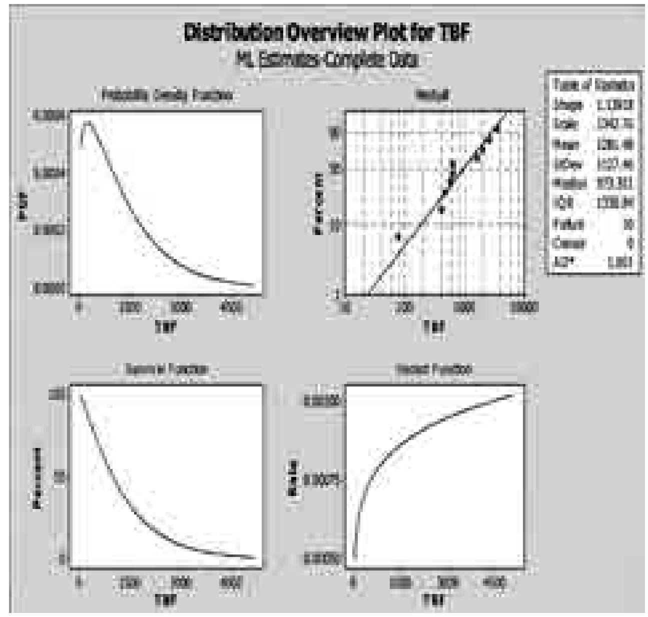

Fig. 13. Distribution overview plot for turbocharger system

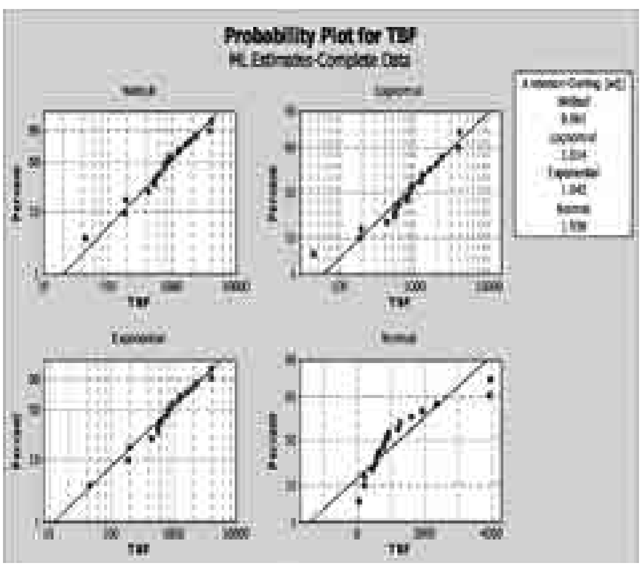

Fig. 14. Weibull, exponential, normal, lognormal distribution plot for self-starting system

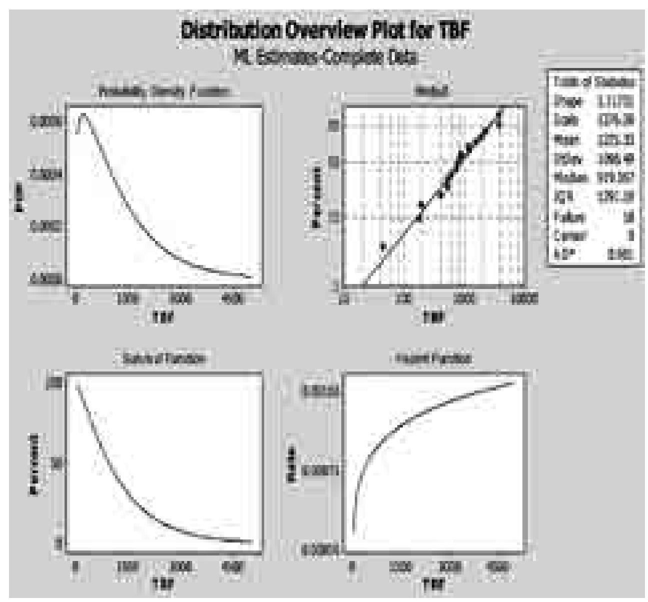

Fig. 15. Distribution overview plot for self-starting system

plot, or in other words, the reliability graph, shows the variation of life of a subsystem over time. The hazard plot shows the instantaneous failure rate with time. PDF describes the shape of the failure distribution data. Survival (reliability) percentage degrades as the time increases. The hazard function shows an increase over time for nearly all the subsystems of the engine. Using parameter distributions for the subsystems of engines, the reliability for the next 1000 hours, the MTBF and shape parameter were calculated. The respective values are presented in Table 4. Table 4 shows that the fuel supply system has the lowest reliability (0.007) and the lowest MTBF value of 243.50 hours.

Table 4. Statistical treatment of system failures.

Serial number	Defective System	MTBF (hours)	Best Fit Distribution	Reliability for Next 1000 hrs	Shape Parameter(β)
1	Turbocharger system	1052.91	Weibull	0.642	1.360
2	Self-starting system	1260.12	Weibull	0.44	1.057
3	Fuel supply system	243.50	Lognormal	0.007	1.643
4	Lubrication system	962.92	Normal	0.47	Normal distribution. Do not have shape parameter.
5	Cooling system	1444.34	Weibull	0.50	0.988

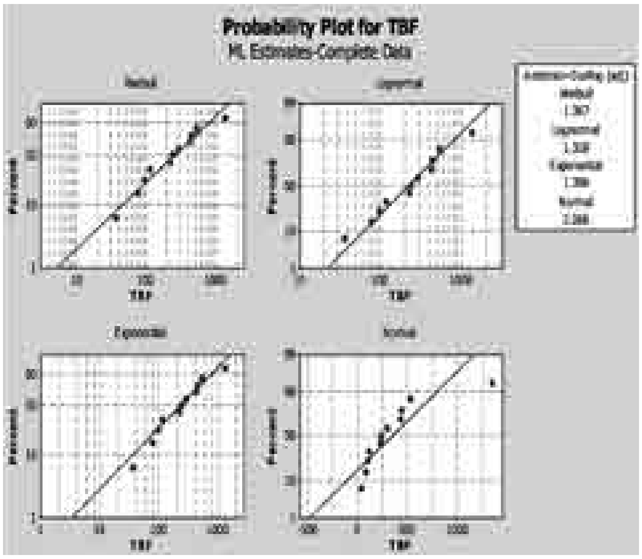

Fig. 16. Weibull, exponential, normal, lognormal distribution plot for fuel supply system

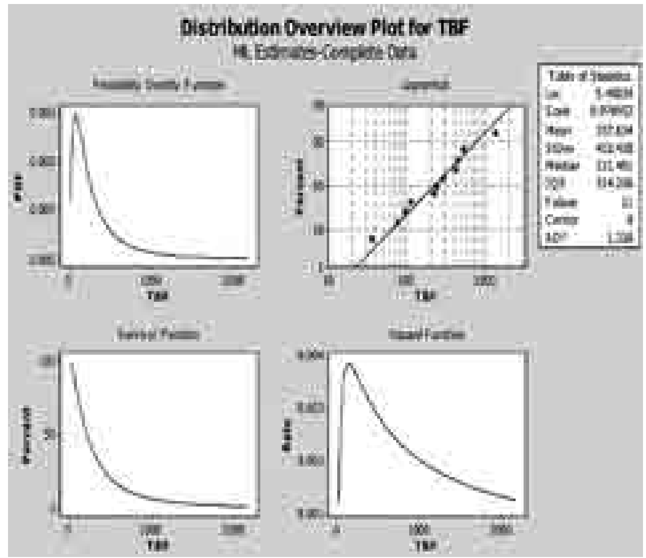

Fig. 17. Distribution overview plot for fuel supply

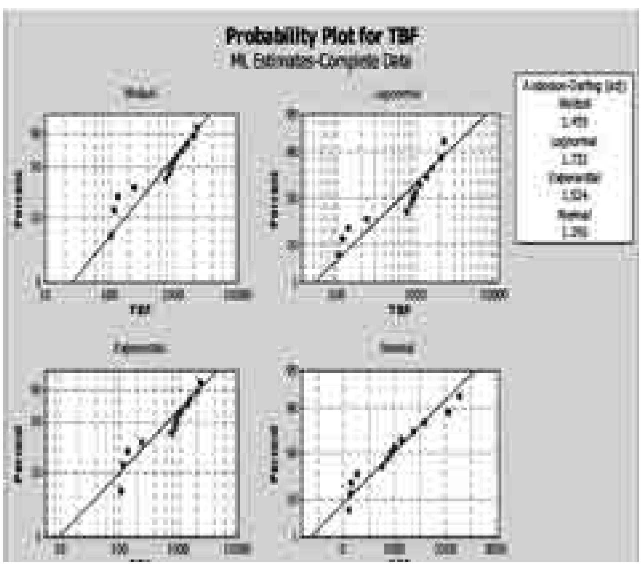

Fig. 18. Weibull, exponential, normal, lognormal distribution plot for lubrication system

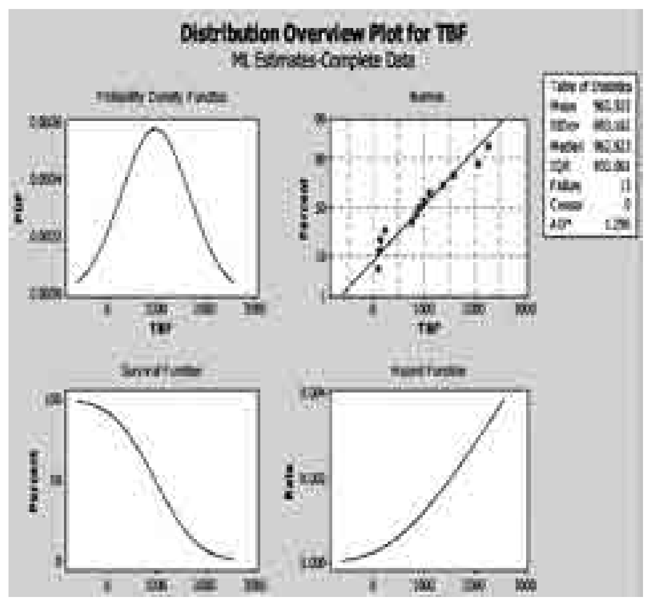

Fig. 19. Distribution overview plot for lubrication system

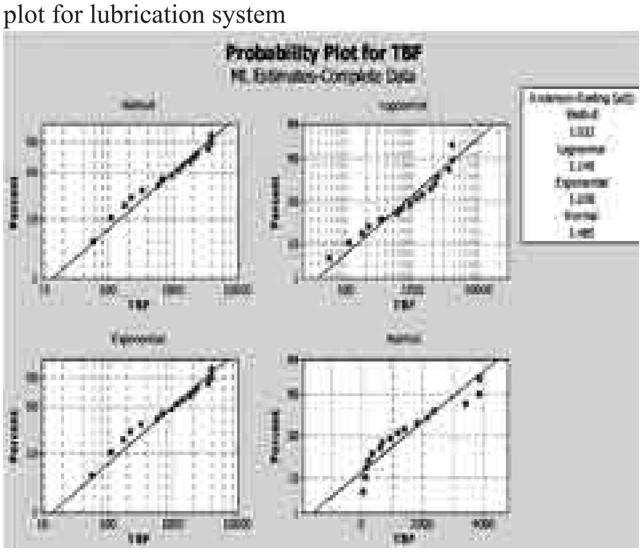

Fig. 20. Weibull, exponential, normal, lognormal distribution plot for cooling system

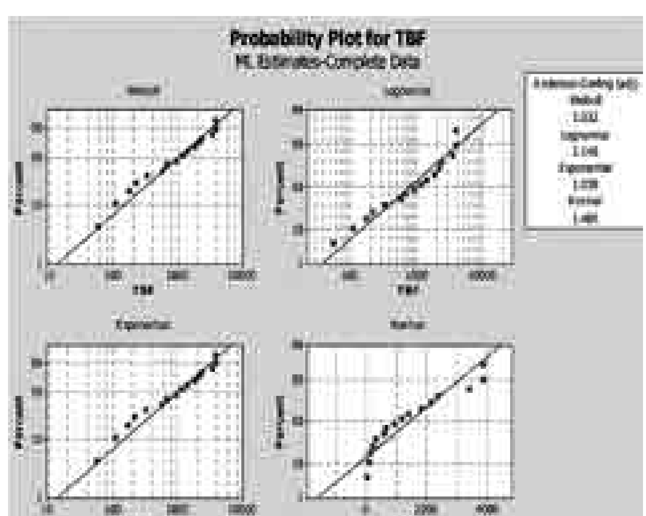

Fig. 21. Distribution overview plot for cooling system

In an engine Reliability Block Diagram series arrangement (Fig. 27), the dumper engine is comprised of a system of subsystems connected in series. Hence, if one unit is down due to failure, the whole system is unavailable, thereby reducing availability. The reliability of a unit comprising subsystems in the series is evaluated by multiplying the reliability of individual subsystem. The engine reliability is calculated by considering the product of its component reliability.

Reliability of engine =Turbocharger system x Self-starting system x Fuel supply system x Lubrication system x Cooling system.

Reliability of engine = 0.642 x 0.44 x 0.007 x 0.47 x 0.50 = 0.000464.

As discussed in the methodology, to estimate reliability of subsystems of a single engine, the Bayesian approach is used. The best fit probability distribution was found by using the MLE method for each subsystem. This is taken as the prior probability distribution of the particular subsystem. Model for data is Weibull distribution and data is the TBF data for single engine and for posterior distribution the Weibull Distribution is considered. Table 5 shows the reliability, MTBF and shape parameters of each subsystem for the single engine. They were estimated using the Weibull++ software.

The graph of reliability versus time graphs are shown in Figures 22, 23, 24, 25 and 26 for turbocharger, fuel supply, self-starting, lubrication and cooling, respectively. These were generated using Weibull ++ software. Figures show a decrease in reliability over time for all subsystems. The posterior Weibull distribution, MTBF and reliability are calculated by following equations.

For the Weibull distribution (Ebeling, 2000):

$$\mathrm{MTBF} = \theta\Gamma\left(1+\frac{1}{\beta}\right) \tag{1}$$

and the reliability is calculated as

R (t) = e-(t/θ) β, (2)

where ‘θ’ is the scale parameter and ‘β’ is shape parameter.

Table 5 shows the value of reliability and the MTBF for each subsystem. The fuel supply system has the lowest reliability (0.00166) and the lowest MTBF with a value of 255.34 hrs. The shape parameter (β) indicates the different life periods of equipment based on which suitable maintenance policies are suggested. When the shape parameter is less than 1, it represents an infant mortality period of the equipment. When β equals 1, it is the equipment’s normal useful period. A value greater than 1 refers to the wear out period of the equipment. So, based on the shape parameter, the following maintenance policies are suggested:

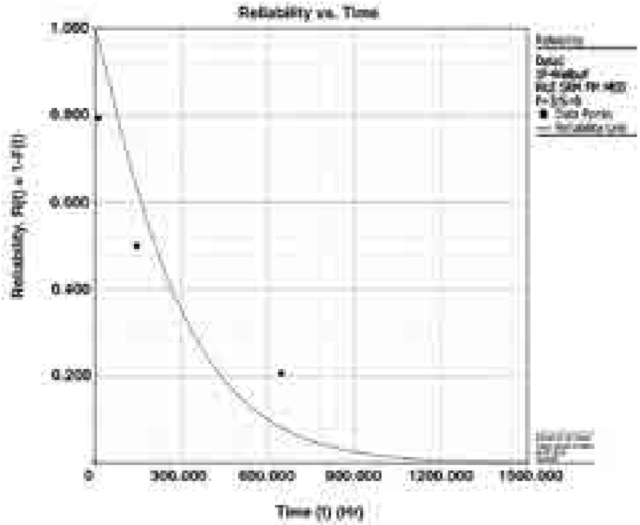

Fig. 22. Reliability vs. time plot for turbocharger system using Bayesian approach

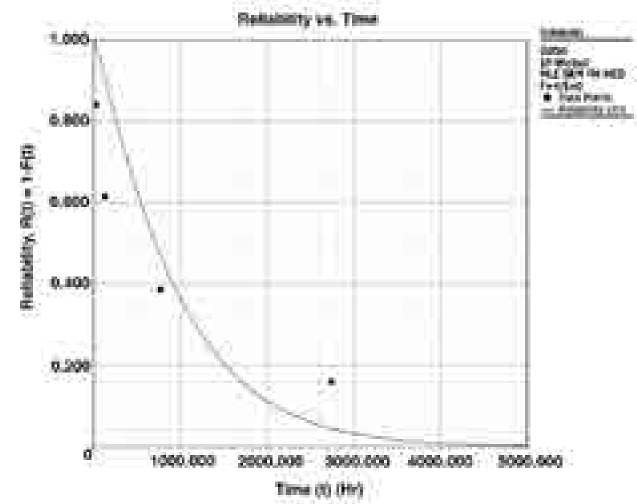

Fig. 23. Reliability vs time plot for self-starting system using Bayesian approach

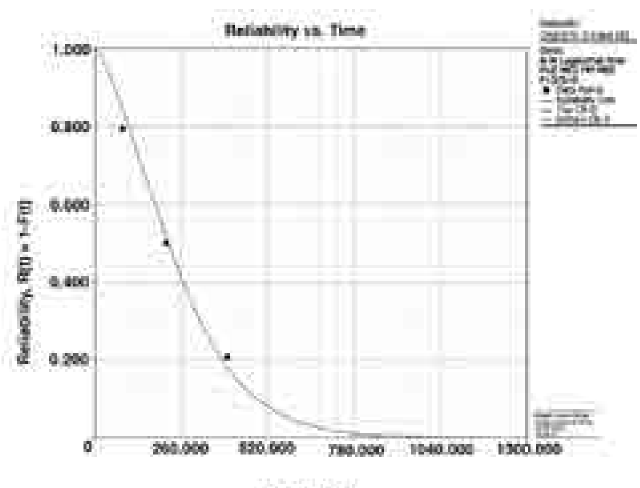

Fig. 24. Reliability vs time plot for fuel supply system using Bayesian approach

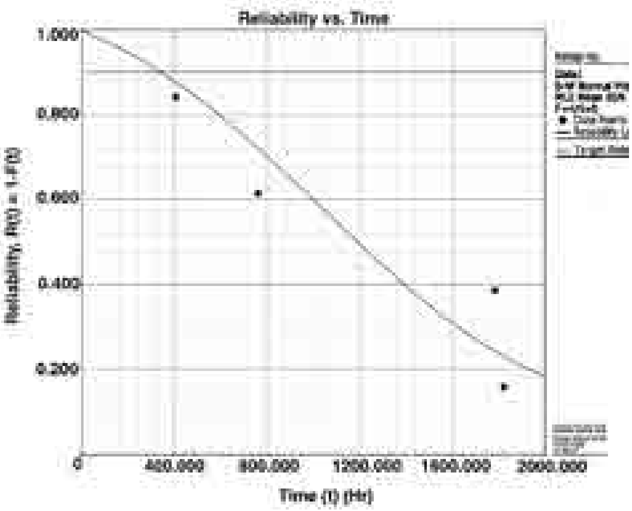

Fig. 25. Reliability vs time plot for lubrication system using Bayesian approach

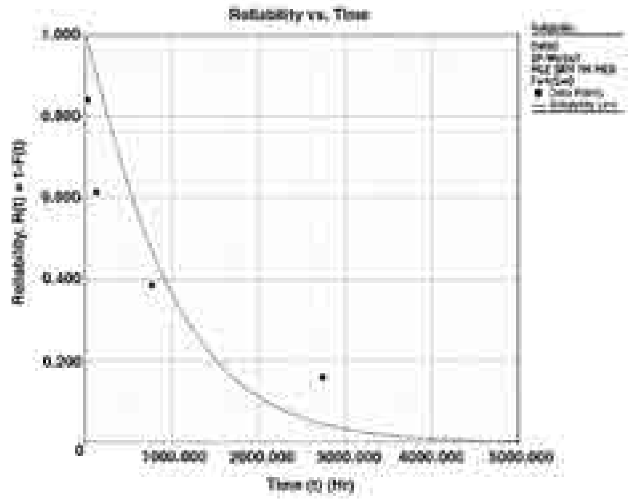

Fig. 26. Reliability vs time plot for cooling system using Bayesian approach

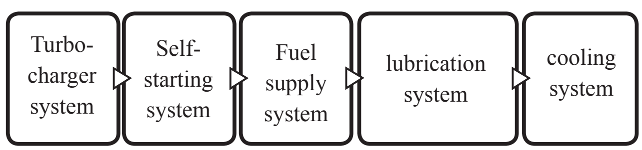

Fig. 27. Reliability block diagram of dumper engine

β>1: Condition-based maintenance

β=1: Preventive maintenance

β<1: Design out maintenance

Table 5 shows that β>1, thereby suggesting condition-based maintenance policies for the turbocharger, fuel supply, self-starting, lubrication and cooling subsystems of the engine. Hence, TBI in hours pertaining to 70%, 80%, and 90% reliability were calculated for all engine subsystems. TBI data were calculated using values of R(t) = 70%, 80% and 90%, and using Equation 2 (Table 6). The values of scale parameter (θ) and shape parameter (β) are found in Table 5.

6. Conclusion

The MLE and RBD were found to be effective statistical methods that can improve operational reliability of dumper engines and its components. The results reveal that a fuel supply system is more prone to failure. The MTBF for each subsystem has been examined, which shows that a respective engine's subsystem should be taken care of before its MTBF is reached. The survival plot shows the variation of reliability over time for each subsystem. The Bayesian approach is effectively used for a single new engine from the fleet with small TBF data. Moreover, an

Table 5. Reliability, shape parameter and MTBF estimation for engine subsystems using Bayesian approach.

Serial number	Defective system	MTBF (hours)	Shape Parameter (β)	Scale Parameter (θ)	Reliability for next 1000 hrs
1	Turbocharger system	274.95	1.139	288.81	0.016
2	Self-starting system	949.88	1.1173	990.49	0.3639
3	Fuel supply system	255.34	1.423	281.215	0.00166
4	Lubrication system	1296.235	2.0312	1463.02	0.599
5	Cooling system	404.01	1.108	419.97	0.073

Table 6. TBI for engine subsystems

Serial number	Defective system	TBI in hours for reliability		
		70%	80%	90%
1	Turbocharger system	116.82	77.4	40.04
2	Self-Starting system	393.56	258.62	132.1
3	Fuel supply system	136.27	98	57.85
4	Lubrication system	880.65	699.05	483.112
5	Cooling system	165.63	108.46	55.1

attempt has been made to suggest suitable maintenance policies for the engine subsystems. To improve the reliability of subsystems, TBI was calculated based on the calculated reliability. TBI predicts the time interval after which the component should be inspected for any failure. The TBI was calculated for 70%, 80% and 90% reliability, respectively. This research improve the reliability of engines by formulating maintenance strategies thereby avoiding failure of dumper engines. In so doing, mining costs can be lowered.

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تحقيق عن الموثوقية لمحركات الديزل المستخدمة في الشاحنات القلابة باستخدام طريقة بازيان

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الملخص

تحتل صناعة المناجم مكان مرغوب على مستوى العالم. يؤدي التعقيد المتصاعد للأجهزة والنظم المستخدمة إلى حالات فشل ونتيجة لذلك جاءت في المقدمة اعتبارات درجة الثقة والاستدامة ولاالتيُستخدم شاحنات قلابة لنقل المادة الخام في مناجم التعدين السطحية. أهم جزء في شاحنة النقل هو محركها الرئيسي موتور الديزيل. وأي عطل في الموتور يؤدي إلى توقف الشاحنة. من الضروري عمل تغييرات في سياسة الصيانة لتقليل زمن الأعطال. ولتغيير سياسة الصيانة للشاحنات، يجب تقييم أداء المحركات ودرجة الموثوقية لأجزاء المحركات. لذلك، نقوم في هذا البحث بتقييم أداء المحركات ودرجة موثوقية أجزائها. ولهذا الغرض تم تقسيم المحرك لأجزاء مختلفة. تمت دراسة نتائج تحليل التوجه للزمن المنقضي بين الأعطال (TBF) لبيانات تم الحصول عليها لكل جزء من أجزاء المحرك. وتم بعد ذلك تمثيل هذه البيانات باستخدام أربعة توزيعات احتمالية Weibull، Exponential، Normal و Lognormal بُستخدمت طريقة تعظيم الاحتمالات في برنامج Minitab لتقدير معلمات التوزيع لحساب درجة الموثوقية لأجزاء المحركات. مع أنه تم جمع البيانات على مدى ثلاث سنوات إلا أن البيانات الخاصة لكل جزء من المحرك حجمها صغير. ولذلك، تم دمج البيانات الخاصة بثلاثة محركات متشابهة. ولتعزيز النتائج، تم توليد 100 بيانات أعطال باستخدام طريقة MCS. لتقدير درجة الموثوقية لكل جزء بدون تجميع بيانات الأعطال تم استخدام أدوات البيزيان وايبل في برنامج وايبل ++. وباستخدام تحليل الموثوقية، تم التنبؤ بأعطال أجزاء المحركات وذلك لعمل الصيانة في الوقت المناسب لتقليل تكلفة الصيانة.