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Maintainability measure based on operating environment, a case study: Sungun copper mine

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Abstract
The life cycle cost of a system is influenced by its maintainability. Maintainability is a design parameter, whose operational conditions can affect it significantly. Hence, the effects of these operational conditions should be quantified early in the design phase. The proportional repair model (PRM), which is developed based on the proportional hazard model (PHM), can be used to analyze maintainability considering the effects of the operational conditions. In PRM, the effects of the operational conditions are considered to be time-independent. However, this assumption may not be valid for some cases. The aim of this paper is to present an approach for prediction of the maintainability performance of the mining facilities considering the time-dependent influencing factors. The stratified Cox regression method (SCRM) is used to determine maintainability in the presence of time-dependent covariates for fleet vehicles operating in Sungun Copper Mine, Iran.

Keywords: *Maintainability, Proportional Repair Model (PRM), Stratified Cox Regression Method (SCRM), Environmental Conditions (Covariates), Sungun Copper Mine.*

1. Introduction
At the system level, maintainability has a great influence on reliability and availability. Achieving high maintainability in complex systems requires appropriate activities in the design, development, and operational phases. Having an accurate maintainability estimation of the system and its items will provide essential information for the following purposes [1]:

- Carry out a critical analysis to identify the areas that should receive concentrated redesign, research, and development efforts from the maintainability viewpoint.
- Determine the mean time and the variability of all downtimes whose distributions were determined in the previous item to identify the problem areas, which must be addressed, and predominantly reduce the mean time and variability of the maintenance actions consuming a large amount of the total downtime.
- Determine the expertise level of the maintenance staff and the required skill levels for each type of system.

Extensive research works have been conducted on maintainability of the mining equipment. For example, in 1993, Kumar and Huang have studied the effect of LHD machine maintainability on a mine production system [2]. Once again, in 1997, Vagenas et al. have used time-to-repair data for availability analysis of LHD in an underground mining region in Ontario [3]. Hall and Daneshmend have addressed the issue of maintainability of mobile haulage equipment fleet including load-haul-dump vehicles and underground haul trucks from a gold mine in Chilean Andes for fifteen months of maintenance historical data [4]. Tjiparuro and Thompson have discussed the maintainability design principles. They first gave a background account of the related research efforts in the field of maintainability. Then a consolidation of that study was undertaken to produce the key maintainability [5]. Elevli et al. have worked on the maintainability of the mechanical systems of electric cable shovels. They used the unit root and serial correlation tests for the independent and identically distributed (iid) assumption test [6]. Hoseinie et al. have studied the maintainability of a drum shearer in a coal mine [7-13]. Rahimdel et al. have studied the maintainability of Rotary Drilling Machines [14-18]. Wijaya et al. have presented a method that provides an imagining of the downtime estimation and the precision and uncertainty of the estimation at a given confidence level as well as the factors influencing the failure. The specific purpose method is based on the Jack-knife diagram that is used to analyze the downtime of a scaling machine [19]. Barabadi et al. have provided a systematic guideline based on point process models for field-repair data by a case study of a crushing plant in a limestone mine. Under this model, the maintainability analysis is similar to the system reliability analysis with the differences that the time-to-repair is the random variable of interest in maintainability rather than time-to-failure in the reliability analysis [20]. Barabadi and Alipour have developed a step-by-step methodology to facilitate the design and operation-phase of maintainability in a new tunnel in an underground coal mine belonging to Svea Coal Mine, Norway [21].

The operating surroundings of amine are dynamic, with many unknowns. Operating practices, varying production demands, and changes within the ore types can all have significant influences on the equipment behavior. However, most maintainability tools described previously rely on the historical data and tends towards generation of classical models, none of which may be the present effective dynamic operational conditions. Recently, Barabadi and Markest have discussed the maintainability performance under distinct conditions. They reviewed the technical challenges for the offshore oil and gas industry from the reliability and maintainability viewpoints and available appropriate statistical approaches for the reliability and maintainability performance analysis under the arctic conditions [22]. Barabadi et al. have improved the concept of proportional repair model (PRM) based on the proportional hazard model (PHM) in a mining filed. The PRM approach was introduced to assess the repair rate/maintainability considering the environmental conditions [23]. Despite this effort, the literature regarding the effect of time-dependent operational conditions on maintainability is not well detailed. The aim of this paper is thus to study the effects of the time-dependent covariates on the analysis of maintainability using the stratified Cox regression method (SCRM).

The rest of this paper is organized as follows. In Section 2, the theoretical concept, data, and their gathering process are briefly discussed. In Section 3, the application of PRM for analyzing covariates is briefly discussed using the Cox regression model in the maintainability field. In Section 4, the application of this method is demonstrated using a real-case study of the mining equipment in Sungun Copper Mine in Iran. Maintainability is formally defined as ‘‘the ability of an item under given conditions of use to be retained in, or restored to, a state in which it can perform a required function when maintenance is performed under given conditions and using stated procedures and resources’’. This, in turn, can be paraphrased as ‘the probability of repair in a given time’ [22, 24].

2. Theoretical concepts

Maintainability of a sub-system plays an important role in controlling both the quantity and the quality of products, and thus it must be kept at a specified level. Generally, it is represented in terms of a Mean-Time-To-Repair (MTTR). Another parameter to be considered is the maximum time repair, which could be determined for each one of the various levels of maintenance [25].In parametric methods, if T is a random variable, which represents the Time-To-Repair (TTR) of a failed sub-system, the mathematical description of maintainability is expressed as follows:

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

where $M(t)$ is the maintainability at time t or the cumulative repair distribution function, and $m(t)$ is the repair density function. Maintainability can be calculated using the classical approaches or covariate-based models such as the proportional repair model. A classical maintainability approach is based on the time distribution or time model of the event records or the historical time data. It is mainly useful to the manufactures whom produce item in bulks because it can be provided general view of item behavior. This approach can be broken down into the following steps [26]:

1. Determine TTR for each sub-system.
2. Test the data for the independent and identically distributed (iid) assumption in order to fit the data to the theoretical probability distributions or models.
3. Fit the theoretical probability distributions to the TTR data using the iid assumption and a time-dependent model such as the power law process (PLP) model for data-reject-it.
4. Assess the goodness-of-fit of a theoretical probability distribution to the data.
5. Estimate the maintainability of each sub-system and of the entire system using the system configuration relations.

The classical approaches consider the TTR (or total TTR) variable as the only variable of interest. To address the individual maintainability of a system in dynamic operating environment conditions, a covariate-based hazard model such as the proportional hazard model should be used. Then for repair-data assessment, the proportional repair model based PHMis proposed to be used for analysis of the covariates' effects on the maintainability performance. PRM assumes that the repair rate of a system/component is a product of an arbitrary and unspecified baseline repair rate $\mu_0(t)$, dependent on time only, and a positive functional term (the linear form $1 + w\beta$, te log-linear ex$(w\beta)$, and the logistic form $\log(1 + \exp(w\beta))$, basically independent from time including the effects of a number of covariates. The common form of PRM is log-linear, and can be defined as Eq.(2) [23]:

$$\mu(t,w) = \mu_0(t)\phi(w\beta) = \mu_0(t)exp\left(\sum_{j=1}^{m} w_j\beta_j\right) \quad (2)$$

The sub-system maintainability is influenced by the covariates [23] according to the following relation:

$$M(t,w) = 1-\left(1-M_0(t)\right)^{exp\left(\sum_{j=1}^{m} w_j\beta_j\right)} \quad (3)$$

where $\mu(t,w)$ and $M(t,z)$ are the repair and maintainability functions, respectively, β is a regression coefficient of the corresponding m covariates (w),and $\mu_0(t)$ and $M_0(t)$ are, respectively, the baseline repair rate and baseline maintainability (cumulative distribution function of TTRs).

The proportionality assumption of PRM imposes the severe limitation that the repair curves for a sub-system with different covariates must never cross. In other words, the estimated repair at different levels of covariates are in constant proportion at each time interval for covariates. Due to the above-mentioned PRM weaknesses, the stratified Cox regression method (SCRM) was developed. In this method, for repairing data, the model is stratified using a covariate with a non-proportional repair. The same approach can be useful in modeling the time-dependent covariates. In this method, based on the different levels of time-dependent covariates, the data is grouped and classified. Each group of data is called a stratum, which has its own maintainability and repair rate. For each stratum, separate baseline repair rates are calculated, while the regression coefficients for all strata are equivalent. The repair rate of an asset in the g^{th} stratum can be calculated as follows [23, 27]:

$$\mu_g(t,w) = \mu_{0g}(t)exp\left(\sum_{j=1}^{m} w_j\beta_j\right) \quad (4)$$

$$g = 1, 2, \ldots, u$$

where β is the regression parameter, and $\mu_{0g}(t)$ is the baseline repair function for each stratum. The baseline repair function for u stratais allowed to be arbitrary, and it is assumed completely unrelated. Figure 1 shows a systematic method that is used for selecting an appropriate approach for the maintainability analysis of a set of repair data.

3. Case study

To gain a better understanding of the proposed measure, an analysis of the repair time and the operating environment of different system configurations is performed. In this work, a case study of a mining process at Azarbayjan Molybdenum-Copper Mine (Sungun Copper Mine) in Iran was defined. The Sungun Copper Mine, which is operated by the National Iranian Copper Industries Company (NICICO), is an excellent project of inordinate complexity. Sungun Copper Deposit is the second largest copper mine in Iran. The mining operation is managed in the mine site by employing a fleet of dump trucks, loaders, shovels, excavators, bulldozers, and drilling rigs. In this work, we used the maintenance data for two dump trucks, a bulldozer, and a loader. In addition, each machine was defined as a sub-system. The overall definitions of the machines and their codes are displayed in Table 1.

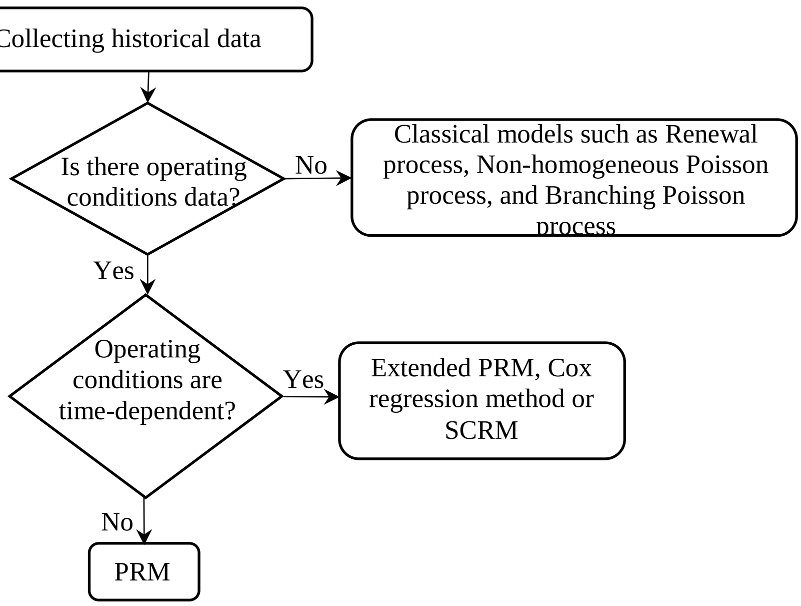

Figure 1. Schematic representation of methodology used to evaluate maintainability.

Table 1. Sub-systems of mining fleet system and their codes.

No.	Sub-system	Model	Code
1	Loader	Caterpillar 988B	Lo.
2	Bulldozer	Caterpillar D8N	Bl.
3	Dump-Truck	Komatsu HD-785-5	DT. 1
4	Dump-Truck	Komatsu HD-785-5	DT. 2

3.1. Data collection from Sungun copper mine

The failure data used in this study was collected over a period of 15 months. As previously considered, the database was composed of two types of data, time and covariates. The data came from different sources like the daily operation and production reports of mine supervisors and the maintenance reports of the mine mechanics. The historical and covariates in formations had been collected in the forms of quantitative (in the form of numbers) and qualitative (in the form of words, archival records, existing statistics, documentation, direct observation and interview).All events (repairs) of sub-systems of the machines were selected from the database. Then a new data set was formed especially for each one of them, and the time-to-repairs (TTRs) were calculated. Due to the lack of space, only a part of the bulldozer (Bl.) sub-system is presented in Table 2. The last column is the total time to repairs (cumulative TTRs),time, and cumulative form of TTRs.

In real-life situations, industrial societies would hardly allow their sub-systems to run to failure. In most applications, once a defect is detected, a sub-system is replaced or overhauled before it fails. Therefore, the exact point at which a sub-system stops operating (for repair data start operating) is not always available and recorded. There is only information in which a sub-system has survived up to the replace/repair times (time to repair); such information is called the censored data. The third column defines information about the repair censorship status (failure (1), censored (0)),and is dichotomous variable. The formulations of the Bl. sub-system covariates presented in the 4thto8thcolumns in Table 2 are as follow:

- Categorical covariates: 'Shift' that is a dummy variable(presented in Table 3), maintenance condition, and weather condition. The classification and quantification of these covariates are as indicated in Table 4.
- Continuous covariates: Precipitation (mm) and temperature (^{o}C).

The covariates for all sub-system repair data are formulated as displayed in Table 5.

3.2. Proportional repair model for Sungun copper mine sub-systems

In order to determine the behavior of each sub-system, a proportional repair model is used. The PRM model formula says that the repair at time t is the product of two quantities:

- First part: baseline repair rate function ($\mu_0(t)$), which is only dependent on time.
- Second part: the covariate function ($exp\left(\sum_{j=1}^{m} w_j \beta_j\right)$).This quantity is the exponential expression e to the linear sum of $w_j \beta_j$, where the sum is over the m explanatory w variables named as covariates and time-independent.

In the first step, the proportionality assumption must be checked to avoid any bias in the results. This assumption imposes a common baseline repair on sub-systems, even in a case in which the sub-system should be stratified according to the baseline. The SPSS software accommodates a statistical test on the proportionality assumption using the Schoenfeld residuals. The idea behind the statistical test is that if the proportionality assumption holds for a particular covariate, the Schoenfeld residuals for that covariate will not be related to repair time. Rejection of the null hypothesis leads to the conclusion that the proportionality assumption is violated. Table 6 illustrates the proportionality assumption statistical test for effective covariates of sub-systems.

Table 2. Sample of collected failure data of Loader sub-system.

Frequency	TTRs	Status	Shift	Maintenance Condition	Weather Condition	Precipitation (mm)	Temperature (°C)	Cumulative TTRs (Hr)
1	4.50	0	B	1	1	2	4.8	4.50
2	6.75	1	B	2	1	0.3	5.8	11.25
3	93.00	1	B	2	2	0.3	7.9	104.25
4	6.75	1	B	2	2	2	9.2	111.00
5	0.50	1	A	1	2	2	9.2	111.50
6	4.25	1	C	1	2	2	11.4	115.75
7	9.75	1	C	1	1	2	13.3	125.50
8	1.00	1	A	1	3	0.1	11.5	126.50
9	57.00	1	B	2	3	6.5	0.6	183.50
10	6.75	1	B	2	3	15.5	1.2	190.25

Table 3. Coding of dummy (shift) covariates.

		Shift-1	Shift-2
Shift	**A=Morning**	1	0
	B=Midday	0	1
	C=Night	0	0

Table 4. Classification and quantification of repair covariates for bulldozer sub-system.

Covariates (w)	Classification	Quantification
Shift	Morning	A
	Midday	B
	Night	C
Maintenance condition	Overhaul	2
	Repair	1
Weather condition	Sunny & Clear	1
	Semi Cloudy	2
	Overcast	3
	Dense fog	4

Table 5. Covariates labelof repair operating environment of sub-systems.

Dump truck	Loader	Bulldozer
Shift (w_{t1})	Shift (w_{l1})	Shift (w_{b1})
Maintenance Condition(w_{t2})	Maintenance Condition(w_{l2})	Maintenance Condition(w_{b2})
Weather Condition (w_{t3})	Weather Condition (w_{l3})	Weather Condition (w_{b3})
Precipitation (w_{t4})	Precipitation (w_{l4})	Precipitation (w_{b4})
Temperature (w_{t5})	Temperature (w_{l5})	Temperature (w_{b5})

Table 6. P-value ofproportionality assumption assessment for variables in the equation.

subsystem	P-values					
	Shift-1	**Shift-2**	**Maintenance Condition**	**Weather Condition**	**Precipitation**	**Temperature**
Lo.	0.73	0.184	0.000**	0.372	-	-
Bl.	0.177	0.040*	0.708	-	-	0.569
DT. 1	0.003**	0.34*	0.0**	0.658	0.977	0.448
DT. 2	0.002**	0.123*	0.753	-	0.988	-

*. Correlation is significant at the 0.05 level

**. Correlation is significant at the 0.01 level

In this table, the P-values are quite high for the variables without asterisk, suggesting that these variables satisfy the proportionality assumption. Note that each one of these p-values tests the assumption for one variable, given that the other predictors are included in the model. For example, the P-value of 0.73 assesses the proportionality assumption for the Lo. sub-system, assuming that the proportionality assumption is satisfied for shift-2 and weather condition. However, the P-value for the maintenance condition is significantly below the 0.01 and 0.05 levels; this result suggests that the maintenance condition converts does not satisfy the proportionality assumption.

For sub-systems with proportionality assumption, for the first part (the baseline repair rate $\mu_0(t)$) of sub-systems, prior to fitting the collected TTRs to the corresponding distribution, the data should be tested for the validity of the assumption of independent and identically distributed (iid) data. The trend test and an auto-correlation test were utilized for trend and serial correlation testing. The parameters of the corresponding distribution or PLP were then determined using the maximum likelihood estimation (MLE) method, and their fitness to the corresponding distribution was assessed using the Kolmogorov–Smirnov test or probability plot test for distributions and PLP. In this study, the Minitab 16,ReliaSoft's Weibull ++9 and RGA 9 software was used for distribution or model fitting [18,19].In the second part (the covariate function), all the tests were conducted using the SPSS software, and the alpha significance level (α) used in all the tests was 0.05. "Backward-Wald" elimination (backward stepwise method) with all step wise procedures estimated regression coefficients, as it is less likely to miss potentially valuable predictors. Thus the covariates found to have no significant value were eliminated in the subsequent calculations. The corresponding estimates of a 'regression coefficient' were obtained and tested for their significance based on Wald statistics and/or p-value (obtained from the table of unit normal distribution). Table 6 includes just the significant covariates inserted in the model. Here, due to space limitations, the backward stepwise method steps are not listed.

For a sub-system without proportionality assumption, we carry out a SCRM procedure for the analysis. SCRM assumes that the repair is proportional within the same stratum but not necessarily across different strata. Actually, the effect of stratified covariates appears in the baseline repair rate. The baseline function (first part) estimations for each stratum and the second part for each sub-system have the same process as PRM.

Results of the analytical iid tests and the statistical distribution estimations of sub-system baseline repair function are given in Appendix 1.It presents the results of the analytical trend test on the TTRs in each stratum. For example, the null hypothesis was not rejected at a 5 percent significance level (p-value>α) in stratum 1 of the Lo. sub-system. Thus this sub-system was identically distributed, but in stratum 2 of the Bl sub-system, the data rejected the iid assumption. In addition, this table presents the analytical tests for the serial correlation of lag 1. First one is auto-correlations (AFC statistic) of lag 1 of the data set for α=0.05. The hypothesis is defined as the correlations equal to zero by Minitab. It is seen that the auto-correlations less than the critical bands, which suggest that there is no significant correlation in all strata of sub-systems. The TSTA and LBQ statistics compare the values of the test statistic with the critical value for evaluating the null hypothesis of no auto-correlation. These statistics also confirm the acceptance of no auto-correlation for all sub-systems. The TTR data set for the stratum 2 of Bl and DT.1 sub-system exhibit the presence of trends, and no correlation. Therefore, the NHPP method is the best method for their baseline repair rate modeling. In this research work, PLP, which is a special form of NHPP, was selected for fitting data of the mentioned sub-systems. The results obtained from the trend test and serial correlation of the other stratum of sub-systems show that they are trends and serial correlation free. Therefore, the data of these sub-systems are independent and identically distributed (iid) and classic approach used for analysis.

Results of the analysis for covariate function of each sub-system is presented in Table 7. The second column of this table recognizes the model (PRM or SCRM). The third column identifies the variables that have been included in the model, and gives the estimates of the regression coefficients corresponding to each variable in the model. This column, labeled as repair ratio, gives e^{Coef} for each variable in each model. As we will discuss, e^{Coef} gives an estimated repair ratio for the effect of each variable adjusted for the other variables in a model without product terms.

For a greater clarity, we explain the SCRM results for the Lo. sub-system. As mentioned, the test for the significance of all variables is given by the Wald statistic P-value. This is a two-tailed P-value, and the test is (bare) significant at the 0.05 level. For this sub-system shift-1, shift-2,weather condition and maintenance condition have significant effective in model based on backward stepwise method and p-value of proportionality assumption of them calculated in Table 6. As shown in this table, the P (proportionality assumption) values for shift-1, shift-2, and weather condition are not significant. However, the P-value for the maintenance condition is significantly below the 0.05 level. These results indicate that shift-1, shift-2, and weather condition satisfy the proportionality assumption, whereas the maintenance condition variable does not. Since we have a situation where one of the predictors does not satisfy the proportionality assumption, we carry out a SCRM procedure for the analysis. Using this, we can control the maintenance condition variable that does not satisfy the proportionality assumption by stratification in two strata, while simultaneously including in the model the shift-1, shift-2, and condition variables that satisfy the proportionality assumption. Thus the maintainability function of this sub-system contains two strata that are stratified based on the "maintenance condition" covariate$\left(w_{l2}\right)$, indicated in the "stratum" column in Table 7. To ensure a different baseline hazard function for each stratum, we include Weibull-3P for the first and Loglogistic-2P for the second stratum (Appendix 1). The second part of formula that contains the effect of the covariates (regression coefficients) include the0.525, –0.45, and 0.211 values for shift-1, $\left(w_{l11}\right)$, shift-2 $\left(w_{l12}\right)$, and weather condition(w_{l3}), respectively.

As mentioned before, in this model, it is assumed that in the real life of a system, the repair rate is influenced by the time during which, and the covariates under which, it operates. In other words, the repair rate of a system is the product of the baseline repair rate, dependent on time only, and another positive functional term independent from time. This term incorporates the effects of a number of covariates such as temperature, maintenance condition, shift, weather condition, and precipitation. The effects of covariates may be to increase or to decrease the hazard rate. For example, in the loader sub-system, Figure 2, in the case of stratum2, the observed repair rate is greater than the baseline hazard rate. However, in the case of stratum1, the observed repair rate is smaller than the baseline repair rate.

Also, results of the analysis of maintainability performance using stratification (SCRM)approach (Eq.(4)) for subsystems with their strata, which is labeled with a number after the sub-system code (For example, DT11 means stratum 1 of dump truck-1) are shown in Figure 3. The mean value of covariates is used for the maintainability analysis.

Table 7. Estimation of regression coefficients for each stratum.

Sub-systems	Approach	$exp\left(\sum_{j=1}^{m} w_j \beta_j\right)$
Lo.	SCRMstratify by $\left(w_{l2}\right)$	$exp\left(0.525w_{l11} - 0.450w_{l12} - 0.211w_{l3}\right)$
Bl.	SCRMstratify by $\left(w_{b22}\right)$	$exp\left(-5.178w_{b2}\right)$
DT. 1	SCRMstratify by $\left(w_{t12}, w_{t2}\right)$	$exp\left(-0.016w_{t4}\right)$
DT. 2	SCRMstratify by $\left(w_{t12}\right)$	$exp\left(-4.412w_{t2}\right)$

Note: w_{xij} : Dummy covariate, w_{xi} : Categorical covariates

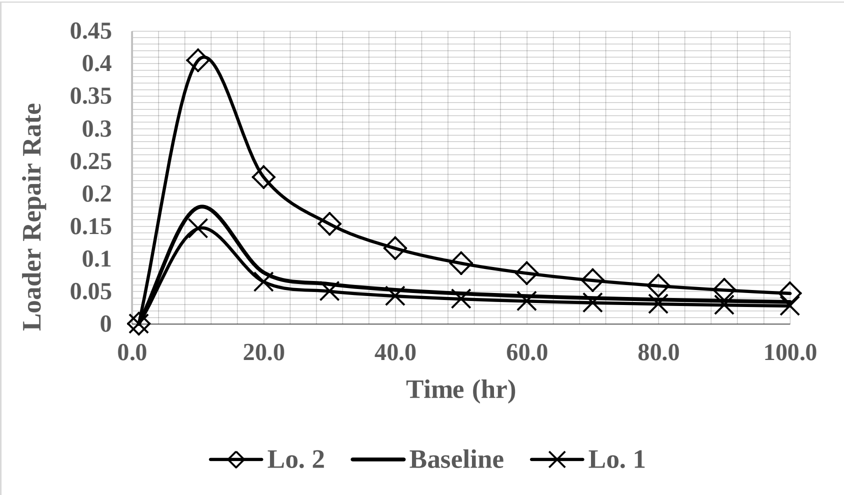

Figure 2. Effects of covariates on repair rate of loader sub-system.

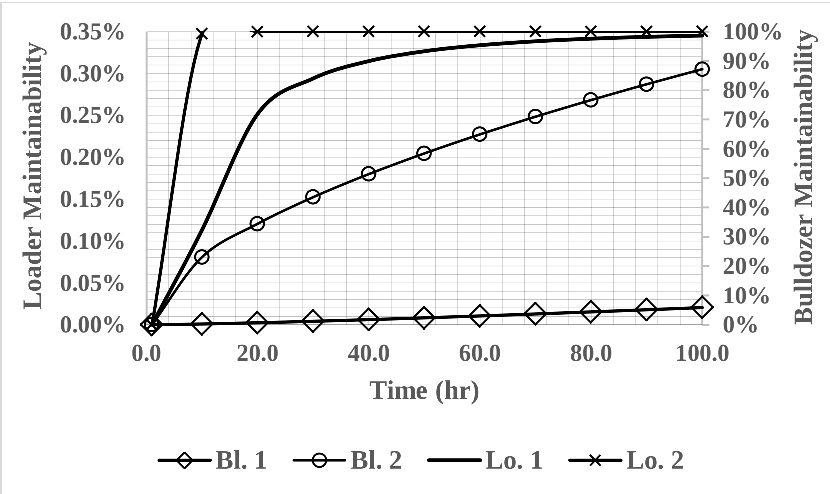

Figure 3. Maintainability of loader and bulldozer sub-systems using SCRM.

The result of the analysis using stratification approach shows that there is a significant difference between the maintainability of different strata, for example, the bulldozer in minor repairs and overhaul maintenance. The probability that the bulldozer can be repaired in 40 min is about 5 percent if the maintenance is minor (repair). However, the probability that the bulldozer can be repaired at the same time is about 52 percent if the maintenance is overhauled. Therefore, it is important to consider the difference for optimization of the maintenance strategy.

It should be noted that to reflect the influence of the operating conditions, there are various scenarios based on different strata of repair characteristics of the sub-system using the SCRM process and different values of the covariates. In this study, we supposed a scenario based on the first stratum of each sub-system and the main value of each covariates for the maintainability importance measure.

4. Conclusions

Maintainability management is an interesting new attention in the today's corporate world. Remaining competitively linked effectively with all the sub-systems of a system is partly responsible for this interest. A company cannot adopt itself to this competition if its system is unavailable. In addition, it causes an increasing need to ensure that the equipment is properly maintained and comes back quickly to operation. On the other hand, in a mining business, the operating environment is dynamic, with many unknowns (covariates) that affect the operating life of the equipment. Operator practices, varying production demand, and changes within the rock kind all have significant influences on the repair pattern and maintenance characteristic of the equipment. Therefore, a proposed approach can be used as a multi-lateral index in a maintainability analysis, and providing useful information for various branches of engineering such as availability and supportability. In addition, maintainability has a significant effect on the safety and performance of production facilities. Our measure consisted of two main portions including the performance characteristic obtained from historical data (time to repair) and operating environment obtained from covariates. Furthermore, it provided the techniques, mathematical and practical, to accomplish the pinpoint areas where the research and development money could best be spent from a maintainability view point. In this paper, the proposed concept was used to study the mining equipment in Sungun Copper Mine, which consisted of a loader, a bulldozer, and two dump trucks. The case study shows the maintainability of different operating conditions for the sub-systems representing different values. Hence, using a static and classical model can mislead the planners and mangers in confronting the variable and dynamic operating environment. It could be seen in the maintainability performance of the loader sub-system that the probability of doing minor repair (stratum 1) and overhaul repair (stratum 2)in 8 h was about 25 and 80 percent, respectively, while the probability (maintainability) for baseline ignoring the effect of covariates was 30 percent. This means that the operating conditions such as overhaul repair leads the loader's maintenance actions to perform poorly, and in a longer time than minor repair or baseline conditions. The results of the analysis showed that the most effective ways for increasing the maintainability performance of system maintainability is to improve the loader, dump truck 1and dump truck 2sub-systems,respectively. There are some other ways to improve the maintainability (growth of the repair rate or decrease in the mean time to repair) of a repairable system such as maintenance, loading on sub-system remains nominal during operation, minimizing probability that spare part unavailable at the time of the demand and employment expert maintenance crow, utilization of new filed tools and methods.

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References

[1]. Kececioglu, D. (2003). Maintainability, availability, and operational readiness engineering handbook. Vol. 1. DEStech Publications, Inc.

[2]. Kumar, U. and Huang, Y. (1993). Reliability analysis of a mine production system-a case study. Reliability and Maintainability Symposium. Proceedings. Annual . pp. 167-72. doi:10.1109/RAMS.1993.296859.

[3]. Vagenas, N., Runciman, N. and Clément, SR. (1997). A methodology for maintenance analysis of mining equipment. International Journal of Surface Mining, Reclamation and Environment. 11: 33-40. doi:10.1080/09208119708944053.

[4]. Hall, R.A. (2003). Daneshmend LK. Reliability and maintainability models for mobile underground haulage equipment. CIM Bulletin. 96: 159-65.

[5]. Tjiparuro, Z. and Thompson, G. (2004). Review of maintainability design principles and their application to conceptual design. Proceedings of the Institution of Mechanical Engineers . Part E: Journal of Process Mechanical Engineering. 218:103-13.

[6]. Elevli, S., Uzgoren, N. and Taksuk, M. (2008). Maintainability analysis of mechanical systems of electric cable shovels. Journal of Scientific and Industrial Research. 67: 267-71.

[7]. Hoseinie, 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 17 (2): 192-197.

[8]. Hoseinie, H., Khalokakaie, R. and Ataei, M. (2011). Reliability-based Maintenance Scheduling of Haulage System of Drum Shearer; case study- Tabas Coal Mine- Iran. Int. J. Mining and Mineral Engineering 3 (1): 26-37.

[9]. Hoseinie, H., Ataei, M., Khalokakaie, R. and Kumar, U. (2011). Reliability modelling of water system of longwall shearer machine . Archives of Mining Science. 56 (2): 291-302.

[10]. Hoseinie, H., Ataei, M., Khalokakaie, R. and Kumar, U. (2011). Reliability modeling of hydraulic system of drum shearer machine . Journal of coal science and Engineering 17 (4): 450-456.

[11]. Hoseinie, S.H., Ataei, M., Khalokakaie, R., Ghodrati, B. and Kumar, U. (2012). Reliability analysis of the cable system of drum shearer using the power law process model. International Journal of Mining, Reclamation and Environment. pp. 1-15.

[12]. Hoseinie, S.H., Ataei, M., Khalokakaie, R., Ghodrati, B. and Kumar, U. (2012). Reliability Analysis of Drum Shearer Machine at Mechanized Long wall Mines . Journal of Quality in Maintenance Engineering (JQME). 18 (1): 98-119.

[13]. Hoseinie, S.H., Khalokakaie, R., Ataei, M., Ghodrati, B. and Kumar, U. (2013). Monte Carlo Reliability Simulation of Coal Shearer Machine . International Journal of Performability Engineering. 9 (5): 487- 494.

[14]. Rahimdel, M.J., Ataei, M., Khalokakaei, R. and Hoseinie, S.H. (2013). Reliability analysis of drilling operation in open pit mines . Archives of Mining Science. 58 (2): 563-572.

[15]. Rahimdel, M.J., Ataei, M., Khalokakaei, R. and Hoseinie, S.H. (2013). Reliability-based maintenance scheduling of hydraulic system of rotary drilling machines . International Journal of Mining Science and Technology. 23 (5): 771-775.

[16]. Rahimdel, M.J., Hoseinie, S.H., Ataei, M. and Khalokakaei, R. (2014). The Reliability and Maintainability Analysis of Pneumatic System of Rotary Drilling Machines. Journal of the Institution of Engineers (India): Series D . 94 (2): 105-111.

[17]. Rahimdel, M.J., Ataei, M., Khalokakaei, R. and Hoseinie, S.H. (2014). Maintenance Plan for a Fleet of Rotary Drill Rigs . Archives of Mining Science. 59 (2): 441-453.

[18]. Rahimdel, M.J., Ataei, M. and Khalokakaie, R. (2016). Reliability Analysis and Maintenance Scheduling of the Electrical System of Rotary Drilling Machines, Current Trends in Reliability, Availability, Maintainability and Safety, Part of the series Lecture Notes in Mechanical Engineering. pp. 623-632.

[19]. Wijaya, A.R., Lundberg, J. and Kumar, U. (2012). Downtime analysis of a scaling machine. International Journal of Mining, Reclamation and Environment. 26: 244-60.

[20]. Barabadi, A., Garmabaki, A., Yuan, F. and Lu, J. (2015). Maintainability analysis of equipment using point process models, IEEE. pp. 797-801.

[21]. Barabadi, A. and Aalipour, M. (2015). Maintainability management of production facilities in complex and challenging operating conditions, IEEE. pp. 817–20.

[22]. Barabadi, A. and Markeset, T. (2011). Reliability and maintainability performance under Arctic conditions. International Journal of System Assurance Engineering and Management. 2: 205-17.

[23]. Barabadi, A., Barabady, J. and Markeset, T. (2011). Maintainability analysis considering time-dependent and time-independent covariates. Reliability Engineering & System Safety. 96: 210-217.

[24]. Smith, D.J. (2011). Reliability, Maintainability and Risk 8e: Practical Methods for Engineers Including Reliability Centred Maintenance and Safety-Related Systems. Elsevier.

[25]. Barabady, J. and Kumar, U. (2007). Availability allocation through importance measures. International Journal of Quality & Reliability Management. 24: 643-257.

[26]. Hoseinie, H., Ataei, M., Khalokakaie, R., Ghodrati, B. and Kumar, U. (2012). Reliability analysis of the cable system of drum shearer using the power law process model. International Journal of Mining, Reclamation and Environment. pp. 1-15. doi:10.1080/17480930.2011.622477.

[27]. Ghodrati, B. and Kumar, U. (2005). Reliability and operating environment-based spare parts estimation approach: a case study in Kiruna Mine, Sweden. Journal of Quality in Maintenance Engineering. 11: 169-184.

Appendix 1. Results of analytical iid tests and statistical distribution or model fitting.

Subsystems	**Approach**	**Stratum**	**Trend Tests**				**Auto-correlation Tests**				**iid**	**Model or Distribution**			
			P-Value			Test result	Test Statistic-Log 1			Test result					
			MIL	La.	A.D.		ACF	TSTA	LBQ				1st.	2nd.	3rd
Lo.	**SCRM**	**1**	0.713	0.247	0.038	No trend	–0.028	–0.190	0.040	No Auto-correlation	Accept	Weibull-3P	0.59	35.369	8.425
		2	0.31	0.142	0.1	No trend	0.032	–0.33	0.11	No Auto-correlation	Accept	Loglogistic-2P	1.349	0.522	
Bl.	**SCRM**	**1**	0.678	0.581	0.955	No trend	0.077	0.2	0.06	No Auto-correlation	Accept	Loglogistic-2P	6.148	0.735	
		2	0.005	0.006	0.002	Trend	0.203	0.84	0.83	No Auto-correlation	Reject	PLP	0.578	39.129	
DT.1	**SCRM**	**1**	0.248	0.511	0.733	No trend	0.012	0.1	0.01	No Auto-correlation	Accept	Exponential-2P	1.969	0.5	
		2	0.692	0.929	0.95	No trend	0.034	0.3	0.09	No Auto-correlation	Accept	Weibull-3P	0.813	2.756	0.43
		3	0.491	0.794	0.33	No trend	–0.011	–0.06	0.000	No Auto-correlation	Accept	Weibull-3P	0.936	4.318	0.194
		4	0.026	0.032	0.024	Trend	–0.176	–0.74	0.65	No Auto-correlation	Reject	PLP	0.656	23.028	
		5	0.937	0.863	0.971	No trend	0.023	0.050	0.000	No Auto-correlation	Accept	Weibull-3P	8.403	10.821	7.346
DT.2	**SCRM**	**1**	0.0	0.0	0.0	Trend	0.015	0.16	0.03	No Auto-correlation	Reject	PLP	0.633	0.759	
		2	0.57	0.799	0.966	No trend	0.044	0.37	0.15	No Auto-correlation	Accept	Weibull-3P	1.180	2.271	0.435

A.D.: Anderson-Darling**, La.:** Laplace test**, MIL:** MIL-Hdbk-189

سنجش قابلیت تعمیر پذیری مبتنی بر تأثیر شرایط محیطی، مطالعه موردی: معدن مس سونگون

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چکیده:

هزینه چرخه عمر یک سیستم متأثر از قابلیت تعمیر پذیری آن است. خود قابلیت تعمیر پذیری نیز به عنوان یک شاخص طراحی به شدت متأثر از شرایط محیطی است؛ بنابراین تأثیرات ناشی از شرایط محیطی باید در فازهای اولیه طراحی مورد سنجش قرار گیرد. بدین منظور می‌توان از مدل نرخ تعمیرات متناسب (PRM)، برگرفته از مدل نرخ مخاطرات متناسب (PHM) بهره جست که این تأثیرات را در قالب فاکتورهای ریسک در تحلیل قابلیت تعمیر پذیری وارد می‌کند. در مدل RPM تأثیرات شرایط محیطی به صورت مستقل از زمان در نظر گرفته می‌شود که این فرض در برخی موارد قابل پذیرش نیست. هدف این تحقیق ارائه رویکردی برای پیش‌بینی عملکرد قابلیت تعمیر پذیری تجهیزات معدنی با در نظرگیری تأثیرات شرایط محیطی وابسته به زمان است. مدل رگرسیون لایه‌بندی کاکس (SCRM) رویکردی پیشنهادی برای تحلیل ناوگان استخراجی معدن مس سونگون ایران در حضور فاکتورهای ریسک وابسته به زمان است.

کلمات کلیدی: قابلیت تعمیر پذیری، نرخ تعمیرات متناسب (RPM)، مدل رگرسیون لایه‌بندی کاکس (SCRM)، شرایط محیطی، معدن مس سونگون.