Spare Part Management Considering Risk Factors

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ABSTRACT
The spare parts provision is a complex process, which needs a precise model to analyze all factors with their possible effects on the required number of spare parts. The required number of spare parts for an item can be calculated based on its reliability performance. Various factors can influence the reliability characteristics of an item, including operational environment, maintenance policy, operator skill, etc. Thus, the statistical approach of choice for reliability performance analysis should assess the effects of these factors. In this study, Reliability Regression Models (RRM) with risk factors have been used to estimate the required number of crane shovels in the Jajarm bauxite mine. For this, at the first stage, all risk factors and failure data have been collected. The required data were extracted from a database of 15 months, which were collected from different sources, such as daily reports, workshop reports, weather reports, meetings, and direct observations in the format of time to failures and risk factors. After that, the potential distribution has been nominated to model the reliability of the crane shovels bucket teeth. The Akaike information criterion and Bayesian information criterion have been used to identify the best fit distribution. The candidate distribution with the smallest AIC and BIC value is the best distribution that fits the data. After that, the required number of spare parts is calculated. The results show 18% differences between the forecasted number of required spare parts when considering and non-considering the risk factors.

Keywords
Spare part, Reliability, Risk factors, Jajarm bauxite mine

1. INTRODUCTION
A system without failure can never be designed due to technological and economic issues. Thus, to provide support and spare parts to guarantee a proper level of availability throughout the system's lifecycle, appropriate and well-scheduled activities need to be performed [1]. However, the provision of spare parts appears to be a complex process, which needs an accurate analysis of all factors affecting the required number of spare parts.

The spare parts availability is surely a highly important factor, increasing the system's performance and effectiveness. If all needed spare parts for the repair can be immediately provided in a system failure, we can significantly reduce downtime. Otherwise, the increased waiting time can cause dramatic production losses. Yet, the overstocking of unnecessary spare parts or the many outdated stored units may also lead to huge losses due to the investment costs. Thus, we need to provide an accurate prediction rate of spare parts in the design and operation phases as a major factor in the product support activity [2,**[3**]. However, spare parts prediction and optimization are also complex problems, which need to identify all effective factors and choose a proper model to quantify their effects on the required number of spare parts. Some major effective factors are operational conditions, climatic conditions (temperature, wind, snow, dust, ice, etc.), operators and maintenance crew skills, the history of repair activities done on the machine, etc. [4,[**5**].

The first step in the reliability-based spare parts provision is to identify the item's reliability performance and failure rate. We can then estimate the number of the required spare parts and the availability rate of spare parts [[**6**]. However, we need to consider all factors influencing the reliability performance of the item for effective forecasting. The factors with a possible effect on the reliability performance of an item are called risk factors, ignoring which may lead to inaccurate results in the reliability performance analysis and the provision of spare parts [7-[**10**].

In the recent two decades, Kumar, Ghodrati, Barabadi, and Nouri Qarahasanlou introduced Proportional Hazard Model (PHM) in the spare parts provision process [[**11**-16]. For example, in 2015-2018, Nouri Qarahasanlou demonstrated the Cox regression method for mining fleet, spare tire analysis of dump truck in Sungun mine, Iran.

The required number of spare parts is calculated in the reliability-based statistical approaches according to the item reliability. Hence, we should measure their effects on the item reliability performance to assess the impact of operational conditions on the required number of spare parts. However, operating time is the only variable evaluated in most available studies, and operational conditions have not been considered a variable [17]. Thus, the RRM has been rarely used and implemented as a proportional hazard model for spare parts predictions.

A review of the relevant literature showed the occasional use of reliability models with risk factors for spare part predictions. This paper was designed to examine the use of RRM in the provision of spare parts for bucket teeth in the Jajarm bauxite mine, Iran. Bucket teeth are considered important parts of the crane shovels, and the shortage of such items can stop production in the mine. The operational conditions in a mine are more difficult than in most other industries. The reliability characteristics of the bucket teeth are believed to be influenced by operational conditions in the Jajarm bauxite mine. Hence, investigating the issue seems important to accurately estimate the number of spare parts needed while considering operational conditions to reduce downtime.

Moreover, as different types of bucket teeth can be used for the loading process, we need to find the most cost-effective one to minimize the loading process costs. The reliability performance of the bucket teeth by considering operational conditions can provide essential information for such a cost analysis. One of the most important issues in using a regression model such as the PHM or family model is the baseline function. Because the risk factors shift it up or down. Most industrial machines or systems deprived of baseline function and researchers are forced to find it from Time between Failures (TBFs). In this way, most of them did not discuss "how" or "why" selected special baseline function. This paper used the goodness of fit test for choosing the best parametric regression model and best analysis method. Model selection plays a fundamental role in choosing the best model from a series of candidate models for data-driven modeling and system identification problems. In general, system identification and data-driven modeling consist of several important steps, including data collection, data processing, selection of representation functions, model structure selection, model validation, and model refinement [17]. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are two most popular measures among various model selection methods. The rest of the paper is organized as follows: Description of the basic concept and methodology for spare parts prediction by RRM in Section 2. Section 3 demonstrated using this methodology through a case study followed by showing how an appropriate RRM can be found for specific data sets. Finally, section 4 provided relevant conclusions.

2. RELIABILITY ANALYSIS CONSIDERING RISK FACTORS EFFECTS

The RRM can be categorized into two main groups: Parametric and non-parametric models. In the parametric method, like the family of accelerated failure time models, the lifetime of a system is assumed to have a specific distribution, such as lognormal distribution. However, parametric methods may be misleading if the historical data does not follow the selected distribution pattern associated with incorrect assumptions about the parametric method. On the other hand, in non-parametric methods such as the proportional hazard models family, no specified distribution is assumed for a system lifetime [17–19].

A major contribution to the concept of non-parametric models for modeling the effects of risk factors is the PHM suggested by Cox [18]. In general, the basic theory of these non-parametric models is to build the baseline hazard function using historical failure data and the risk factor function by using the risk factor data. The baseline hazard function is the hazard rate experienced by an item when the effect of the risk factors is equal to zero. The risk factor function shows how the baseline hazard model will be changed due to risk factors. To see the most available RRM see references []. After identifying the distribution of failure data using the appropriate model, we can calculate the number of item failures in a specific period. Finally, the required spare parts can be calculated using an existing model like birth and death or Palm's theorem and considering other factors such as expected preventive maintenance frequency and repair rates for the repairable items [21]. This is a continuous procedure, which should be updated by upcoming historical data.

The PHM model is based on the proportionality of the hazard ratio (PH). The risk factors are time-independent variables, suggesting that the ratio of any two hazard rates is constant concerning time [22]. In PHM, the hazard rate Proportional Hazard Model (PHM) for an item is a product of the baseline hazard function, λ_0 (t) of the item and a function $\psi(z,\alpha)$ incorporating the effect of risk factors. The generalized form of PHM that is most commonly used is written as [23]:

$$\lambda(t,z) = \lambda_0(t)\psi(z,\alpha) \quad (1)$$

Where λ_0 (t) is the baseline hazard function, and $\psi(z,\alpha)$ is a function incorporating risk factors. And z is a row vector consisting of the covariates, and α is a column vector consisting of the regression parameters. If the $\psi(z,\alpha)$ function be a log-linear, therefore, the common form of PHM is expressed as equation (*2* [13]:

$$\lambda(t,z) = \lambda_0(t)\psi(z\alpha) = \lambda_0(t)exp\left(\sum_{i=1}^{n} z_i\alpha_i\right) \quad (2)$$

Where Z_i , i = 1, 2 ... n, are the covariates associated with the system and α_iI = 1, 2 ... n, are the model's unknown parameters, defining the effects of each one of the n covariates. For example, the "t" multiplicative factor,$exp(z\alpha)$ may be termed the relative risk of failure due to the presence of the covariate z.

The reliability influenced by the risk factors is given as [11]:

$$R(t,z) = \left(R_0(t)\right)^{exp\left(\sum_{i=1}^{n} z_i\alpha_i\right)} \quad (3)$$

Where $\lambda(t,z)$ and $R(t,z)$ are the hazard and reliability functions, respectively; and α (column vector) is the unknown parameter of the model or regression coefficient of the corresponding n risk factors, and z is row vector consisting of the risk factor parameters indicating the degree of influence of each risk factor on the hazard function; and $\lambda_0(t)$ and $R_0(t)$ are the baseline failure rate and baseline reliability, respectively.

As mentioned earlier, the PH assumption suggests that the risk factors are time-independent variables; thus, the ratio of any two hazard rates is constant concerning time. Different approaches have been used to determine whether PH assumption fits a given data set. The graphical procedure, a goodness-of-fit testing procedure, and a procedure that involves the use of time-dependent variables have been used most widely in PH assumption evaluations [23]. There are two general approaches to check the time-dependency of risk factors: i) graphical procedure, ii) goodness-of-fit testing procedure [24]. The developed graphical procedure can generally be categorized into three main groups as i) cumulative hazards plots, ii) average hazards plots, and iii) residual plots [25]. For example, in the cumulative hazard plots, the data will be categorized based on different risk factors to be checked for time dependency. Hence, if the assumption of PH is justified, then the logarithm plots of the estimated cumulative baseline hazard rates versus time for the defined categories should simply be shifted by an additive constant coefficient of risk factors. In other words, they should be approximately paralleled and separated, corresponding to the different values of the risk factors. Departure from parallelism of the above plots for different categories may suggest that z_r is a time-dependent risk factor. For the review of other graphical approaches, see [26]. Like the cumulative baseline hazard rate, a Log-log Kaplan-Meier curve over different (combinations of) categories of variables can be used to examine the PH assumption. A log-log reliability curve is simply a transformation of an estimated reliability curve, which results from taking the natural log of an estimated survival probability twice. If we use a PHM model and plot the estimated log-log reliability curves for the defined categories on the same graph, the two plots would be approximately parallel[40]. In the residuals plots at the first step, the residual should be estimated by using the estimated values of the cumulative hazard rate, $H_0(t_i)$, and the regression vector η as:

$$e_i = -H_0(t_i)\exp(\eta_r z_r) \quad (4)$$

Where $H_0(t_i)$ is cumulative hazard rate, η regression vector; and z_r is r^{th} row vector consisting of the risk factor parameter.

If the PH assumption is justified, then the logarithm of the estimated reliability function of e_i against the residuals should lie approximately on a straight line with slope -1.

When the risk factor is time-dependent, the component will have different failure rates based on different values of the time-dependent risk factors. In this case, the Stratified Cox Regression Method (SCRM) can analyse the data [26]. The "stratified Cox model" is an extension of the PHM, allowing the control process by "stratification" of a predictor not to satisfy the PH assumption. Each level is defined as a stratum in this model when there are n levels for the time-dependent risk factors. Under these circumstances, the historical data will be classified into various strata. Then, separate baseline reliability functions are computed for each stratum, while the regression coefficients for all strata are equal. We can write the hazard rate using the stratification approach in the s^{th} stratum as follows [22]:

$$\lambda_s(t,z) = \lambda_{0s}(t) exp\left(\sum_{i=1}^{n} z_i \alpha_i\right) \qquad s = 1,2,\ldots,r \tag{5}$$

The component reliability influenced by risk factors in the s^{th} stratum Eq. 6:

$$R_s(t,z) = \left(R_{0s}(t)\right)^{exp\left(\sum_{i=1}^{n} z_i \alpha_i\right)} \qquad s = 1,2,\ldots,r \tag{6}$$

Where $\lambda_s(t,z)$ and $R_s(t,z)$: are the hazard and reliability functions in the s^{th} stratum; and $z\alpha = \sum_{i=1}^{n} z_i\alpha_i$, and α (column vector) is the unknown parameter of the model or regression coefficient of the corresponding n risk factors; and z row vector consisting of the risk factor parameters, indicating the degree of influence which each risk factor has on the hazard function; and $\lambda_{0s}(t)$ and $R_{0s}(t)$ are the baseline failure rate and baseline reliability in the s^{th} stratum.

3. RELIABILITY-BASED SPARE PART PROVISION CONSIDERING RISK FACTORS

The Reliability Spare Part Provision (RSPP) was used to provide spare parts based on the renewal theory, which is one of the popular mathematical models. The renewal process model provides an approach to describe the rate of events occurring, in our case, the number of failures, over time. It seems reasonable to assume that the number of spare parts required is equal to the number of failures since the non-repairable components are thrown away. The renewal process can be employed whenever the failure rate is not constant. However, at constant failure rates, we use the homogeneous Poisson process as a special case of a renewal process to forecast the demands for spare parts. It is important to note that the above statement is valid only for non-repairable spares [12]. In cases of quite a long operation time (and planning horizon) of the machine, during which the parts are installed, and when we should make several replacements during this period, the average number of failures in time t, E[N(t)] = M(t) will be stabilized to the asymptotic value of the function as follows [12]:

$$M(t) = E\left[N(t)\right] = \frac{t}{\bar{T}} + \frac{\zeta^2 - 1}{2} \tag{7}$$

where ζ denotes the coefficient of variation of the time to failure and defined as [12]:

$$\zeta = \frac{\sigma(T)}{\bar{T}} \tag{8}$$

where $\bar{T}$ is the average time to failure for replacements of a part and $\sigma(T)$ is the standard deviation of time to failure []. The approximated number of spares (N_t) needed during period of planning horizon with a probability of shortage = $1 - p$ is given by [12]:

$$N_t = \frac{t}{\bar{T}} + \frac{\zeta^2 - 1}{2} + \zeta\sqrt{\frac{t}{\bar{T}}}\Phi^{-1}(p) \tag{9}$$

Where $\Phi^{-1}(p)$ is the inverse normal distribution function Thus, estimation of N_t need to calculate ζ in different distribution, specified t, and p. As mentioned before, PHM or SCRM used for the model time dataset in incorporating the effects of risk factors. The problem originates here that determining $\bar{T}$ and $\sigma(T)$ for PHM. Hence, we had to change the parameter of the best fit classic distributions (e.g., Exponential, Weibull, Lognormal, etc.) in the reliability baseline function to consider the risk factors' effects. Unfortunately, as stated above, most of the studies conducted on RSPP (almost all of them) had used just two exponential and Weibull distributions instead of the best-fit one. Thus, we tried to fix it in our study.

4. SPARE PARTS INVENTORY MANAGEMENT

Every inventory management system's major goal is to obtain a good spare part rate with a minimum inventory investment and the lowest managerial costs. This may be fulfilled directly by reducing the ordering cost by ordering spare parts more than required. Insufficient provision level increases unacceptably long downtime, while unreasonably high levels can also trap the capital sources in the inventory section [[]. We can use the Economic Order Quantity (EOQ) to balance the inventory management, which minimizes the total inventory costs in holding and ordering phases by eliminating the shortages that can be calculated as follows [11]:

$$EOQ = \sqrt{\frac{2DS}{H}} \tag{10}$$

Where: "D" is the annual demand (units/year) [equals N_t in one year], "S is the cost of ordering or setting up one lot ($/lot), and "H" is the cost of holding one unit in the inventory for a year (often calculated as a proportion of the item's value). We had to calculate the "Reorder Point (ReP)" for obtaining the "continuous review system" as inventory position controlling and management. The ReP is[11]:

$$ReP = d \times L + \overline{\sigma_D \times \sqrt{L}\Phi_{\left(p/2\right)}} \tag{11}$$

where d: is the average demand, L is the lead time, $\Phi_{(p/2)}$: is the confidence level of the cycle service, and σ_D: is the number of standard deviations from mean and calculated as [11]:

$$\sigma_D = \sqrt{\frac{t}{\bar{T}}} \tag{12}$$

5. CASE STUDY

Spare parts for maintenance tasks, except for preventive maintenance activities, are usually required at random intervals. Hence, due to the uncertainty about the time of failure, the spare parts can be modeled using the probability distribution illustrated in previous sections. As Figure 1 presents, the methodology is based on five main tasks:

- Establishing the context
- Data collection, identification, and formulation of risk factors.
- Identification of the model of failure data considering risk factor effects.
- Calculation of the required number of spare parts.
- Inventory management

5.1 Establishing the Context

The case study refers to the crane shovels bucket teeth (m = 5) from the Kaj-Mahya company put into service in the Jajarm bauxite mine. Jajarm bauxite mine in Iran has 19 main open mines in the city of Jajarm. The longitudinal expanse of the mine from west to east (namely: Golbini 1-8, Zou 1-4, Tagouei 1-6, and Sangtarash) is 16 kilometers. The length of these sections is as follows: Golbini: totally 4.7 km, Zou mines: totally 3.3 km, Tagouei mines, totally 5 km, and Sangtarash mine is about 3 kilometers in length. The Jajarm bauxite falls in the lens-like layer category. The expanse of bauxite is mostly in the form of layers. The mineral lies on the karstic-dolomites that make up the Elika formation, which lies under the shales and sandstones of Shemshak formation. The bauxite layer is not of even thickness and consistent quality. In general, the bauxite layer ranges from less than 1 meter to about 40 meters in thickness. The main design characteristics (weight, size, maximum load capacity, etc.) of the crane shovels are nearly identical.

5.2 Data Collection

Using the developed framework in Figure 1, the failure data and associated observed risk factors should be collected at the first stage. For this aim, the observed risk factors should be identified. Table 1 shows the selected observed risk factors. As this table shows, 6 risk factors are identified which may affect the reliability of the crane shovels bucket teeth. The number in the branches in Table 1 is used to nominate the risk factors. For example, crane shovels work in three different shifts named morning, afternoon, and night shifts; here, zero, 1, and 2 are used to represent these shifts, respectively. Table 2 shows a sample of data.

Table 1: The identified observed risk factors for the crane shovels.

Risk factor	Risk factor level	Risk factor	Risk factor level
Working Shift (z_{wf})	Morning shift [0]	Rock Kind (z_{rk})	H. Bauxite [1]
	Afternoon shift [1]		
	Night shift [2]		LG. Bauxite [2]
Humidity (z_p)	Continuous		Kaolin Bauxite [3]
Temperature (z_t)	Continuous		Chile Bauxite [4]
System ID (Crane shovels number)	DT1 (1) to DT4 (4)		Tailings [5]
			Dolomite [6]

To formulate the risk factors, we used observation, repair shop cards and reports, and the experience of managers, operators, and maintenance crews, especially with the field data. The part of data with risk factors is shown in Table 2.

Table 2: A sample of failure data and their associated risk factors.

No.	TBF(Hours)	z_{id}	z_{wf}	z_{bt}	z_{rh}	z_t oC	z_{rk}
1	408	1	2	5	53	5	2
2	422	1	1	1	28	5	5
3	447	2	3	2	57	1	3

5.3 Reliability Model Identification

We present the test of Harrell and Lee (1986), a variation of a test originally proposed by Shenfield (1982) and based on the residuals defined by Shenfield, now called the Shenfield residuals. This study used the goodness-of-fit (GOF) test to check the PH assumption. The GOF testing approach is attractive because it provides a test statistic and p-value (P (PH)) for checking the PH assumption for a given predictor of interest. Thus, a more objective decision provides by a statistical test than a graphical approach. The P (PH) is used for evaluating the PH assumption for that variable. An insignificant (i.e., large) P(PH), say greater than 0.10, suggests that the PH assumption is reasonable. In contrast, a small P(PH), say less than 0.05, suggests that the variable being tested does not satisfy this assumption [27]. Table 3 is illustrated the mean value and the statistical GOF test outcomes of influence risk factors for data.

Table 3: Statistical test approach results for PH assumption

		Rock type	Temperat ure	Humidity	System ID	Shift
TBF	Pearson Correlation (P-PH)	.[a]	.[a]	.[a]	-.087	.279
	Sig. (2-tailed)				.681	.176
	N	0	0	0	25	25
a. Cannot be computed because at least one of the variables is						

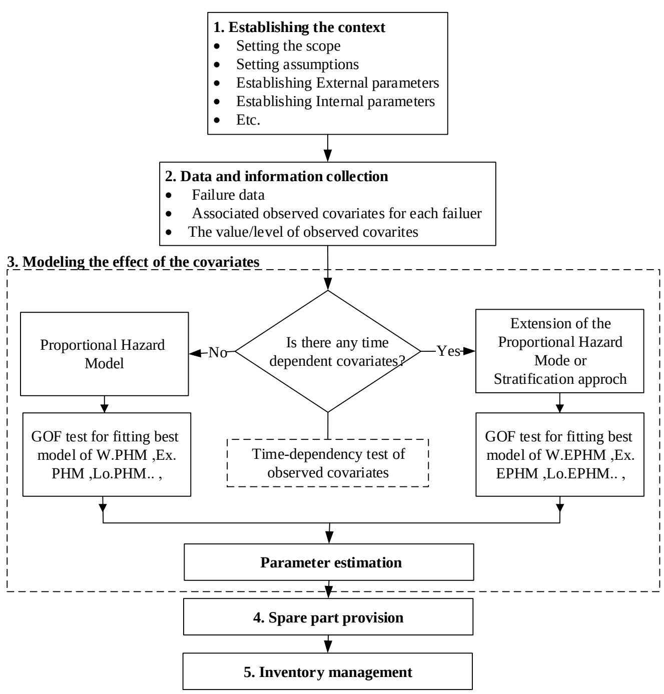

Figure 1: A methodology for calculating required numbers of spare parts considering the effect of risk factors.

The P(PH) values given in this table provide GOF tests for each variable in the fitted model adjusted for the other variables in the model. The P (PH) values are quite high for all variables satisfying the PH assumption. Also, the log minus log survival plot was used as a graphical test for PH assumption. In this test, if the risk factors are time-independent, Log Minus Log (LML) survival. To check the time-dependency of risk factor effect on equipment performance, collected data of mine equipment were stratified based on rock types and system ID. Plot or log cumulative failure plot versus time graphs for the different selected risk factors yield parallel curves. The results show that the plotted curves are parallel for five types using LML and log cumulative failure plots. For example, Figure 2 shows the results of such analysis for teeth in both rock types and system ID. Thus, according to Figure 1, the PHM can assess the risk factors of the teeth.

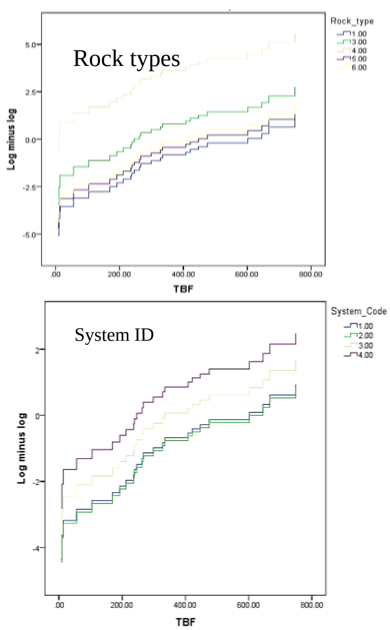

Figure 2: The Log minus log graph for the time between crane shovels based on rock kind and system ID.

According to methodology steps in Figure 1 on the left side of the algorithm, the GOF test needs to fit the best baseline function for data. The AIC and BIC can be used to find the best fit distribution for the baseline hazard rate [28]. The candidate distribution with the smallest AIC and BIC value is the best fit distribution to model the baseline hazard rate [29]. Many variations of AIC have been developed for model selection. The AIC was designed to estimate the Kullback–Leiber information of models in 1998; also, the delta AIC and the Akaike weights were introduced to measure how much better the best model is when compared with the other models. The AIC, delta AIC and AIC weights are calculated for each candidate model in the model selection process. Usually, the 'best' model is chosen to be the model with the smallest AIC. The BIC model selection criterion proposed by Schwarz in 1978. It referred to as the Schwarz information criterion, or the Schwarz BIC. Similar to AIC, BIC is also calculated for each candidate model and the model with the smallest BIC is chosen to be the best mode. The only difference between AIC and BIC is that BIC uses a larger penalty on the increment of the model terms. In recent years, BIC has also been increasingly used as model selection criterion [**1**31,32]. It can be noted that both AIC and BIC have their own advantages and limitations. It cannot be guaranteed that one is better than another regardless of application scenarios. The reason is that the data, model type and other aspects of the modelling problems can be significantly important in determining which of the criteria is more suitable.

As mentioned, the AIC and BIC are applied to select the best fit distribution for the baseline hazard rate under two different techniques for model estimation (complete and backward stepwise) with for different distribution (Weibull, Exponential, Lognormal and Log-Logistic). Table 4 shows the values of the AIC and BIC for the different nominated distributions for the baseline hazard rate with the same risk factors. As a result in Table 4: shows, the Weibull PHM is the most suitable model for the data, as it has the smallest AIC or BIC among all the models. Therefore, the model with unobserved heterogeneity can better estimate the reliability of the teeth data. In stepwise methods, the score statistic is used to select variables for the model. In this study, corresponding estimates are obtained by a backward stepwise method and tested for their significance based on the Wald statistic (P-value).

Table 4: Goodness of fit of different reliability models.

Model	AIC	BIC
Weibull Model - Estimation stepwise	349.77	354.26
Weibull Model - Estimation complete	359.47	369.94
Exponential Model - Estimation complete	357.74	368.21
Lognormal Model - Estimation stepwise	425.31	425.31
Lognormal Model - Estimation complete	403.84	414.31
Log-Logistic Model - Estimation stepwise	356.13	362.12
Log-Logistic Model - Estimation complete	360.92	371.40

SYSTAT software is used to estimate the value of the regression vector. The asymptotic distribution of the Z statistic is chi-square with degrees of freedom equal to the number of parameters estimated. In the backward stepwise procedure, the effects of one risk factor, "Temperature ($\mathbf{z_t}$)"is found significant at the 10% level. The estimates of α (coefficient of the risk factor) and parameters of two parameters, Weibull baseline distribution (Shape and Scale), are listed in Table 5.

Table 5: Estimation of reliability baseline parameters and risk factor coefficient.

Parameter	Estimate	Standard Error	Z	p-Value
Shape	1.344	0.228	5.904	0
Scale	238.766	123.304	1.936	0.053
Temperature	0.031	0.032	0.975	0.329

The operational reliability considering the environmental conditions are represented respectively as:

$$R(t,z) = \left(exp\left(-\frac{t}{238.766} \right)^{1.344} \right)^{exp(0.031 z_t)} \tag{13}$$

The reliability and hazard rate of the teeth of crane shovels is now calculated and plotted for the mean value (150C), low value (-70C), and high value (200C) as normal, cold, and hot weather of zt, as shown in Figure 3. The results show the teeth in hot weather are less reliable than the teeth in other weather conditions. As can be seen, their reliability reaches about 58% after about 100 hours of operation. Furthermore, there is a 93% and a 95% chance that teeth will work without failure for 24 hours in normal and cold weather, respectively. The results can help engineers and managers decide operation planning, maintenance strategy, sales contract negotiations, spare parts management, etc.

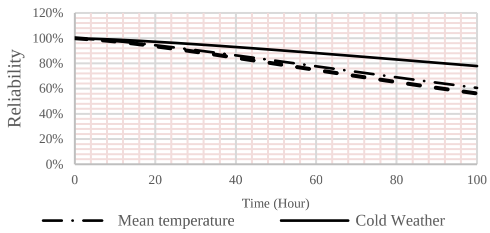

Figure 3. Comparison of reliability performance of teeth in normal, cold, and hot weather.

5.4 Spare Part-Provision

According to the existing literature, if the distribution of baseline hazard rate of an item is Weibull, the effect of risk factors only changes the scale parameter of the distribution, and the shape parameter remains unchanged. Therefore, shape parameter (β) and scale parameter (η), of Weibull distribution considering the effect of risk factors are defined by [12]:

$$\begin{cases} \beta = \beta_0 \\ \eta = \eta_0 \left[exp\left(\sum_{i=1}^{n} z_i \alpha_i \right) \right]^{-\frac{1}{\beta_0}} \end{cases} \tag{14}$$

The $\bar{T}_s$ and $\sigma_s(T)$ of the Weibull distribution and the Power Law Process (PLP) can be calculated based on the shape and scale parameter, expressed as Eq.15:

$$\bar{T}_s = \eta_s \Gamma\left(1 + \frac{1}{\beta_s}\right) \tag{15}$$

$$\sigma_s(T) = \eta_s \sqrt{\Gamma\left(1 + \frac{2}{\beta_s}\right) - \Gamma^2\left(1 + \frac{1}{\beta_s}\right)} \tag{16}$$

The number of required spare parts for teeth is calculated using equations (*13*and (*14*for considering the effect of risk factors and without them. The operation with the probability of storage is equal to 95%. The results of the analysis for five years are shown in Table 6.

Table 6: Spare part-provision based on WPHM and without risk factor effect.

Year	Spare part	
	with risk factors	**without risk factors**
1	21.49	15.67
2	40.24	29.09
3	58.51	42.09
4	76.52	54.89
5	94.37	67.55

The result of the data analysis of the case study shows that the required number of spare parts according to the WPHM approach is more than ignoring the effect of risk factors. In addition, Table 7 provides the number of spare parts required in 5 years considering the influence factor. As Table 7 shows, there is a big difference between cold and hot weather spare part required that is about hot weather two times bigger than a cold one.

Table 7: Required number of spare parts for different weather conditions over 5 years.

Year	Spare part	
	cold weather	**hot weather**
1	13.60	23.60
2	25.14	44.31
3	36.31	64.50
4	47.28	84.43
5	58.12	104.19

5.5 Spare Part Inventory Management

We start with the following assumptions:

- The cost of one tooth equals 20 USD$
- The cost of ordering one lot equals 2 USD$
- The annual holding cost equals 2 USD$ of the part cost
- The average lead-time is 5 days
- Cycle service confidence level is 95%

The EQO and ReP concerning annual demand rates in different scenarios are calculated based on equations (*10* and (*11* and tabulated in Table 8 for considering and ignoring the condition. Table 8 shows that for 1 year with considering risk factors' effect whenever the inventory position reaches 6.56 units/teeth, we should order 3.04. However, ignoring the risk factor, the EOQ and ReP of teeth for one year are equal to 5.6 and 2.51, respectively. In comparison, the EOQ and ReP in both conditions, with or without considering the operating environment's effect, illustrate the significance of these factors and their role in the actual life of the parts. In other words, the operating environment parameters should be considered in the process management of machines, in this case, the crane shovels.

Table 8: Economic order quantity.

Year	With risk factors		With risk factors	
	EOQ	**Reorder point (ReP)**	**EOQ**	**Reorder point (ReP)**
1	6.56	3.04	5.60	2.51
2	8.97	4.44	7.63	3.65
3	10.82	5.56	9.18	4.56
4	12.37	6.54	10.48	5.35
5	13.74	7.44	11.62	6.07

6. CONCLUSION

The operational environment may have a significant influence on the required number of spare parts. Hence, any method, which is used, for spare parts provision must be able to quantify such effects. The reliability-based spare part provision considering the effect of risk factors can quantify the effect of the operational environment. In these methods, the operational environment can be considered a risk factor. Their effects on the reliability characteristic and consequently on the required number of spare parts can be analyzed. Available regression methods such as PHM can be used by defining the risk factors for spare parts provision properly to quantify influence factors. However, it is necessary to examine the historical data to find an appropriate model, which fits the data more appropriately. For example, the reliability analysis of the bucket teeth in Jajarm mine using Weibull PHM shows that the reliability of a part in cold weather is higher than in other conditions. Moreover, the temperature has a significant effect on the reliability characteristics of the bucket teeth and, consequently, on the required number of spare parts. The noticeable difference in spare parts estimation is caused by considering and neglecting the temperature effect. The economic order quantity and reorder point calculation show about an 18% difference between the two cases.

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