Shahrood University of Technology
Iranian Society of Mining Engineering (IRSME)

Journal of Mining and Environment (JME)

journal homepage: www.jme.shahroodut.ac.ir

THOMSON REUTERS

Vol. 10, No. 4, 2019, 1045-1059.
DOI: 10.22044/jme.2019.8646.1745

Analysis of reliability and maintainability for multiple repairable units (Case study: Sungun copper mine)

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Received 6 July 2019; received in revised form 27 August 2019; accepted 3 September 2019

Keywords

Reliability

Maintainability

Multiple Repairable Units

Sungun Copper Mine

Abstract

The appropriate operating of mining machines is affected by both the executive and environmental factors. Considering the effects and the related risks lead to a better understanding of the failures of such machines. This leads to a proper prediction of the reliability parameters of such machines. In this research work, the reliability and maintainability analysis of the loading and haulage machines in the Sungun Copper Mine, considering the repair condition as multiple repairable units, was performed. For this purpose, the data necessary for the loading and haulage equipment including 2 loaders and 8 dump trucks for a 15-month period was collected and categorized in 10 operational units after the system and sub-systems of the department were determined. Initially, the time between failures (TBFs) and time to repair (TTR) for each unit was calculated. Then 20 sub-systems were developed. Primarily, the Stata software was utilized to carry out the heterogeneity test for all the sub-systems. In consequence, most of the sub-systems were regarded as the heterogeneous ones, except for 7 of them including the dump truck units 1, 2, 3, 4, 5, 7, and 8 in TBFs. Hence, "PHM" that is a covariate-based model displayed the heterogeneous group. Its reliability function was also estimated. For the next step, the trend tests were done on the non-heterogeneous sub-systems by means of the Minitab software. The homogeneous sub-systems with failure trend were modeled by “NHPP”. Afterwards, the non-trended sub-systems formed the data group. Later, the correlation tests were modeled by “HPP”. Finally, the reliability and maintainability functions were calculated with the 95% confidence level.

1. Introduction

In the mining industry, it is essential to consider the operational capacity in order to meet the demand, achieve annually planned production, and follow the contracts. The operational capacity of the fleet is directly associated with the quality of the machinery and its operation. Hereafter, it is indispensable to identify the behavior of the existing equipment. The review of the performed work suggests that some of the system behavioral indicators such as reliability have been considered, and classical statistical methods have been used to analyze these indicators [1]. From the mid-1960s to the late 1980s, reliability has been introduced in the field of mining engineering by the researchers such as Levkovich and Chalenko, Al’tshuler, Ivko *et al.*, Freidina *et al.*, Bondar’ and Mernov, and Garakavi *et al.* [5-10]. Their articles are mostly incomprehensive and are not very robust in terms of content due to the weakness of the database, lack of development of statistical modeling software, and knowledge of system. The system of the maintenance perspective is divided into the two categories of repairable and non-repairable. Repairable systems are referred to as the ones that can be restored to fully satisfy the performance by a method rather than the replacement of the entire system [2]. The reliability analysis of the repairable units can be

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classified into the parametric and non-parametric methods. Among the parametric methods, the stochastic point processes, homogeneous Poisson process (HPP), renewal process (RP), trend renewal process (TRP), branching Poisson process (BPP), and non-homogeneous Poisson process (NHPP) are used for data analysis [3]. The reliability analysis relies on the time data. Thus the first step is the collection of this data. The three challenges of the reliability data collection are data censoring, data aggregation (pool or combine), and data with small failure events [3]. In some cases, the analyst is often faced with several repairable similar items that may have different reliability performances. This is because these units may be installed in different locations and may be functioned under different operating conditions, and maintained by different maintenance policies. In other words, differences in the operating environment (due to humidity, temperature, etc.) may change the pattern of failures from item to item [4]. These variations in failure patterns may lead to differences in the failure time distributions or processes of units. Hence, the population of multiple repairable units can consist of units with different failure patterns as well as homogeneity and heterogeneity levels [3]. Data analysis may hinder the reliability prediction by ignoring the above factors. The data has been categorized into homogenous groups to analyze the multiple repairable units in this study. They have also been and classified based on their failure trends. The various trend tests proposed in the literature can be used to make groups of units based on improving and deteriorating the items or trend-free units [3]. In fact, the trend test analysis is one of the main benchmarking tools in the reliability analysis. Ascher and Feingold have discussed the importance of trend tests to verify the improvement/deterioration property before using the parametric models [2]. Kvaløy and Lindqvist have proposed two approaches for the trend analysis of multiple repairable units. Initially, they pooled data chronologically and derived the total time on test (TTT-statistic) [11]. The same work was later developed by Hall and Daneshmend, Vagenas *et al.* and Samanta *et al.* until Lindqvist presented a framework where the observed events were modeled as marked point processes by labeling the types of events [12-15]; throughout these papers, the emphasis is more on modeling than on the statistical inference. Years later, Barabadi *et al.* used a stratified proportional hazard ratio model to analyze the reliability of the bauxite mine. In this study, the covariate influence on the reliability calculation was applied [16]. Garmabaki *et al.* presented a decision framework to identify an appropriate reliability model for massive multiple repairable units. When dealing with massive and non-homogeneous multiple repairable units, the application of the proposed framework can facilitate the selection of an appropriate reliability model. This is a system-based framework, and is presented as multi-component sub-systems [3]. In the early 1990s, Kumar and Huang scrutinized the introduction of maintainability in the mining field. In the following years, Vagenas, Samanta *et al.*, Barabady and Kumar, and Hoseinie analyzed the maintainability using the classical method (TTR data) [13, 14, 17-22]. In the latest case study of classical maintainability studies, Wijaya *et al.* also examined the stoppage time of an underground mining machine [22]. For the first time, Barabadi *et al.* analyzed the maintainability considering the environmental conditions [16].

The previous research work has only addressed this issue in terms of reliability. This paper briefly discusses the challenges related to using the available methods for repairable units; it suggests a procedure to detect an appropriate reliability and maintainability model for multiple repairable units based on a review of available trend tests. In consequence, it introduces the associated key analytical steps. It provides a procedure for grouping homogeneous units and classifies them based on their statistical trend tests in the presence of observed and unobserved heterogeneity. The proposed framework was applied in a real case involving 10 units in each time dataset (10 units of TBFs and 10 units of TTRs) of the Sungun Copper Mine haulage system. Nevertheless, various methods are mainly applicable in the field of reliability. However, up to the present time, a user-friendly framework has not been presented to analyze the reliability and maintainability of repairable systems. The main purpose of this research work is to provide an algorithm, suggesting a suitable model for the analysis of the system's repairable sub-systems. In this research work, the Sungun Copper Mine is regarded as a system to evaluate the performance of loading and haulage sub-systems via calculating the reliability and maintainability of the sub-systems. Eventually, an appropriate reliability of the engineering policy is proposed. The failure data for the sub-systems is investigated after classification through risk factor models. Furthermore, all sub-systems are reviewed and categorized into a timed data group and subjected to multiple repairable sub-systems.

The main structure of this paper is outlined in four general steps. The first step refers to the analytical concepts used in the case study calculations including the common analytical trend tests for single and multiple repairable units, Bartlett's test, and heterogeneity test. The second step describes the proposed decision framework for reliability and maintainability model selection. The third step presents numerical examples using data from the Sungun Copper Mine transportation system holding two loaders and eight dump trucks as sub-systems. Finally, the fourth step provides the conclusion.

2. Analytical Concepts

After the data is collected, sorted, and categorized, other statistical analysis should be analyzed to calculate the reliability. In fact, the trend tests determine the distribution pattern or not distributing data in the time intervals. There are two kinds of systems illustrating the existence or absence of the failure trend. The trend tests can be practiced for both the single repairable unit and the multiple repairable units.

2.1. Trend tests for single repairable unit

The trend analysis is a common statistical method used to investigate the operation changes in a repairable unit over time. A trend in the pattern of failures can be either monotonic or non-monotonic. This work considers the repairable units observed from time t = 0 with successive failure times denoted by $t_1, t_2, \ldots$. An equivalent representation of the failure process can be in terms of the counting process $\{N(t), t \geq 0\}$, where N(t) equals the number of failures in $(0, t)$. It assumes that the simultaneous failures are not possible. It also supposes that the repair times are negligible in comparison with the times between the failures. In the present work, we consider the processes to be either single or several independent similar processes observed at (possibly different) time intervals $(0, T)$. Notably, the main possible processes discussed in this work are HPP, RP, TRP, NHPP, HNHPP, and BPP [23].

In case of a homogenous trend, the system has a convex shape. The trends are non-homogenous when they are changed based on time or they repeat themselves in cycles. One common non-homogenous trend is the bath-tub shape trend, in which the failure rate is decreased at the beginning of the equipment life, tends to be constant for a period, then increases at the end [23]. Some trend tests widely applied in reliability studies include the Laplace trend test, military handbook test, Mann test, and Anderson–Darling test; these are described in [24, 25].

Laplace trend test: In the Laplace process, the mean time of occurrence of the failures is compared with the mid-points of the observed time intervals. There is a significant deviation between the mean time of the occurrence of failures and the mid-points of the relevant intervals. Hence, it means that the TBF data will be available. This test is practiced to determine the existence of a process for repairable systems so that the homogeneous Poisson process is applied and the direction of the failure process is specified (improvement or degradation). The Laplace trend test has a null hypothesis of "No trend" ($\mathbf{H0_1}$) versus the alternative hypothesis of "monotonic trend ". For more information, see [11, 24, 26].

Military handbook test: As in the Laplace test, the null hypothesis ($\mathbf{H0_2}$) for the military handbook test is "no trend" versus the alternative "monotonic trend". Note that the military handbook test is optimal for the power law intensity function. For more information, see [4, 24].

The Mann-Kendall test: The null hypothesis ($\mathbf{H0_3}$) for this non-parametric test is an RP versus a monotonic trend. This trend test is calculated by counting the reverse arrangements among the times between failures. The Mann test statistic is approximately distributed as a standard normal distribution. The null hypothesis ($H0_3$) is rejected on the significant level of α%. For more information, see [27].

Anderson-Darling test: The Anderson–Darling (AD) test rejects the null hypothesis ($\boldsymbol{H0_4}$ is "no trend") in the presence of both the monotonic and non-monotonic trends when the value for AD is large. For more information, see [3]. The null hypothesis ($H0_4$) is rejected at the level of 5% if $|AD| > 2.492$ [11, 24].

Besides the AD test, other tests such as the generalized AD, V1, V2, V3, and V4 tests [24] can be used to identify the non-monotonic trends. The AD test and the V1, V2, and V3 tests have HPP, while the generalized AD test and V4 have RP as the null hypothesis of the test statistics. The interested readers are referred to [24] and [28]. Moreover, in some cases, combinations of the tests are required to identify the existence of a trend. Furthermore, the combinations of the tests are vital to detect the existence of a trend in some

cases. For example, if the military handbook and the Laplace tests reject the null hypothesis, the data does not follow an HPP. However, the data can still be trend-free [15].
The significant level is one of the important issues in testing the null hypothesis. The selection of the significant level can be affected by the sample size and expected losses. The hypothesis testing without considering the potential losses is not ethically and economically defensible [29]. Leamer has demonstrated how an optimal level can be chosen by minimizing the expected losses [30]. In addition, he has indicated that the sample size and expected losses are the two main factors for achieving an optimal significant level. Neither the quantity nor the quality of the data influences the selection of the significant level. Henceforth, this should be done before data collection [31-33].

2.2. Trend test for multiple repairable units (combined and pooled tests)

In some cases, it may be impossible to determine changes in the pattern of failures when each system is separately analyzed. However, it is possible to distinguish such changes when a simultaneous analysis is done [2], [4]. If simultaneous analysis is justified, this will be much more powerful than distinctly analyzing each system. This section considers two types of trend tests: the combined and the pooled data test (the TTT-based test). For more information, see [3].

Corrected TTT-based trend test for multiple repairable units (pooled type): Kvaløy and Lindqvist [11] have proposed using the TTT-based Laplace trend test and the TTT-based military handbook test for combined data from multiple units. They presumed that each system was governed by the same intensity function shed by the null hypothesis of "no trend", denoted here by $H0_5$ and $H0_6$ for the two tests, correspondingly.

Laplace trend test for multiple repairable units (combined type): The mathematical formulation of the statistical test for k units is an extension of the statistical test for one unit by adding the Brownian bridge type processes for various systems and scaling through the square root of the number of processes. For more information, see [34, 35].

2.3. Bartlett's test

The Bartlett's test is practiced to examine the null hypothesis, $(\boldsymbol{H0_8})$ that all k population variances are equal against the alternative and at least two are different. Generally, when the failure/repair data is from more than one system, the Bartlett's test can be used, as below:

- A test for equal shapes–if a known shape is not provided;
- A test for the equality of the scale parameter–if a known shape is provided;
- A test for equal MTBFs–if the shape is set at 1.

For more information, see [36].

2.4. Heterogeneity test for multiple repairable units

In case several units are simultaneously deliberated, there is a possibility of heterogeneities between the units even if the repairable units appear to be identical. Considering this effect in the model, the structure may affect the failure intensities. The differences in the failure intensity are called heterogeneities and can be either observed or unobserved. Lindqvist, Elvebakk [37], Kvaløy [34], Kvist, and Andersen [38] have pre-meditated the heterogeneity effect on NHPP and TRP. Lawless [39], and Cook and Lawless [40] have used the power law intensity function and calculated the probability of the function. A probability ratio test is applied to figure out the important hypothesis $H0_9$: η = 0 (no heterogeneities), given by:

$$\boldsymbol{R = 2\left(ln\,L\left(\hat{\lambda}.\hat{\beta}.\hat{\eta}\right) - ln\,L\left(\widehat{\lambda_0}.\widehat{\beta_0}.0\right)\right)} \quad (1)$$

Here, $\hat{\eta}$ may be interpreted as the degree of heterogeneity, and $\hat{\lambda}\ \widehat{and}\ \beta$ are the estimated parameters of the power law intensity function. In Eq. (1), the parameters $\hat{\lambda}, \hat{\beta}$, and $\hat{\eta}$ can be estimated by maximizing the full likelihood function and the $\widehat{\lambda_0}, \widehat{\beta_0}, 0$ likelihood function under the null hypothesis. Since η = 0 is not in the interior of the parameter space ($\eta < 0$ not allowed), R does not have the usual asymptotic X_1^2 distribution. In fact, asymptotically, $\hat{\eta}$ has the X_1^2 distribution with a probability mass of 0.5 at R = 0. This means that on a 5% significance level, $H0_9$ is rejected if $R \geq 2.706$, the 10% quantile in the distribution; for more details, see [39].

3. Proposed decision framework

The proposed frameworks before could not distinguish the pooled and combined trend test when dealing with multiple repairable units. However, the proposed user-friendly framework in this work is more accurate than the previous examples and describes all the steps of calculating reliability and maintainability from data collection and trend tests to the best modeling approach. Figure 1 features out the decision flow of the model selection. The method begins with collecting and sorting the data of each unit based on the occurrence date of the failure. Then the best method for modeling the reliability and maintainability of the sub-systems is fitted based on the homogeneity of the units and their failure trend behavior. These analyses have been provided in the following steps.

Step 1- Collect and sort data of each sub-system based on occurrence date of failure; the failure data of each sub-system is collected based on the prioritization on the occurrence of each failure. Afterward, the required data is extracted in the form of TBFs and TTRs to analyze the reliability and maintainability of each sub-system using the data. In this algorithm, the process progress is described for reliability data similar to the same steps for maintainability (Node number 1, Figure 1).

Step 2- Separation of process based on number of sub-system data; at this stage, the sub-systems with less than 5 data are modeled using the Bayesian approach or the composite models. The sub-systems with a greater number of data are referred to in the next step (Node number 2, Figure 1).

Step 3- Analyze data and evaluate heterogeneity of TBFs and TTRs data sub-systems; for this purpose, the probability of a null hypothesis for the "heterogeneity" test is considered $H0$. If the value for P is less than 5% for the null hypothesis, the data group is measured as homogeneous. If the heterogeneous sub-systems were not divided into homogeneous sub-systems, the reliability was modeled using the methods based on covariates such as the proportional hazard model (PHM). However, if the sub-systems were homogeneous or the heterogeneous sub-systems were separable into the homogeneous sub-systems, the next step provides the answer (Node 4, Figure 1).

Step 4- Categorize failure sub-systems based on their trend behavior; this step provides a method to categorize the sub-systems based on their failure trend using the specific statistical tests. The sub-systems are classified into concave, convex or linear forms, which are characterized by the graphical or statistical tests. It is noteworthy how the type of process in which shape of the risk function is allocated. The curvature in the graphic test indicates the trend in the failure dataset. Furthermore, linearity specifies that the dataset has no trend. In this algorithm, the three-step procedure consisting of the Laplace's test, military handbook test, Mann-Kendall, and Anderson-Darling have been reflected for classification. These three steps are as follow (Node 8, Figure 1):

- ✓ At first, the Laplace trend test and the military handbook test are applied for each one of the homogeneous sub-systems. If both $H0_1$ and $H0_2$ (which indicate the null hypothesis for the Laplace test and military handbook for non-trended) are not rejected, the dataset is considered to be non-trended (Node number 9, Figure 1).
- ✓ If $H0_1$ or $H0_2$ is not rejected, the Anderson's Darling test is applied. In this case, the null hypothesis is not rejected for this test. Additionally, the sub-system is considered to be non-trended (Nodes 10 and 12, Figure 1).
- ✓ If $H0_1$ and $H0_2$ are rejected, the Mann-kendall test for the sub-systems will be employed. For this test, the non-trended null hypothesis is $H0_3$. If $H0_3$ is rejected for the tested sub-systems, the sub-systems are deliberated to be trended. If not, they are non-trended (Node number 11, Figure 1).

Step 5- Formation of trended groups; For the homogeneous sub-systems that are the result of a trend test, known as trended, if the datasets are of the same type (all from the same machine type), the trended data group is created (Node number 13, Figure 1) and modeled through the non-homogeneous Poisson process (NHPP) or the trend-renewal processes (TRP) (Node number 14, Figure 1).

Step 6- Forming non-trended groups for multiple repairable sub-systems; For the homogeneous sub-systems that are known as non-trended after the process of trend tests, if they are of the same type (all of the same machine type), they form the non-trended data groups (Node number 15, Figure 1). At this stage, the failure data is divided into the two groups of TTT-based and combined-type based on intensities to continue the analysis. To determine the intensity of the data, the Bartlett's modified likelihood test is used (Node number 16, Figure 1). For this purpose, $H0_4$, the null hypothesis, is "not uniformity of intensity" of the Bartlett test. For the confidence level of 95%, the P-value is calculated for it. Thus it is confirmed that the Bartlett test is accepted for values less than 5%. If the intensities are the same, the group is combined (Node number 17, Figure 1). If not, the group is TTT-based (Node number 18, Figure 1).

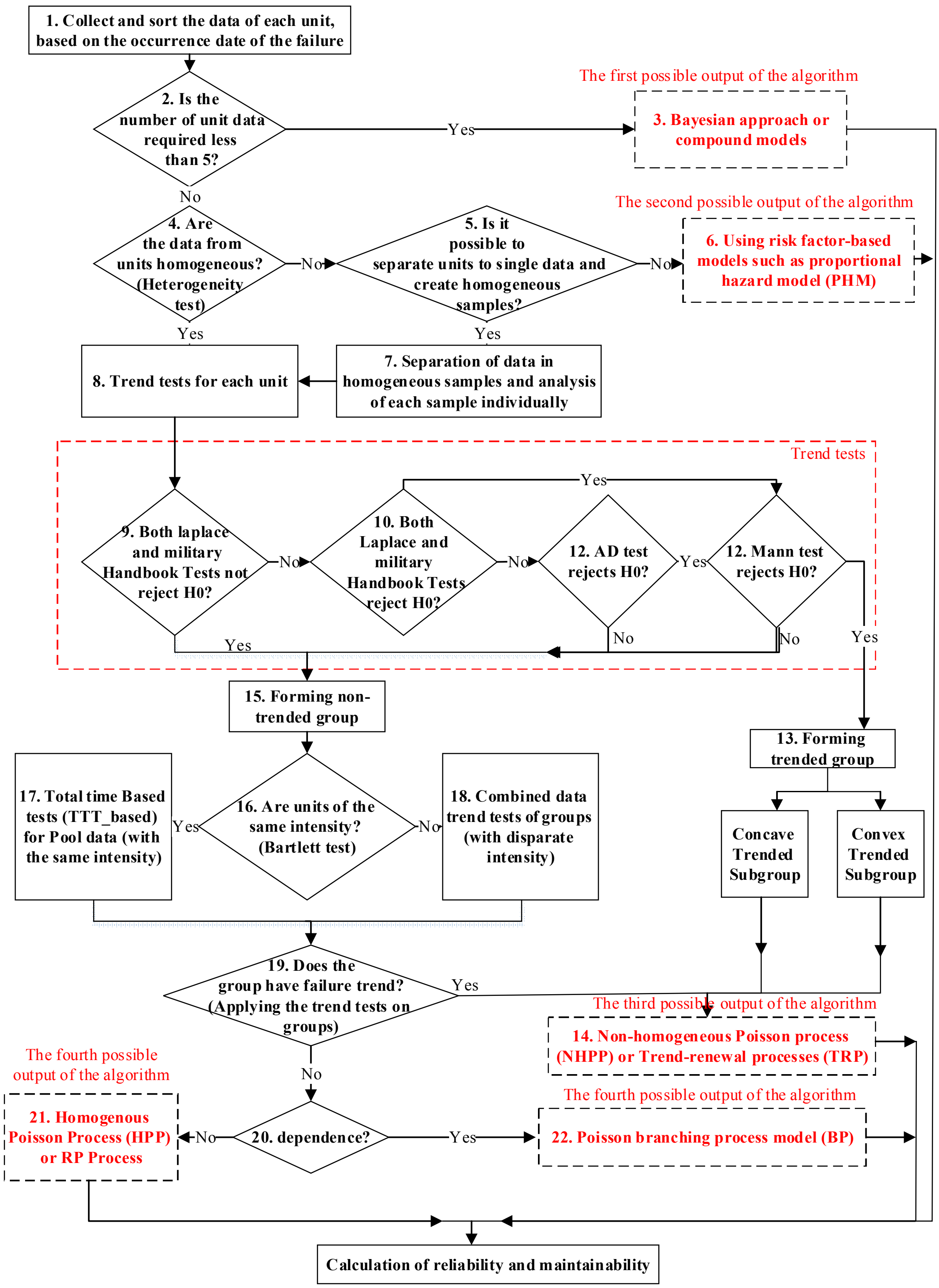


Figure 1. Main framework of reliability and maintainability of multi-component units.

Step 7- Categorize the new group of dataset based on the trend behavior; The trend tests in step 3 will be practiced in new groups. If the group is trended, the modeling method of this group will be similar to Step 4 (Node No. 14, Figure 1) through the NHPP or TRP process; otherwise, the next step provides the answer.

Step 8- Dependency study of group; At this stage, the dependency of the failure data in the group will be examined (Node number 20, Figure 1). For this purpose, the data chart is plotted against its i-th data. In case of a dependence existence between the data, the modeling will be based on the BP model (Node number 22, Figure

1) or else, the model will be the homogenous Poisson process (HPP) or the RP process.

4. Case study

In this work, the case studies are the transportation machines including two Komatsu WA470-3 loaders and eight Komatsu HD785-5 dump trucks. These machines are from the Sungun Copper Mine located in the East Azerbaijan province in Iran.

The type of data required to calculate the reliability and maintainability is the time between the failure (TBF) and the time to repair (TTR). On the other hand, the covariates associated with the sub-systems should be determined to define the impact of environmental conditions on reliability and maintainability. In general, the time data (TBF and TTR) and qualitative data (covariates) are counted as the two types that should be quantified to be applicable for statistical analysis. The data is directly collected from various sources such as the documented sources (daily reports of the maintenance and mechanical and other groups), archival documents (previous reports, machinery catalogs), meetings, and interviews. For this purpose, the mechanical repair sub-system shifts are extracted and respectively sorted by each failure time in the openings for about 15 months and from July 2016 to October of 2017 after studying a case study and reviewing the conditions of the five main sources of monitoring information, weather stations, meetings and interviews, direct observations, and data bank of contractors.

Time data*:* As aforementioned, the data is divided into the two categories of time data: the time between failures (TBFs) and the time to repair (TTRs). The first one is used for reliability analysis and the second one is used for the maintainability analysis. At each stage, time data (TBF or TTR) is extracted into one form for all sub-systems (loading and haulage). Ultimately, the output data will have a totally similar structure.

Risk factors (covariates): Basically, the covariates of failure dependent on the sub-system are defined in accordance with the environmental conditions governing it. Consequently, the covariates for repairs are expressed in the same way because of the shared aims of the repair shop and the conditions governing it. The covariates mentioned in this paper are "shifts", "temperature", "weather conditions", "precipitation", "road condition", and "rock kind" in the reliability engineering analysis of the sub-systems. Also the failure status was shown by "1" for complete failure and "0" for censored failures in the failure status column.

Number of data in studied sub-system: According to the algorithm shown in Figure 1, if the number of sub-system data is less than 5, they are considered as the low-number sub-systems. Thus they will be subjected to model by the Bayesian approach or the composite models. In this case study, all the intended sub-systems include more than 5 data in view of the time length of the analyzed interval and the aging system. Accordingly, a heterogeneity test will be applied to all units (next step).

Heterogeneity test: According to the previous discussions, for determining heterogeneity of the sub-systems, a null hypothesis is considered in the confidence level of 95% for heterogeneity, as pointed out, a null hypothesis is considered in the confidence level of 95% for heterogeneity to determine the heterogeneity of the sub-systems, and this assumption is rejected for a P-value less than 5%. Remarking Equation (1), the null hypothesis of "heterogeneity" $\boldsymbol{H0_9}$ is rejected and the sub-system of data is considered homogeneous for values of the probability of θ less than 5%. The result of heterogeneity analysis for sub-systems is presented in Table 2 (Lo stands for loader and Dt stands for dump truck). About asterisk (*) in the table used for showing that in order to model heterogeneous sub-systems, sub-systems of the same type, and gender (same type of machine) should be from the heterogeneous data groups and use "covariate" based models such as proportional hazard model (PHM).

Trend tests: According to the main framework shown in Figure 1 and Table 3, the sub-systems are classified into two main groups of the trended and non-trended groups by analyzing the trend tests. These groups are individually analyzed. The Laplace and military tests are performed on the homogeneous TBF and TTR failures. Thus the sub-systems under study will be 2 loaders and 1 dump truck (number 6) from the TBF dataset and all datasets from TTRs. Table 3 illustrate the results of the trend tests.

- According to the main algorithm (Figure 1), sub-systems holding a convex or concave failure process form a trended group, on the condition that they are identical, they can be modeled through NHPP or TPR.
- Non-trended sub-systems consist of groups: loader 1 in TBFs, loader 1 and dump truck

group 2, 3, 4, 5, and 8 in TTRs. Hence, the sub-systems of the loader join one separate group and directly move to the determination of dependency because they do not hold the same data in their own right. Nevertheless, the group consisting of 2, 3, 4, 5, and 8 dump trucks develops a group of non-trended data, which will be tested in the next step for their intensities through the Bartlett test.

Table 1. Studied covariates.

Covariates	Quantity	Covariates	Quantity
Shifts (Z_1)	Morning (A) Noon (B) Night (C)	**Road condition (Z_4)**	Normal (1) Slippery (2) Slippery and blocked (3)
Weather conditions (Z_2)	Sunny (1) Partly cloudy (2) Cloudy (3) Foggy (4)	**Rock kind (Z_5)**	Ore, oxide, sulfur (1) Monzonite (2) Dump (3) Trachyte (4)
Temperature (Z_3)	Celsius degrees	**Precipitation (Z_6)**	Millimeters

Table 2. The heterogeneity test of sub-systems.

Sub-system	TBFs			TTRs		
	P-value	Heterogeneity status	Modeling method	P-value	Heterogeneity status	Modeling method
Lo1	0	Homogeneous	Trend tests	0	homogeneous	Trend tests
Lo2	0.007	Homogeneous	Trend tests	0	homogeneous	Trend tests
Dt1	1	Heterogeneous	*	0	homogeneous	Trend tests
Dt2	0.222	Heterogeneous	*	0	homogeneous	Trend tests
Dt3	1	Heterogeneous	*	0	homogeneous	Trend tests
Dt4	0.216	Heterogeneous	*	0	homogeneous	Trend tests
Dt5	0.303	Heterogeneous	*	0	homogeneous	Trend tests
Dt6	0.004	Homogeneous	Trend tests	0	homogeneous	Trend tests
Dt7	0.304	Heterogeneous	*	0	homogeneous	Trend tests
Dt8	0.114	Heterogeneous	*	0	homogeneous	Trend tests

Table 3. Trend test analysis of sub-systems.

Data type	Sub-system	$H0_1$	$H0_2$	$H0_3$	Trend result
TBF	Lo1	rejected	rejected	Not rejected	No trend
	Lo2	rejected	rejected	rejected	Trended (Convex)
	Dt6	rejected	rejected	rejected	Trended (Concave)
TTR	Lo1	rejected	rejected	Not rejected	No trend
	Lo2	rejected	rejected	rejected	Trended (Concave)
	Dt1	rejected	rejected	rejected	Trended (Convex)
	Dt2	rejected	rejected	Not rejected	No trend
	Dt3	rejected	rejected	Not rejected	No trend
	Dt4	rejected	rejected	Not rejected	No trend
	Dt5	rejected	rejected	Not rejected	No trend
	Dt6	rejected	rejected	rejected	Trended (convex)
	Dt7	rejected	rejected	rejected	Trended (concave)
	Dt8	rejected	rejected	Not rejected	No trend

Forming groups by their trend behavior: This research work is a modeling of reliability and maintainability of multiple repairable sub-systems. Therefore, the sub-systems of the same data type (data collected from the same type of machine) arrange groups with the same trend behavior. Non-specific sub-systems will also form another group. The data grouping is depicted in Table 4.

- **Heterogeneous group;** this group of sub-systems is known as homogeneous sub-systems during the heterogeneity test. All of the sub-systems identified in this test as heterogeneous are the time data between failures and all data has been taken from one type of machine (dump truck). As a result, these sub-systems draw up a heterogeneous group.
- **Trended group;** this group of time data consists of homogeneous sub-systems holding a failure trend upward (convex) or downward (concave), and are modeled through NHPP or TRP. These groups include "loader 2" and "track

6" in "TBFs" and "TTRs" take in "loader 2" and "tracks 1, 6, and 7".

- **Non-trended group;** this group of data consists of homogeneous sub-systems that have lack of trends. After the formation of non-trended sub-system groups, it is necessary to go through the other steps to figure out how their modeling works such as the Bartlett test and the dependency test.

Bartlett adjustment to the likelihood ratio (intensities): Non-trended sub-system groups include loader 1 in TBFs and loader 1 and track 2, 3, 4, 5, and 8 in TTRs. Meanwhile, the only group of tracks contains more than one sub-system. Therefore, the Bartlett's test is performed only on this group to determine how the data is combined (TTT-based or combined). Henceforward, $H0_8$ is regarded as the null hypothesis of the Bartlett's test (not uniformity of intensity) at the 95% confidence level. Table 5 features out the result of this analysis.

Given that the P value for $H0_8$ at the 95% confidence level is less than 0.05, the group of dump trucks is considered to have the same intensity. For that reason, the group is measured as a composite one, and a total time-based test (TTT) is recommended for it.

Study of groups: Now that the different groups of data have been identified, the methods for analyzing their reliability and maintainability are discussed:

a) Failure trend study of multiple sub-system group: In spite of the fact that the group of trucks consists of non-trended sub-systems, the combined data group may have a trend in total. Therefore, the above-mentioned process tests should be applied to this group. The results of these tests are displayed in Table 6.

Table 4. Forming groups by their trend behavior.

Heterogeneous data		TBFs	Dt 1,2,3,4,5,7,8
Homogeneous data	Trended data	TTRs	Lo 2, Dt 1,6,7
		TBFs	Lo 2, Dt 6
	Non-trended data	TTRs	Lo 1, Dt 2,3,4,5,8
		TBFs	Lo 1

Table 5. Bartlett's test result of group of dump trucks.

Bartlett's test static	P-value
685.41	0

Table 6. Results of failure trend study of multiple sub-system group.

Statics	TTT-based trend tests				
	Military handbook	Laplace	Anderson-Darling	Mann-Kendall	
				Convex	Concave
P-value	0	0	0	0.113	0.886
MTBF (H)			0.838		

According to Table 4, the "no trend" null hypothesis is rejected for both the military handbook and Laplace tests. The Mann-Kendell test determines that the data group rejects the null hypothesis neither in the convex state nor in the concave mode. Therefore, the data group is deliberated to be non-trended. In this way, the dependency test will ascertain the modeling method for this group in the next step.

b) Study of single sub-system group: These groups include "loader 1" in "TBFs" and "loader 1" in "TTRs". These two groups are deficient in multiple sub-systems. Subsequently, both of them are remarked as the non-trended ones, and will be applied to the next test of dependency.

Serial-correlation (dependency) test of groups: To do this, the nth data in-group is compared with its n-1 data. In a graphical dependency test, the data group is called correlated, which is the nth data diagram compared to the n-1'th data of the cumulative diagonal state. Therefore, the autocorrelation test for loader 1 data in TBFs and group loader 1, 2, 3, 4, 5, and 8 in TTR is as shown in Figure 2.

The results of the correlation test for the above groups are featured out in Table 7.

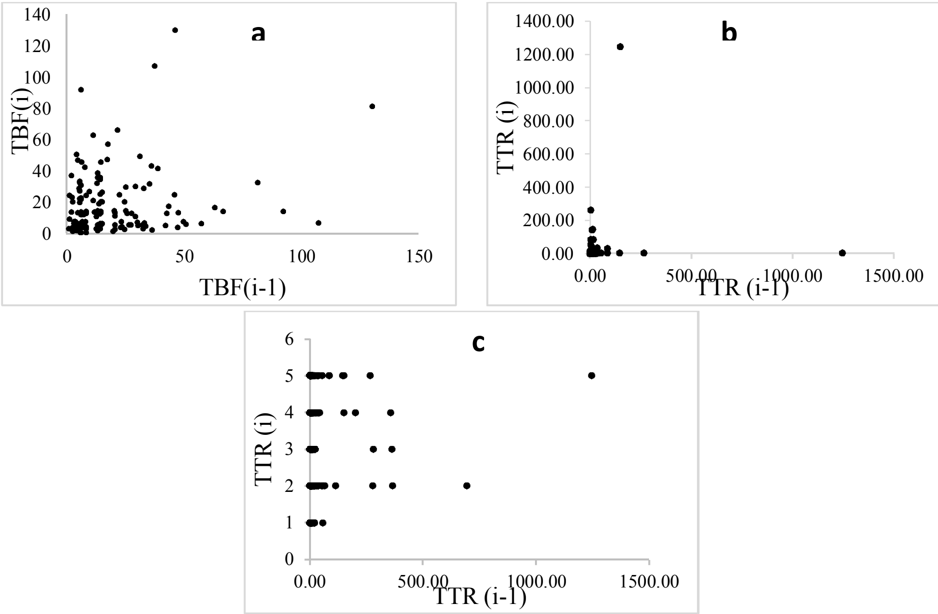


Figure 2. a) Serial-correlation test of group loader 1 (TBF), b) serial-correlation test of group loader 1 (TTR), c) serial-correlation test of group dump trucks 2, 3, 4, 5, 8 (TTR).

Table 7. The results of the correlation test.

Modeling method	Test result	Group	Data type
RP or HP	No dependency	Loader 1	TBF
	No dependency	Loader 1	TTR
	No dependency	Dump truck 2, 3, 4, 5, 8	

5. Performance function fitting

The analysis carried out on the failure data of the Sungun Copper Mine loading and haulage machinery have identified different data modeling methods. Now, the reliability and maintainability of machine failure data will be inspected by identifying specific modeling methods for each sub-system or group. To this end, the TBF data is separately examined for reliability modeling and TTR data for modeling the maintainability. Hence, the types of groups are modeled based on the algorithm for analyzing the case study (Figure 1).

5.1. Reliability

The reliability modeling in this study is done according to the type and categories by means of three groups of methods:

- Proportional hazard model (PHM)
- Hyperbolic Poisson process model (HPP)
- Non-hyperbolic Poisson process model (NHPP)

This type of modeling is based on the TBFs analysis.

1) Proportional hazard model (PHM): According to the algorithm shown in Figure 1, heterogeneous sub-systems are modeled in the PHM model. In this case study, the dump truck sub-systems 1, 2, 3, 4, 5, 7, and 8 were sub-divided into this category, reflecting the given homogeneous of the data form a sub-system group. Regarding PHM, it should be noted that the three-parameter distribution function is used for the fundamental risk function due to the flexibility of the fitness of Weibull function so as to be adjusted with different modes. The reliability analysis steps for the above group are as below:

In order to find the fundamental risk function, it is essential to figure out the most effective covariate associated with the failure behavior of the sub-system. For this purpose, the backward wald is used. In this technique, the exponential (β) value represents the risk ratio. According to Table 8, the covariate with the least impact on the risk ratio (the smallest wald coefficient) at each step is eliminated in order to ultimately remain the effective factors. This operation is repeated until the most important covariate in terms of impact on the risk ratio selected at the final stage (step 3). According to Table 8, the SPSS software analyses, shift, weather conditions, road conditions, and rock type have been identified as the most influential covariates. On the other hand, other outcomes of this software are cumulative risk ratio and time-consuming failures that are used to find the fundamental risk function. For more information, see [41-43].

Table 8. Results of the most influential covariate in PHM analysis.

Steps	Covariates	α	Wald	Exp(α)
Step 3	Shift (Z_1)	-0.843	89.558	0.43
	Weather condition (Z_2)	0.117	10.869	1.124
	Road conditions (Z_4)	0.146	4.987	1.157
	Rock type (Z_5)	-0.434	20.904	0.648

The shape, scale, and position parameters of the sub-system of dump truck 1 were detected. The reliability function of the group of dump trucks 1, 2, 3, 4, 5, 7, and 8 with the effect of covariates is shown in Table 9.

2) Non-hyperbolic Poisson process model (NHPP): Homogeneous trended sub-systems are modeled through the non-hyperbolic Poisson process. In this case study, the sub-system loader 2 and dump truck 6 were modeled by this method. The power law process (PLP) with the parameters of shape and scale employed to model the reliability of these sub-systems along the reliability function are specified in Table 9.

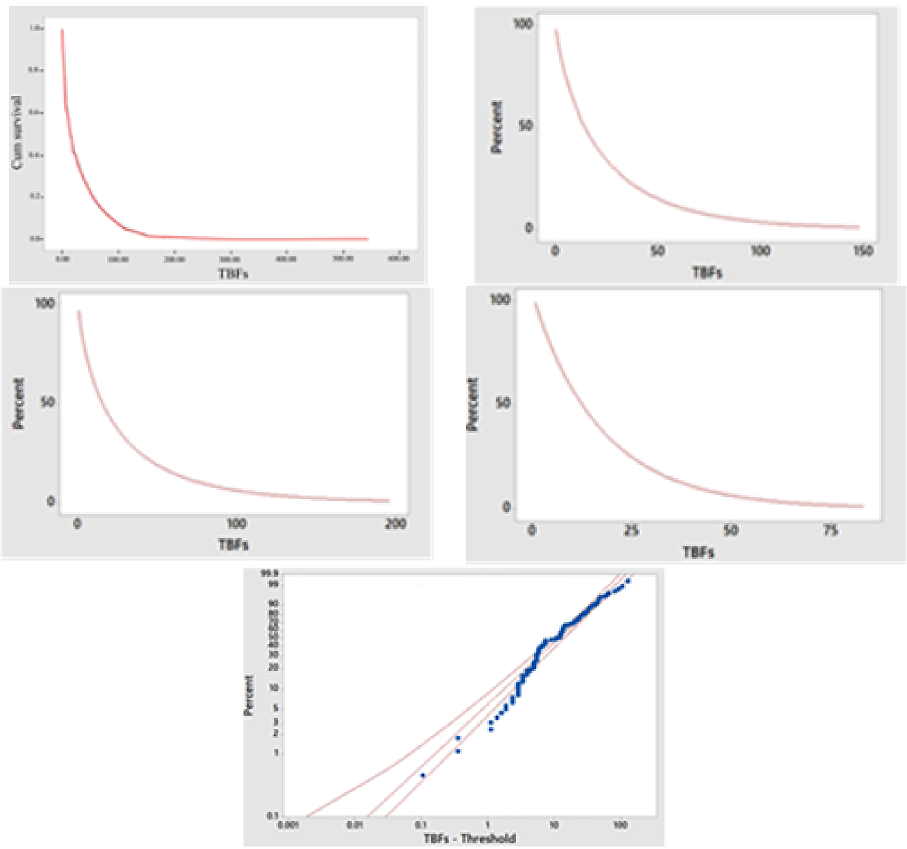
3) Hyperbolic Poisson process model (HPP): The sub-system loader 1, as a non-trended sub-system, is analyzed through the hyperbolic Poisson process. In the HPP process, the Anderson-Darling (A-D) Goodness of Fit (GOF) test is also used to find the fit of the best distribution. In the A-D test, the distribution function with the least amount of statistics is selected as the best distribution function. The 3-parameter Weibull distribution with the parameters of shape, scale, and location employed to model the reliability of this sub-systems along the reliability function are specified in Table 9.

5.2. Maintainability

In view of the type and categories of data, the maintainability is modelled in this study with the contribution of two sets of methods. The function of the maintainability is in accordance with Equation (1):

$$M(t) = \int_0^t m_r(t)dt \tag{1}$$

d e f g



h

Figure 3. d) Functional graph of cumulative reliability in average covariates (PHM), e) function of reliability of loader 2, f) reliability of dump truck 6, g) reliability dump truck 7, h) the probability distribution diagram loader 1.

1) Non-hyperbolic Poisson process model (NHPP): In this case, the sub-system loader 2 and dump trucks 1, 6, and 7 were modeled. Henceforward, this modeling is done for the two groups due to the similarity of the sub-systems of the dump truck (the group loader 2 and the group of dump trucks 1, 6, and 7). The power law process (PLP) with the parameters of position and scale employed to model the maintainability of these sub-systems along the maintainability function are specified in Table 9.

2) Hyperbolic Poisson process model (HPP): The two groups of non-trended data sub-systems comprised of TTRs are made up of the following groups: group of loader 1 and group of dump trucks 2, 3, 4, 5, and 8.

The Anderson-Darling's "GOF" test is utilized to find the best distribution fit for HPP modeling. The distribution function with the least amount of A-D statistics is designated as the distribution function.

The GOF test with the 3-parameter lognormal distribution with the parameters of position and scale is the best option to model the maintainability of these sub-systems along the maintainability function specified in Table 9.

6. Discussion

Finally, as the TBFs datasets were used in the reliability computation, the sub-systems of dump trucks 1, 2, 3, 4, 5, 7, and 8 identified as heterogeneous were modeled by the covariate based method PHM. Trend tests applied for the rest of the sub-systems that were identified as homogeneous and trended sub-systems including loader 2 and dump truck 6 were modeled by NHPP. Non-trended sub-system loader 1 was modeled by HPP method. TTRs were calculated to obtain the maintainability functions for sub-systems. Primarily, it was indicated that all sub-systems were identified as homogeneous. Subsequently, trended sub-systems including loader 2 and dump trucks 1, 6, 7 were modeled by means of the NHPP method through applying the trend tests. Henceforth, non-trended sub-systems including loader 1 and dump trucks 2, 3, 4, 5, and 8 were modeled by the HPP method.

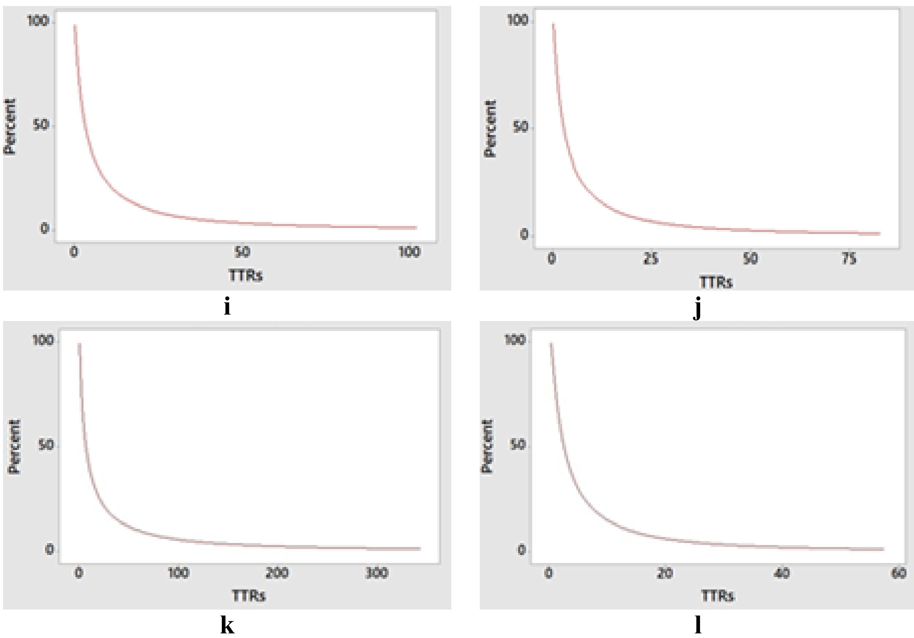


Figure 4. i) Maintainability function of group loader 1, j) maintainability function of group dump trucks 1, 6, 7, k) maintainability plot for group loader 1, l) maintainability plot for group dump trucks 2, 3, 4, 5, and 8, respectively.

Table 9. Reliability and maintainability functions of sub-systems.

Reliability

Data group	Model	Model or baseline parameters in regression model			Function
		β	θ	γ	
D.T 1,2,3,4,5,7,8	PHM	2.408	0.924	0.21	$\left(\text{Expo}\left[-\left(\frac{t-0.2105}{0.9247}\right)^{2.4089}\right]\right)^{(-0.843z_1+0.117z_2+0.146z_4-0.434z_5)}$
LO 2	PLP	0.8123	0.7418	-	$\text{Expo}\left[-\left(\frac{t}{0.7418}\right)^{0.8123}\right]$
D.T 6	PLP	22.5857	25.037	-	$\text{Expo}\left[-\left(\frac{t}{25.037}\right)^{22.5857}\right]$
Lo 1	3P-Weibull	0.9785	17.243	0.6494	$\text{Expo}\left[-\left(\frac{t-0.6494}{17.243}\right)^{0.9785}\right]$

Maintainability

Data group	Model	Model or baseline parameters in regression model			Function
		β (or μ)	θ (or σ)	γ	
LO 2	PLP	1.169	1.484		$1 - \text{Expo}\left[-\left(\frac{t}{1.484}\right)^{1.169}\right]$
D.T 1,6,7	PLP	1.002	1.465	-	$1 - \text{Expo}\left[-\left(\frac{t}{1.465}\right)^{1.002}\right]$
LO 1	3P lognormal	1.854	1.71	0.433	$1 - \int_{-\infty}^{t} \frac{1}{4.286(t-0.433)} exp\left[-\frac{(ln(t-0.433)-1.854)^2}{4.405}\right]$
D.T 2,3,4,5,8	3P lognormal	0.834	1.379	0.209	$1 - \int_{-\infty}^{t} \frac{1}{3.453(t-0.209)} exp\left[-\frac{(ln(t-0.209)-0.834)^2}{3.807}\right]$

7. Conclusions

This paper presents a decision framework for the identification of an appropriate reliability and maintainability model when dealing with multiple repairable units. It is challenging to perform the reliability and maintainability analysis of multiple repairable units installed in different positions or working under different operating conditions. The reliability and maintainability of identical units may vary from unit to unit due to different factors such as diverse design concepts, manufacturing processes, materials, and operational and environmental conditions. Hence, determining homogeneity and classifying the units using the trend tests should be considered as the first benchmark in the process. This may require splitting an inhomogeneous sample into several homogeneous groups. Furthermore, the current paper mulls over heterogeneities between units. For units with trend, it modelled the effect of unobserved heterogeneity based on a random factor, typically modelled based on the gamma distribution with mean 1 and variance η. In this research work, we also considered the proportional hazard models and their extinctions to cover the influence of the observed covariates on the reliability performance. In this paper, we discussed different scenarios for analyzing multiple repairable units based on trend, intensity, and dependency. The case studies verified the proposed framework in the Sungun Copper Mine haulage system. The results obtained suggest that the reliability and maintainability model of multiple repairable units may contain a mixture of different stochastic models, i.e. HPP, NHPP, HNHPP, and covariate based models. It is not effective to represent the behavior of the whole population using a single model. Hence, the traditional aggregation model may not be a valid model for reliability and maintainability estimation of multiple repairable units, and can lead to wrong conclusions and decisions. This problem has been remedied by the methods and framework suggested in this work.

References

[1]. Dhillon, B.S. (2008). Mining equipment reliability, maintainability, and safety. Springer;

[2]. Ascher, H. and Feingold, H. (1984). Repairable system reliability. Dekker.

[3]. Garmabaki, A., Ahmadi, A., Block, J., Pham, H. and Kumar, U. (2016). A reliability decision framework for multiple repairable units. Reliability Engineering & System Safety.150: 78-88.

[4]. Rausand, M. and Høyland, A. (2004). System reliability theory: models, statistical methods, and applications. Vol. 396. John Wiley & Sons;

[5]. Levkovich, P. and Chalenko, N. (1969). Use of reliability theory to calculate the reqsuired number of reserve longwall faces. Journal of Mining Science. 5:160-165.

[6]. Al'tshuler, V. (1969). A method of constructing a mathematical model to study the reliability of mine transportation systems. Journal of Mining Science.5: 72-76.

[7]. Ivko, V., Ovchinnikova, L. and Plotnikova, V. (1973). A method of estimating the operational reliability of kinematic mechanized support systems. Journal of Mining Science. 9: 333-335.

[8]. Freidina, E., Kovalenko, A. and Rudenko, O. (1975). Effect of mine-transport-equipment reliability on the productivity of a quarry system. Journal of Mining Science. 11: 50-54.

[9]. Bondar, S. and Mernov, V. (1979). Operational reliability of conveyer lines with intermediate storage capacity. Journal of Mining Science. 15: 268-270.

[10]. Garakavi, A., Manevich, I. and Merkin, V. (1984). Technological reliability and its safeguards in mining operations. Journal of Mining Science. 20: 456-462.

[11]. Kvaløy, J.T. and Lindqvist, B.H. (1998). TTT-based tests for trend in repairable systems data. Reliability Engineering & System Safety. 60: 13-28.

[12]. Hall, R.A. and Daneshmend, L.K. (2003). Reliability and maintainability models for mobile underground haulage equipment. Canadian Institute of Mining, Metallurgy and Petroleum (CIM) Bulletin. 96: 159-165.

[13]. Vagenas, N., Runciman, N. and Clément, S.R. (1997). A methodology for maintenance analysis of mining equipment. International Journal of Surface Mining, Reclamation and Environment. 11: 33-40.

[14]. Samanta, B., Sarkar, B. and Mukherjee, S. (2004). Reliability modelling and performance analyses of an LHD system in mining. South African Institute Mining And Metallurgy. 104: 1-8.

[15]. Lindqvist, B.H. (2006). On the Statistical Modeling and Analysis of Repairable Systems. Statist Sci. 21: 532-551.

[16]. Barabadi, A. (2011). Production Performance Analysis: Reliability, Maintainability and Operational Conditions. University of Stavanger.

[17]. Kumar, U. and Huang, Y. (1993). Reliability analysis of a mine production system-A case study, IEEE. pp. 167-172.

[18]. Vagenas, N., Kazakidis, V., Scoble, M. and Espley, S. (2003). Applying a maintenance

methodology for excavation reliability. International Journal of Surface Mining, Reclamation and Environment.17: 4-19.

[19]. Barabady, J. and Kumar, U. (2005). Maintenance Schedule by Using Reliability Analysis: A Case Study at Jajram Bauxite Mine of Iran. vol. 2, Tehran, Iran: World Mining Congress. pp. 831-838.

[20]. Barabady, J. and Kumar, U. (2007). Reliability analysis of mining equipment: A case study of a crushing plant at Jajarm Bauxite Mine in Iran. Reliability Engineering & System Safety. 93: 647-653.

[21]. Hoseinie, S.H., Ataei, M., Khalokakaie, R. and Kumar, U. (2011). Reliability and maintainability analysis of electrical system of drum shearers. Journal of Coal Science and Engineering (China). 17: 192-197.

[22]. Wijaya, A.R., Lundberg, J. and Kumar, U. (2012). Downtime analysis of a scaling machine. International Journal of Mining, Reclamation and Environment. 26: 244-260.

[23]. Louit, D.M., Pascual, R. and Jardine, A.K. (2009). A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data. Reliability Engineering & System Safety. 94: 1618-1628.

[24]. Garmabaki, A.H.S. (2016). Reliability Engineering and System Safety.

[25]. Taghipour, S. (2011). Reliability and maintenance of medical devices. Mechanical and Industrial Engineering University of Toronto.

[26]. Jardine, A.K., Lin, D. and Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing.20: 1483-1510.

[27]. Mann, H.B. (1945). Nonparametric tests against trend. European Environment Agency n.d. https://www.eea.europa.eu/data-and-maps/indicators/nutrients-in-freshwater/mann-h.b.-nonparametric-tests (accessed May 22, 2019).

[28]. Viertävä, J. and Vaurio, J.K. (2009). Testing statistical significance of trends in learning, ageing and safety indicators. Reliability Engineering and System Safety. 6: 1128-1132.

[29]. Ziliak, S.T. and McCloskey, D.N. (2008). The Cult of Statistical Significance: How the Standard Error Costs Us Jobs, Justice, and Lives. 1st edition. Ann Arbor: University of Michigan Press.

[30]. Leamer, E.E. (1978). Specification Searches: Ad Hoc Inference with Nonexperimental Data. 1 edition. New York: Wiley.

[31]. Quantitative and Statistical Approaches to Geography (accessed May 22, 2019). - 1st Edition n.d. https://www.elsevier.com/books/quantitative-and-statistical-approaches-to-geography/matthews/978-0-08-024295-8 (accessed May 22, 2019)..

[32]. Caroni, C. (2010). "Failure limited" data and TTT-based trend tests in multiple repairable systems. Reliability Engineering & System Safety. 95: 704-706.

[33]. Lewis, P.W. and Robinson, D.W. (1973). Testing for a monotone trend in a modulated renewal process (No. NPS-55LW73121). Naval postgraduate school monterey ca.

[34]. Kvaløy, J.T. (1998). Tests for Trend in More Than One Repairable System.

[35]. Bartlett, M.S. (1937). Properties of sufficiency and statistical tests. Proceedings of the Royal Society of London. Series A-Mathematical and Physical Sciences. 160 (901): 268-282.

[36]. Held, L. and Bové, D.S. (2014). Applied Statistical Inference: Likelihood and Bayes. Berlin Heidelberg: Springer-Verlag.

[37]. Elvebakk, G. and Lindqvist, B. (2002). The Trend-Renewal Process for Statistical Analysis of Repairable Systems.

[38]. Kvist, K., Andersen, P.K., Angst, J. and Kessing, L.V. (2008). Repeated events and total time on test. Statistics in medicine. 27 (19): 3817-3832.

[39]. Lawless, J.F. (1987). Regression methods for Poisson process data. Journal of the American Statistical Association. 82 (399): 808-815.

[40]. Cook, R.J. and Lawless, J. (2007). The Statistical Analysis of Recurrent Events. Springer Science & Business Media.

[41]. Vaurio, J.K. (1999). Identification of process and distribution characteristics by testing monotonic and non-monotonic trends in failure intensities and hazard rates. Reliability Engineering & System Safety. 64: 345-357.

[42]. Proschan, F. (1963). Theoretical Explanation of Observed Decreasing Failure Rate. Technometrics.5: 375-383.

[43]. Nouri Qarahasanlou, A. (2017). Production Assurance of Mining Fleet Based on Dependability and Risk Factor(Case Study: Sungun Copper Mine). Shahrood University of Technology Faculty of Mining, Petroleum & Geophysics.

[44]. Razzaghzadeh, R. (2019). Reliability and maintainability study of Mining Equipment. Imam Khomeini university, MSc thesis.

تحلیل قابلیت اطمینان و تعمیرپذیری برای واحدهای تعمیرپذیر چندگانه (مطالعه موردی: معدن مس سونگون)

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ارسال ۲۰۱۹/۷/۶، پذیرش ۲۰۱۹/۹/۳

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چکیده:

عملکرد مناسب دستگاه‌های معدن از عوامل اجرایی و محیطی تأثیر می‌پذیرد. توجه به اثرات عوامل مختلف و ریسک مرتبط با آن‌ها، موجب درک بهتر علل خرابی‌های این ماشین‌آلات و پیش‌بینی مناسب پارامترهای قابلیت اطمینان این ماشین‌آلات می‌شود. در این پژوهش، قابلیت اطمینان و قابلیت تعمیرپذیری دستگاه‌های بارگیری و باربری در معدن مس سونگون با در نظر گرفتن شرایط تعمیر به عنوان واحدهای تعمیرپذیر چندگانه انجام شد. بدین منظور، داده‌های لازم ماشین‌آلات بارگیری و باربری شامل ۲ لودر و ۸ دامپتراک در یک دوره ۱۵ ماهه پس از تعیین سیستم و زیرسیستم‌های زیرمجموعه در ۱۰ واحد عملیاتی جمع‌آوری و طبقه‌بندی شدند. ابتدا، زمان بین خرابی (TBF) و زمان مورد نیاز تا تعمیر (TTR) برای هر واحد محاسبه و ۲۰ زیرسیستم ایجاد شد. در مرحله اول، تحلیل ناهمگونی برای همه زیرسیستم‌ها با نرم‌افزار Stata انجام شد و عمده زیرسیستم‌ها به عنوان زیرسیستم‌های ناهمگن به جز ۷ مورد از جمله واحدهای دامپتراک ۱، ۲، ۳، ۴، ۵، ۷ و ۸ در نظر گرفته شدند. از این‌رو از مدل مبتنی بر شرایط محیطی "PHM"، گروه ناهمگن مشخص شد و با انجام تحلیل‌های مربوطه، قابلیت اطمینان آن تخمین زده شد. در مرحله بعد، آزمون‌های روند روی زیرسیستم‌های همگن با استفاده از نرم‌افزار Minitab انجام شد. زیرسیستم‌های همگن و دارای روند خرابی توسط "NHPP" مدل‌سازی شدند و برای زیرسیستم‌های بدون روند، با تشکیل گروه داده و انجام آزمون‌های همبستگی، توسط "HPP" مدل‌سازی شدند. در نهایت، قابلیت اطمینان و قابلیت تعمیرپذیری تمامی زیرسیستم‌های مورد مطالعه با سطح اطمینان ٪۹۵ محاسبه شد.

کلمات کلیدی: قابلیت اطمینان، قابلیت تعمیرپذیری، واحدهای تعمیرپذیر چندگانه، معدن مس سونگون.