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A comparative study between the system reliability evaluation methods: case study of mining dump trucks

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Abstract

The shovel-truck system is a widely used technique for haulage systems in surface mining operations. However, predicting the failure patterns of complex systems requires accurate failure prediction techniques. In this study, several major system reliability evaluation groups, including non-parametric, parametric, and semi-parametric methods, are investigated, and their effectiveness is compared to identify the best group for predicting the failure patterns of complex systems such as mining dump trucks, which operate in harsh environments. A historical dataset of time to failure (TTF) and maintenance data was collected. Then, the system's reliability was evaluated using the major TTF data analysis methods. The findings demonstrated that all the major system reliability evaluation groups produced similar curves; however, the semi-parametric method outperformed the other methods. This result underscores that this system reliability evaluation group is the most effective method for complex systems. Also, it was found that the dump truck reliability dropped to 50% after 40 operation hours, demonstrating the critical importance of implementing preventive maintenance to enhance the system's performance and ensure operation safety. In addition, this study provided an appropriate insight into the predictive methods and offered an accurate estimation of the failure pattern of complex systems, resulting in availability and productivity improvement.

Keywords: Mining dump truck, Haulage operation, Reliability evaluation, Maintenance management, Harsh and heterogeneous environment

Introduction

Raw material extraction is one of the fundamental links in the value chain of mineral products. This operation depends on mining equipment such as loaders, dozers, shovels, and dump trucks. Besides, these assets have become more complex and expensive so as to require more accurate maintenance to prevent operation interruption and loss of production capacity. Achieving these goals needs an efficient maintenance plan to implement inspections, preventive maintenance, and corrective maintenance. Therefore, reliability evaluation and maintenance management can remarkably affect haulage system performance and availability, leading to production capacity insurance [1].

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Reliability evaluation is one of the effective metrics for developing comprehensive maintenance strategies [2]. It is employed for different applications and purposes in various engineering sectors. Figure 1 displays a network of reliability applications in previous studies.

Various researchers employed different system reliability methods for analyzing complex systems' performance. Roy et al. [3] determined reliability and maintainability characteristics in a fleet of mining shovels. They analyzed failure and maintenance data for four shovels by dividing the shovel system into several sub-systems. Thus, the maintenance intervals were estimated for each shovel. Ghodrati and Kumar [4] employed the PHM to predict the optimal number of spare parts for the hydraulic jack in load–haul–dump (LHD) machine operations. Barabady and Kumar [5] evaluated the reliability and availability of crushing equipment using the parametric reliability method to identify the most critical components in this system. Uzgören et al. [6] assessed the reliability of two dragline excavators using the parametric reliability method and then compared the results. In addition, Barabadi et al. [7] studied mine haulage throughput capacity considering failure rate and environmental conditions. They utilized the reliability phase diagram to analyze the reliability of the haulage trucks operating in two different production lines. Morad et al. [8] utilized a parametric reliability method to estimate the reliability of mining equipment sub-systems. They divided the mining truck system into several sub-systems and then predicted the reliability of each sub-system. Pandey et al. [9] performed reliability and failure rate evaluations for critical sub-systems of three dragline excavators operating in surface mines. They intended to increase availability

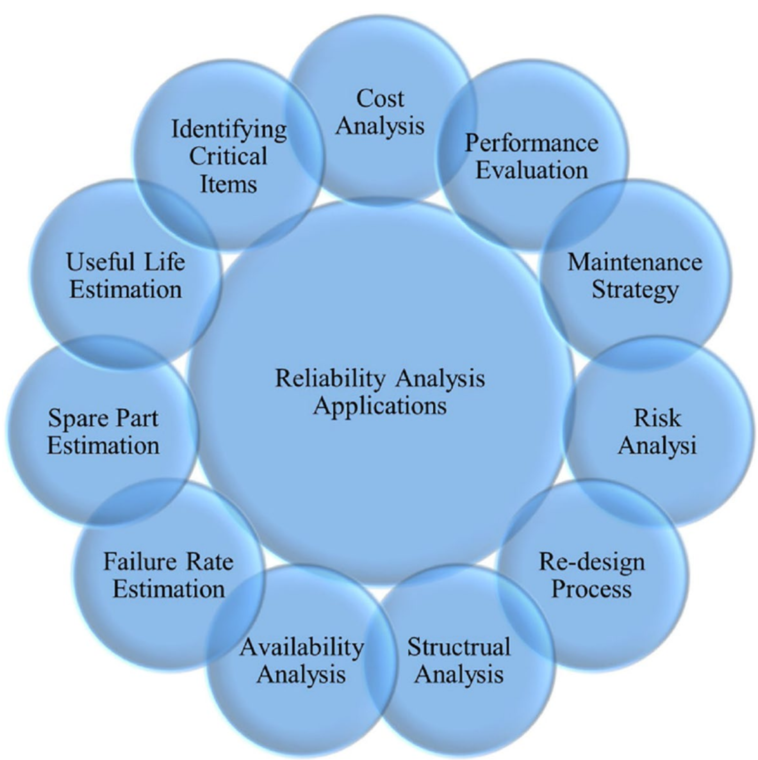

Fig. 1 A network of reliability applications

and decline maintenance and production costs. Angeles and Kumral [10] employed the power law process as a parametric reliability method to estimate optimal inspection and preventative maintenance scheduling in mining equipment. Allahkarami et al. [11] utilized a mixed frailty model to identify the observed and unobserved risk factors affecting the system reliability in mining systems. Moniri-Morad et al. [12] analyzed the haulage fleet production capacity by estimating the system's reliability, availability, and maintainability (RAM). In this case, the discrete-event simulation and PHM have been combined to perform RAM analysis. Toraman Jakkula et al. [13] investigated the RAM in LHD machine operations. Toraman [14] conducted the RAM analysis to compute the performance of large-capacity trucks in mining operations. Florea et al. [15] utilized parametric models to investigate the reliability and maintainability of mining equipment with components subjected to intense wear. They determined the critical failure modes and their effects to establish a comprehensive maintenance plan for the components.

Previous studies have employed various system reliability evaluation models based on their application fields and data availability. However, a majority of these models can be classified into three major groups, including non-parametric, parametric, and semi-parametric methods [16, 17]. Hence, it is necessary to analyze each method and compare their results based on the application field. The main aims and contributions of this work can be summarized as follows:

- Predicting the failure patterns of complex systems operating in the mining industry
- Investigating the practicality and robustness of the major system reliability evaluation groups in challenging and harsh operating conditions
- Identifying the most effective system reliability evaluation group, resulting in superior performance outcomes
- Facilitating data-driven decision-making strategies by comparing the major system reliability evaluation groups, empowering analysts to choose the most accurate and appropriate method for their specific applications
- Demonstrating the applicability of the system reliability methods in various industries dealing with complex systems

The rest of this paper is organized as follows. The "Methods" section describes the study aims, proposed method, procedure, and boundaries for this study. Then, the "Methods" section investigates the major system reliability evaluation groups in a case study. Afterward, the achieved results are discussed in the "Discussion" section. Finally, conclusions and some remarkable findings are presented in the "Conclusions" section.

Methods

Reliability analysis is one of the most significant metrics in evaluating a system's performance. It is a process that encompasses collecting and pre-processing datasets, selecting appropriate reliability techniques (e.g., mathematical, statistical, or simulation), estimating system reliability, and interpreting the results. This process provides an appropriate insight into the system failure patterns, potential failure modes, and system characteristics, enabling analysts to make informed decisions about the system's reliability improvement. There are two kinds of reliability analysis processes: structural and system reliability analyses [17–19]. This study revolves around the system reliability analysis process, particularly reliability methods based on TTF data analysis.

Figure 2 illustrates the proposed step-by-step procedure in this study. As shown in Fig. 2, this study is designed based on two phases, encompassing reliability estimation and comparison processes. The system reliability estimation is started by collecting data and performing data pre-processing. Then, the data distribution is checked. If the dataset has a known distribution function, the parametric reliability method can be considered for analyzing the process. Otherwise, the non-parametric or semi-parametric reliability methods can be employed. Indeed, the non-parametric and semi-parametric reliability methods are used when the dataset does not have a known distribution function or if the distribution is complex or multi-modal. Therefore, it is possible to estimate the system's reliability using the available methods. In the second phase, multiple selection criteria are identified by experts, and then the best system reliability evaluation group is selected among the non-parametric, parametric, and semi-parametric reliability methods.

Non-parametric reliability method

The non-parametric reliability method is focused on collecting and analyzing the TTF dataset without making assumptions about an underlying distribution function. This method revolves around descriptive statistics to analyze the TTF data. Researchers have developed various non-parametric reliability models, such as Kaplan-Meier [20] and Nelson-Aalen [21]. The non-parametric reliability method has a significant advantage over the other reliability methods (i.e., parametric and semi-parametric). In other

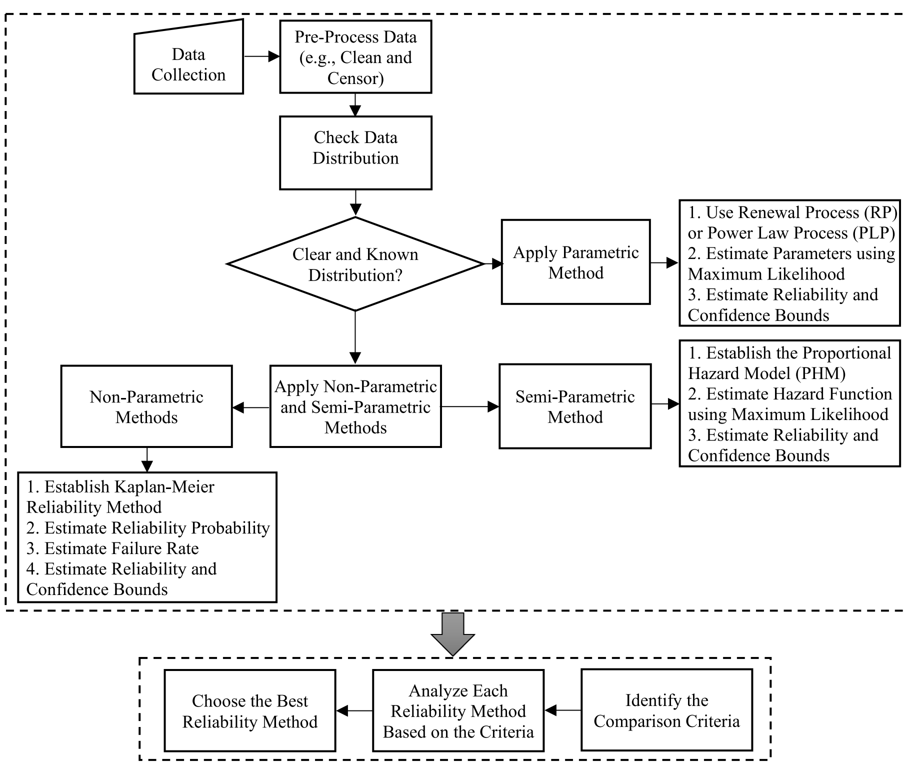

Fig. 2 The designed reliability estimation process for this study

words, it provides accurate outputs without assuming a specific probability distribution function. This procedure eliminates the risk of choosing an incorrect distribution and guarantees robustness in the analysis. However, it is crucial to mention that the non-parametric reliability method is restricted to the observed data, confining their ability to simulate results for other time intervals beyond the available data. Thus, it is necessary to consider this limitation when employing a non-parametric reliability method.

The Kaplan-Meier model is proposed as one of the most conspicuous non-parametric reliability models in analyzing the TTF data. The reliability diagram is drawn as a step function with discontinuities or jumps at the observed failure times. Also, the height and width of these steps vary depending on the reliability function estimations and failure time observations, respectively [20]. The Kaplan-Meier model formulates the reliability function as follows:

$$R(t_j) = \prod_{j|t_j \leq t} \frac{n_j - d_j}{n_j} \tag{1}$$

where t_j ($j = 1, \ldots, m$) represents the failure times, m is the total number of data points, n_j is the number of units at the failure risk just before time t_j, and d_j is the number of failures at time t_j. If the observed data express the failure events, $d_j = 1$. Otherwise, if the observed data describe the censored data, $d_j = 0$.

In the Kaplan-Meier model, the first observation occurs at time $t = 0$. Thus, there is no failure event in the first observation ($R(t_1) = 1$), and then the reliability function goes to zero as a step function.

Parametric reliability method

The parametric reliability method is an effective technique for understanding system reliability. This method provides appropriate insights into the failure mechanisms, and the resulting model can assess the reliability parameters for the system's lifetime. Also, the reliability is evaluated by fitting the standard distribution functions into TTF data. In this case, the estimated model can predict the reliability values beyond the range of the existing dataset.

The parametric reliability method is performed as follows. The trend of TTF data is first tested to identify the failure patterns of a system. The probability plotting method [22] is suggested to examine the data trend. This method is configured based on plotting the cumulative number of events against the cumulative TTFs [23]. The plot output is either a straight line or nonlinear. If the curve has an increasing (or decreasing) trend, the system is repairable, and thus, it is repaired after occurring a failure event. In a repairable system, the PLP is proposed as one of the most significant parametric reliability models in analyzing the failure intensity of a system. The failure intensity is defined as follows:

$$h(t) = \lambda.\beta.t^{\beta-1} \tag{2}$$

where $h(t)$ denotes the intensity function, t is the time between failures (TBFs), β presents the Weibull parameter, and λ is the model parameter.

The PLP is formulated using non-stationary techniques like the non-homogeneous Poisson process (NHPP) [24]. Indeed, a minimal repair process is performed on the system after occurring failure, and the system status returns to its status just before performing the repair action. In this model, the reliability function can be formulated as follows:

$$R(t) = \exp(-H(t)) \tag{3}$$

where $R(t)$ is the reliability function, $H(t)$ is the cumulative intensity function ($H(t) = \int_0^t h(\varnothing)d\varnothing$), and $h(\varnothing)$ is the intensity function.

Also, satisfying the identical and independent distribution (IID) conditions demonstrates that the system is non-repairable. These conditions are fulfilled by evaluating the data trend and dependency. In a non-repairable system, the dataset has a straight-line trend, and the data dependency is examined via the serial correlation test. This test is conducted by plotting the i^{th} incident time versus the $(i\text{-}1)^{th}$ incident time. In this diagram, the dataset is independent if all the points are scattered in a single cluster; otherwise, the dataset is dependent, indicating the violation of IID conditions. In a non-repairable system, the RP model is suggested as one of the most remarkable parametric reliability models in predicting the failure behavior profile of the system.

Semi-parametric reliability method

The semi-parametric reliability method evaluates the TTF data when exogenous factors affect the system's reliability. This study revolves around the PHM as one of the most practical semi-parametric reliability models for evaluating system reliability in a heterogeneous environment.

The PHM has two main elements: a baseline hazard function and a multiplicative term (covariates). This model is mathematically formulated by Eq. (4) [25, 26].

$$h(t|Z) = h_0(t)exp\left(\beta^T Z\right) \tag{4}$$

where $h(t|z)$ is the observed hazard function, and $h_0(t)$ is the baseline hazard function (dependent only on time), which occurs when the covariates have no influence on the failure profile ($Z = 0$ or $\exp\left(\beta^T Z\right) = 1$). Also, Z is a $t \times 1$ vector containing covariates. In addition, β^T is a $1 \times t$ vector of regression coefficients. These coefficients characterize the impact of covariates. The PHM is assumed to be proportional, demonstrating a constant hazard ratio (HR) between any two observations over time. This proportionality is tested as follows:

$$HR = \frac{h_1(t|Z_1)}{h_2(t|Z_2)} = \frac{h_0(t)exp\left(\beta^T Z_1\right)}{h_0(t)exp\left(\beta^T Z_2\right)} = exp[\beta^T(Z_1 - Z_2)] \tag{5}$$

where HR is the hazard ratio, and $h_1(t|Z_1)$ and $h_2(t|Z_2)$ are two different observations.

In the parametric PHM, the unknown parameters for the baseline hazard function and the coefficients of covariates are estimated via the log-likelihood function.

$$\ln(L_i) = d_i\ ln\left[H'(t_i|Z)\right] - H(t_i|Z) \tag{6}$$

where $\ln(L_i)$ is the log-likelihood function for the i^{th} failure event, $H\prime(t_i|Z)$ is the derivative function of the cumulative observed hazard function $(H(t_i|Z))$, and d_i is the event indicator. If the observed event is failure, $d_i = 1$; otherwise, $d_i = 0$.

In this case, the Newton-Raphson technique is utilized to find the roots of the maximum likelihood estimation (MLE). This technique is formulated as follows:

$$\delta_{i+1} = \delta_i + \left(-{}^{g(\delta_i)}\!\big/_{H(\delta_i)}\right) \tag{7}$$

where δ_{i+1} represents the value of the new root, δ_i denotes the root value of the i^{th} iteration, $g(\delta_i)$ describes the gradient vector, and $H(\delta_i)$ characterizes the Hessian matrix.

Finally, it is possible to compute the system reliability function using the following equation:

$$R(t|Z) = \exp(H_0(t)\exp(\beta^T Z)) \tag{8}$$

where $R(t|Z)$ is the observed reliability function, $H_0(t)$ is the cumulative baseline hazard function, Z is a vector containing covariates, and β^T is a vector of regression coefficients.

Results

Historical data analysis

The failure and maintenance data collection process plays a crucial role in assessing the performance and reliability of mining equipment. This process involved systematically gathering data from mining operations to obtain solid insights into failure modes, failure frequency and severity, breakdowns, maintenance activities, and the effectiveness of maintenance strategies. In this case, the data collection spanned one year and specifically was focused on the failure and maintenance data of a Komatsu dump truck with a capacity of 100 tons, which operated at Sungun mine, East Azerbaijan province, Northwest of Iran. The dump truck had accumulated approximately 15,000 h.

The collected dataset included the failure times, restoration or replacement times, type of failed sub-system, and environmental conditions. Table 1 provides a sample of the collected failure dataset for this study. This dataset includes TTFs for the dump truck sub-systems (i.e., Engine, Transmission, Hydraulics, Body and Chassis, and Gearbox), the severity of the failure incident, and average temperature. In Table 1, the value of one denotes the failed sub-systems in each failure observation. For instance, the first failure occurred after 14 operation hours at − 0.1 °C, and the failure incident was due to the failure in the Hydraulics sub-system. Also, the severity value was zero, indicating that this failure was a mild incident. Table 2 provides the preliminary analysis of these data. In this table, the number of data was 92, and the variables were categorized into two groups, encompassing binary and continuous variables. The binary variables are subject to two states of success and failure. The percentage of ones represents the percentage of failure occurrences in each variable. In the continuous variables, the mean, standard deviation, minimum, and maximum values were reported for each variable. After the preliminary analysis of the dataset, it was analyzed based on the three major system reliability evaluation groups.

Table 1 A sample of the collected failure dataset

Time to failure (hour)	Engine	Transmission	Hydraulics	Body & Chassis	Gearbox	Severity	Temperature (°C)
14	0	0	1	0	0	0	-0.1
35	0	0	1	0	0	1	7
36	0	0	0	1	0	0	7
25	0	1	0	0	0	1	3.3
42	0	1	0	0	0	1	3.3
129	1	0	0	1	0	1	9.1
19	1	0	0	0	0	0	9.1
55	1	0	0	0	0	0	7.6
30	1	0	0	0	0	0	7.6
170	0	0	1	0	0	1	11.6
18	1	0	1	1	0	0	11.6
32	0	0	0	1	0	0	11.6
30	1	0	0	0	0	0	7.6
170	0	0	1	0	0	1	11.6

Table 2 A statistical summary of the collected dataset

Type of variable	Variables	Total number of observations	The percentage of ones	The percentage of zeros	Maximum	Minimum
Binary	Engine	92	41.3	58.7	1	0
	Transmission	92	17.4	82.6	1	0
	Hydraulics	92	14.1	85.9	1	0
	Body & Chassis	92	43.5	56.5	1	0
	Gearbox	92	8.7	91.3	1	0
	Severity	92	33.7	66.3	1	0
Continuous	**Variables**	**Total number of observations**	**Mean**	**Standard deviation**	**Maximum**	**Minimum**
	Time to failures (TTFs) (hour)	92	58.6	51.5	225	14
	Temperature (°C)	92	8.7	8.7	22.5	-6.5

Non-parametric analysis of the collected dataset

The non-parametric reliability method was conducted by formulating the Kaplan-Meier model. Table 3 gives the results of the reliability estimation using the Kaplan-Meier model.

Table 3 reports various valuable information, including system reliability at different times, standard error, and uncertainty (95% confidence interval). Also, the reliability value goes from 0.9565 to 0.0109 after 220 operation hours.

Parametric analysis of the collected dataset

The truck reliability was estimated through the parametric reliability method. In this regard, the TTF data trend was first examined using the probability plotting technique. Figure 3 depicts the trend test for the truck system. The results of Fig. 3

Table 3 Evaluating system reliability using the non-parametric method

Time	Reliability function	Standard error	Uncertainty		Time	Reliability function	Standard error	Uncertainty	
			Lower bound	Upper bound				Lower bound	Upper bound
14	0.9565	0.0213	0.8883	0.9835	56	0.3152	0.0484	0.2234	0.4109
15	0.9239	0.0276	0.847	0.963	60	0.2935	0.0475	0.2044	0.3881
16	0.9022	0.031	0.8204	0.9479	65	0.2826	0.0469	0.1949	0.3766
17	0.8804	0.0338	0.7945	0.9319	66	0.2717	0.0464	0.1856	0.365
18	0.8043	0.0414	0.7076	0.8719	68	0.2609	0.0458	0.1763	0.3534
19	0.7826	0.043	0.6836	0.8539	72	0.2391	0.0445	0.1579	0.3299
20	0.7391	0.0458	0.6366	0.8168	73	0.2283	0.0438	0.1488	0.3181
25	0.7065	0.0475	0.602	0.7884	74	0.2174	0.043	0.1398	0.3062
26	0.6957	0.048	0.5906	0.7788	80	0.1957	0.0414	0.1221	0.2821
28	0.6848	0.0484	0.5792	0.7691	84	0.1739	0.0395	0.1047	0.2577
30	0.6413	0.05	0.5344	0.7298	92	0.163	0.0385	0.0962	0.2453
32	0.6304	0.0503	0.5233	0.7199	104	0.1522	0.0374	0.0878	0.2329
33	0.6196	0.0506	0.5123	0.7099	108	0.1413	0.0363	0.0796	0.2203
34	0.5761	0.0515	0.4687	0.6694	123	0.1304	0.0351	0.0714	0.2076
35	0.5326	0.052	0.4259	0.6282	129	0.1196	0.0338	0.0634	0.1948
36	0.5217	0.0521	0.4153	0.6178	135	0.1087	0.0325	0.0556	0.1818
38	0.5109	0.0521	0.4047	0.6073	140	0.0978	0.031	0.048	0.1686
40	0.4891	0.0521	0.3838	0.5862	150	0.087	0.0294	0.0406	0.1553
41	0.4674	0.052	0.363	0.565	155	0.0761	0.0276	0.0335	0.1417
42	0.4565	0.0519	0.3527	0.5543	166	0.0652	0.0257	0.0267	0.1279
43	0.4348	0.0517	0.3323	0.5328	170	0.0543	0.0236	0.0202	0.1138
50	0.413	0.0513	0.312	0.5111	174	0.0435	0.0213	0.0142	0.0993
52	0.3913	0.0509	0.292	0.4891	200	0.0326	0.0185	0.0088	0.0843
54	0.3587	0.05	0.2623	0.4559	210	0.0217	0.0152	0.0042	0.0688
55	0.337	0.0493	0.2427	0.4335	220	0.0109	0.0108	0.001	0.053

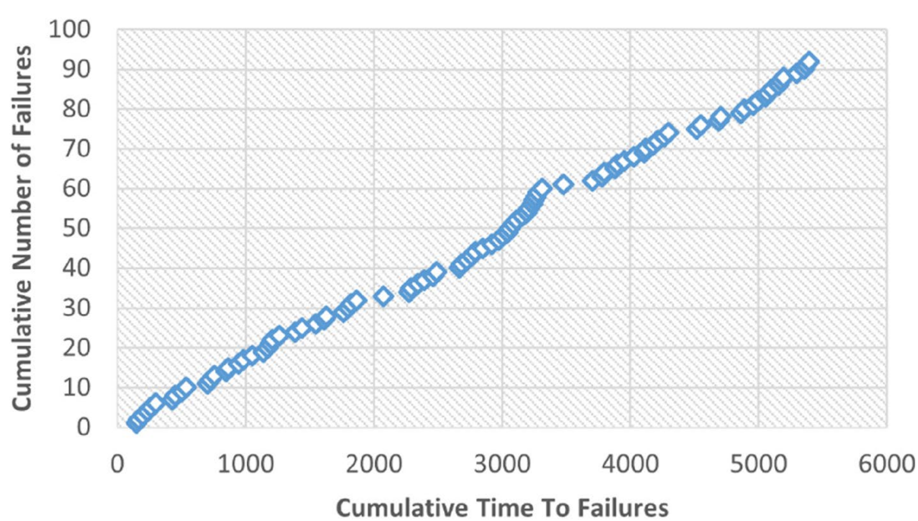

Fig. 3 The trend test for truck system

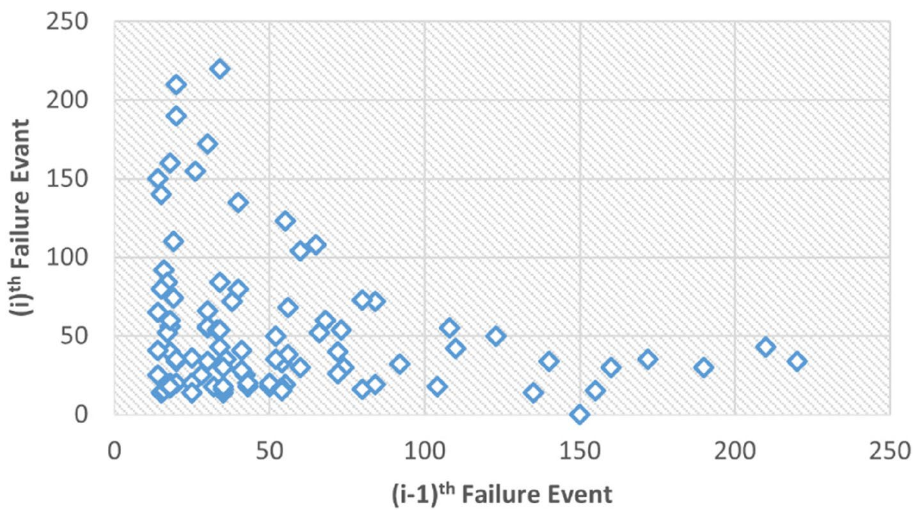

Fig. 4 The serial correlation test for the truck system

Table 4 Evaluating various standard parametric distribution functions for identifying the best fit

Distribution function	Distribution parameters		Log-likelihood value
Log-normal	$\mu = 3.761$	$\sigma = 0.77$	− 452
Weibull	$\alpha = 63.894$	$\beta = 1.283$ B	− 461.86
Log-logistic	$\mu = 3.722$	$\sigma = 0.450$	− 454.54
Gamma	$a = 1.762$	$b = 33.267$	− 459.04

illustrated that this dataset did not have a trend. Then, the serial correlation test was utilized to investigate the TTF data dependency (Fig. 4). According to the results of these two figures, the dump truck system followed the IID conditions, demonstrating that the dump truck should be analyzed as a non-repairable system. Therefore, the RP model was employed to estimate the dump truck failure behavior.

After confirming the IID conditions for the existing dataset, a standard parametric distribution function was fitted to the data to find the best probability distribution. Multiple standard parametric distributions were analyzed for this purpose. Table 4 reports the estimated parameters and the log-likelihood values for four distribution functions. Among these distributions, the Log-normal distribution showed the best fit with a log-likelihood value of − 452. Also, the mean and the standard deviation for the Log-normal distribution are 3.761 and 0.77, respectively.

Then, the system reliability was estimated based on fitting the Log-normal distribution function to the dataset. The system reliability function was formulated by the log-normal distribution as follows:

$$R(t) = \exp\left[\mu + \frac{1}{2}\sigma^2\right] \tag{9}$$

where $R(t)$ is the reliability function obtained from the Log-normal distribution, and μ and σ are the mean and standard deviation of the Log-normal distribution function, respectively.

Table 5 gives the reliability values estimated by the parametric method at various times. The uncertainty of the estimated reliability was also computed using the lower and upper bounds at a 95% confidence interval (Table 5).

Additionally, the parametric method was utilized to estimate the reliability of each truck sub-system. In this procedure, the truck system was decomposed into five sub-systems. Then, the failure data for each sub-system were analyzed. Table 6 gives the best-fitted distribution and the reliability value for each sub-system. The reliability value was estimated at 100 operation hours. Among these sub-systems, the most reliable and unreliable sub-systems were Gearbox and Engine, respectively.

Semi-parametric analysis of the collected dataset

The truck system reliability was estimated using the semi-parametric method, particularly parametric PHM. The estimation process was performed by analyzing the TTFs and the binary and continuous variables.

Table 5 Estimating system reliability at various times using the parametric method

Time	Reliability function	Uncertainty		Time	Reliability function	Uncertainty	
		Lower bound	Upper bound			Lower bound	Upper bound
0	1	10^{-6}	1	125	0.083	0.047	0.136
5	0.997	0.990	0.999	130	0.075	0.042	0.126
10	0.971	0.940	0.987	135	0.069	0.037	0.117
15	0.914	0.860	0.951	140	0.063	0.033	0.109
20	0.840	0.771	0.893	145	0.057	0.030	0.102
25	0.759	0.683	0.825	150	0.052	0.026	0.095
30	0.680	0.599	0.753	155	0.048	0.024	0.089
35	0.605	0.524	0.683	160	0.044	0.021	0.083
40	0.537	0.456	0.617	165	0.040	0.019	0.078
45	0.476	0.396	0.558	170	0.037	0.017	0.073
50	0.422	0.344	0.504	175	0.034	0.015	0.068
55	0.375	0.298	0.456	180	0.031	0.014	0.064
60	0.333	0.259	0.413	185	0.029	0.013	0.060
65	0.296	0.225	0.375	190	0.027	0.011	0.057
70	0.263	0.196	0.341	195	0.025	0.010	0.053
75	0.235	0.170	0.311	200	0.023	0.009	0.050
80	0.210	0.149	0.284	205	0.021	0.008	0.048
85	0.188	0.130	0.260	210	0.020	0.008	0.045
90	0.169	0.114	0.238	215	0.018	0.007	0.042
95	0.152	0.100	0.219	220	0.017	0.006	0.040
100	0.136	0.088	0.201	225	0.016	0.006	0.038
105	0.123	0.077	0.185	230	0.015	0.005	0.036
110	0.111	0.068	0.171	235	0.014	0.005	0.034
115	0.101	0.060	0.158	240	0.013	0.004	0.032
120	0.091	0.053	0.147				

Table 6 Estimating the reliability of each truck sub-system using the parametric method

Truck sub-systems	Best distribution fit	Distribution parameters	Sub-system reliability (after 100 h)
Engine	Log-normal	Log-Mean = 4.38 Lod-Std = 0.94	0.41
Transmission	Exponential	Mean time = 251.36	0.67
Hydraulics	Exponential	Mean time = 309.11	0.72
Body & Chassis	Log-normal	Log-Mean = 4.40 Lod-Std = 0.957	0.42
Gearbox	Exponential	Mean time = 461.14	0.81

According to Table 1, the hazard function was formulated as $h(t|Z)$. In this case, the Weibull distribution function was chosen as the most appropriate function for modeling the baseline hazard function. Then, the Weibull distribution parameters and the model's variables were computed using Eqs. (6) and (7). Afterward, the hazard function was calculated as follows:

$$\begin{aligned} \ln H(t|X) = & -0.98 + 1.29 \times \ln t + 0.66 \times Engine + 0.18 \times Transmisson + 0.65 \times Hydraulics + 0.84 \\ & \times Body\&Chassis + 1.17 \times Gearbox - 1.19 \times Severity - 0.0058 \times Temperature \end{aligned} \tag{10}$$

where $\ln H(t|X)$ is the log cumulative hazard function, the *Engine*, *Transmission*, *Hydraulics*, *Body & Chassis*, *Gearbox*, and *Severity* are binary variables, and *Temperature* is a continuous variable.

Therefore, the reliability function was obtained to estimate the reliability values for the dump truck system. Table 7 gives the reliability results based on the semi-parametric method. This table reports the reliability function and the estimated uncertainty (95% confidence interval) to provide a proper estimate.

Discussion

The truck system has been evaluated using three major system reliability evaluation groups, including non-parametric, parametric, and semi-parametric methods. Figure 5 demonstrates the reliability curves derived from the semi-parametric (parametric PHM), parametric (RP or PLP), and non-parametric (Kaplan-Meier) methods.

As shown in Fig. 5, in the initial 30 operation hours, the non-parametric method estimates the reliability values higher than the other methods (i.e., parametric and semi-parametric methods). The parametric reliability curve coincides with the semi-parametric reliability curve in this interval. The reliability curves indicate different values during the 50–100 operation hours. However, these deviations are negligible. After this period, all reliability curves are approximately matched. Moreover, the reliability estimation curves illustrated that the dump truck system reliability dropped to 0.4 and 0.19 after 50 and 100 operation hours, respectively. This issue revealed the necessity of applying preventive maintenance plans before these operation hours to improve the system availability and prevent dump truck sudden failures.

Although these major system reliability evaluation groups fundamentally had different statistical procedures in the ranking and evaluation process, they nearly predicted

Table 7 Estimating the reliability function using the semi-parametric method

Time	Reliability function	Uncertainty		Time	Reliability function	Uncertainty	
		Lower bound	Upper bound			Lower bound	Upper bound
19	0.967	0.919	0.987	17	0.543	0.236	0.772
20	0.960	0.908	0.983	35	0.539	0.386	0.670
25	0.946	0.881	0.976	60	0.531	0.226	0.763
35	0.908	0.810	0.956	50	0.527	0.274	0.728
14	0.897	0.763	0.957	50	0.526	0.332	0.688
18	0.885	0.792	0.938	40	0.524	0.381	0.649
15	0.881	0.805	0.928	40	0.523	0.379	0.648
42	0.878	0.759	0.940	36	0.522	0.369	0.655
15	0.870	0.762	0.931	25	0.493	0.301	0.659
16	0.868	0.788	0.920	38	0.492	0.338	0.629
15	0.865	0.766	0.925	43	0.485	0.341	0.614
17	0.864	0.697	0.942	18	0.448	0.192	0.676
35	0.856	0.678	0.940	43	0.420	0.268	0.564
19	0.824	0.729	0.888	73	0.402	0.116	0.680
18	0.819	0.707	0.891	14	0.395	0.116	0.670
28	0.798	0.650	0.888	74	0.387	0.223	0.549
18	0.796	0.680	0.874	41	0.382	0.157	0.606
20	0.774	0.658	0.855	65	0.378	0.191	0.565
14	0.773	0.584	0.884	52	0.372	0.233	0.511
14	0.772	0.626	0.866	54	0.344	0.205	0.488
20	0.766	0.644	0.851	54	0.343	0.203	0.487
20	0.765	0.642	0.851	84	0.342	0.192	0.499
16	0.749	0.532	0.876	55	0.339	0.204	0.479
25	0.745	0.631	0.829	123	0.320	0.159	0.493
34	0.741	0.571	0.852	60	0.300	0.174	0.436
26	0.734	0.501	0.871	135	0.280	0.120	0.466
54	0.724	0.579	0.826	68	0.227	0.116	0.360
18	0.687	0.403	0.856	104	0.204	0.088	0.355
18	0.668	0.497	0.793	72	0.184	0.082	0.318
30	0.668	0.539	0.769	225	0.179	0.049	0.376
41	0.661	0.471	0.797	56	0.161	0.015	0.455
30	0.658	0.519	0.765	170	0.141	0.011	0.426
52	0.656	0.426	0.813	166	0.129	0.033	0.291
66	0.655	0.495	0.775	220	0.127	0.019	0.342
18	0.654	0.475	0.784	30	0.116	0.002	0.468
35	0.645	0.370	0.825	150	0.115	0.026	0.276
30	0.607	0.458	0.726	155	0.103	0.022	0.258
34	0.604	0.463	0.719	92	0.088	0.029	0.190
32	0.582	0.432	0.705	84	0.065	0.014	0.174
55	0.577	0.420	0.705	129	0.049	0.006	0.174
33	0.575	0.422	0.701	210	0.049	0.004	0.192
56	0.569	0.265	0.787	140	0.031	0.001	0.172
34	0.556	0.403	0.684	108	0.026	0.003	0.096
80	0.554	0.382	0.695	200	0.010	0.000	0.096
72	0.553	0.310	0.741	80	0.008	0.000	0.077
34	0.549	0.397	0.677	174	0.002	0.000	0.020

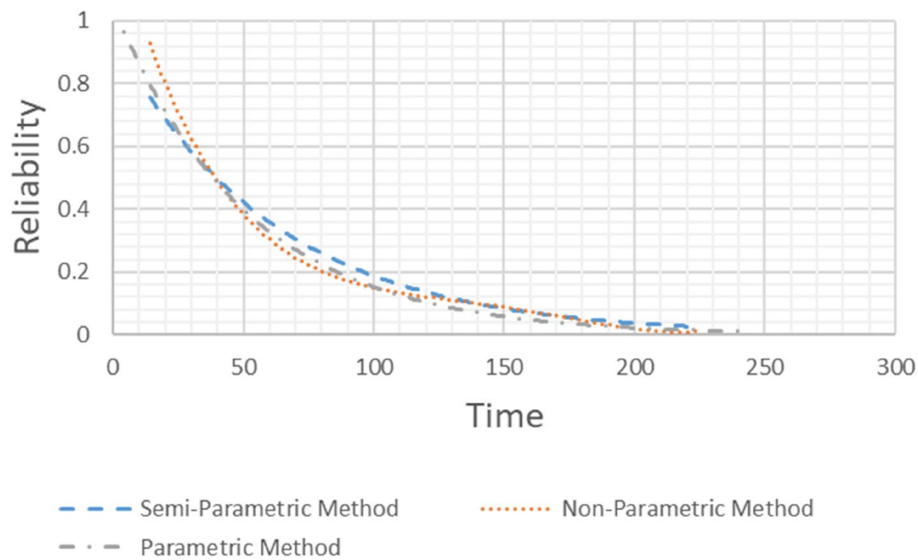

Fig. 5 A comparison between the reliability curves in the non-parametric, parametric, and semi-parametric methods

similar results. However, it is essential to compare the efficiency and performance of these major system reliability evaluation groups to provide better insights into their functionality. For this purpose, multiple criteria were chosen to analyze and compare their performance. Table 8 compares these major system reliability evaluation groups based on several criteria.

According to Table 8, five performance criteria were considered to compare the non-parametric, parametric, and semi-parametric reliability methods, including Method Scope and Completeness, Data Availability and Abundance, Variable Categorization, Uncertainty Quantification and Analysis, and Extrapolation Capability and Predictive Power.

The method scope and completeness criterion demonstrated that the semi-parametric method efficiently estimated the influence of operational and environmental variables together with reliability and failure rate analyses, all in a one-step approach. But the parametric (or non-parametric) methods required a multi-step approach, decomposing the system into several sub-systems to evaluate their individual failures separately.

Table 8 A comparison between the performance of the major reliability evaluation groups

Criteria	Non-parametric method	Parametric method	Semi-parametric method
Method Scope and Completeness	Implementing a multi-step approach for the desired outcomes	Implementing a multi-step approach for the desired outcomes	Implementing a one-step approach for the desired outcomes
Data Availability and Abundance	Employing a partial dataset for each step	Employing a partial dataset for each step	Employing full dataset simultaneously
Variable Categorization	Failure-related variables	Failure-related variables	Failure-related and non-failure-related variables
Uncertainty Quantification	0.28	0.11	0.15
Extrapolation Capability and Predictive Power	Null	Extrapolation beyond the data range	Extrapolation beyond the data range

Data availability and abundance criterion confirmed the advantage of the semi-parametric method over the other methods. Indeed, the semi-parametric method lies in a one-step approach, allowing the utilization of the full dataset for the analysis process. However, the parametric (or non-parametric) method requires the decomposition of the system into multiple sub-systems, each analyzed separately. Consequently, data will be shared between sub-systems, potentially leading to data insufficiency for certain sub-systems.

Variable categorization was another criterion for choosing the best method. In this study, two different variables were considered: failure-related variables (e.g., transmission failure) and non-failure-related variables (e.g., rain and temperature). The parametric (or non-parametric) method could not examine and quantify the effect of non-failure-related variables, whereas the semi-parametric method could efficiently assess these variables and their effects.

Uncertainty quantification was also another criterion for comparing these three major reliability evaluation groups. The confidence interval for the non-parametric method was wider than those of the semi-parametric and parametric methods, with values of 0.28, 0.15, and 0.11, respectively. Therefore, the parametric and semi-parametric methods demonstrated better performance than the non-parametric method from the uncertainty perspective.

The fifth criterion was extrapolation capability and predictive power. Both the semi-parametric and parametric methods could simulate and predict reliability estimations beyond the data range. While the non-parametric method does not have the ability to extrapolate beyond the available data range.

According to these findings, it is concluded that the semi-parametric method provided superior performance compared to the other methods. Thus, this system reliability evaluation group can be used as the most robust and effective method for evaluating the reliability of complex systems that operate in harsh environments.

Conclusions

This study compared three major system reliability evaluation groups to identify the best method for evaluating the mining truck performance. For this purpose, the Kaplan-Meier, RP (or PLP), and parametric PHM were chosen as the most significant system reliability evaluation models to formulate the non-parametric, parametric, and semi-parametric methods, respectively. Also, an actual mine haulage operation dataset was collected to estimate the dump truck reliability. Then, the system reliability was estimated using all three major system reliability evaluation groups at different times. The reliability analysis curves illustrated that the dump truck reliability dropped to 0.4 and 0.19 after 50 and 100 operation hours, respectively. The findings revealed that although these major system reliability evaluation groups had different statistical procedures, the reliability values were almost similar. However, the semi-parametric method outperformed the other methods due to the less computational process and estimating more details. Therefore, it is recommended to consider this method for evaluating the reliability of complex systems like mining dump trucks, which operate in harsh and heterogeneous conditions.

Abbreviations

Z	A vector containing covariates
β^T	A vector of regression coefficients
$h_0(t)$	Baseline hazard function
$H_0(t)$	Cumulative baseline hazard function
$H(t)$	Cumulative intensity function at time *t*
$H\prime(t_i\|Z)$	Derivative function of the cumulative observed hazard function
d_i	Event indicator
$g(\delta_i)$	Gradient vector
HR	Hazard ratio
$H(\delta_i)$	Hessian matrix
IID	Identical and independent distribution
$h(t)$	Intensity function
LHD	Load haul dump
$\ln(L_i)$	Log-likelihood function for the i^{th} failure event
μ	Mean parameter of the log-normal distribution
NHPP	Non-homogeneous Poisson process
$h(t\|Z)$	Observed hazard function
$R(t\|Z)$	Observed reliability function
PLP	Power law process
PHM	Proportional hazard model
$R(t)$	Reliability function obtained from the log-normal distribution
RAM	Reliability, availability, and maintainability
RP	Renewal process
δ_{i+1}	Root value of the $(i+1)^{th}$ Iteration
σ	Standard deviation of the log-normal distribution
$R(t_j)$	System reliability at time t_j
d_j	The number of failures at time t_j
n_j	The number of units at the failure risk just before time t_j ($j=1, \ldots, m$)
δ_i	The Root value of the i^{th} iteration
TBF	Time between failures
TTF	Time to failure
m	Total number of data points
λ	Weibull model parameter
β	Weibull parameter

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Authors' contributions
A.M. participated in all phases of the study, including modeling, formulation analyzing, and interpreting the results. J.S. developed the research methodology and validated the models and outcomes. All authors have read and approved the manuscript.

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Availability of data and materials
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Declarations

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