Original Research Article

Assessment of Spare Parts Requirement by Reliability: A Case Study

Ali Nouri Qarahasanlou[1*], Reza ShakorShahabi[1], Negar Fallahnejad[1]

1. Mining Engineering, Faculty of Technical & Engineering, Imam Khomeini International University, Qazvin, Iran

* ali_nouri@eng.ikiu.ac.ir

Abstract

Spare parts provision is a complex problem and requires an accurate model to analyze all factors that may affect the required number of spare parts. The number of spare parts required for an item can be effectively estimated based on its reliability. The reliability characteristics of an item are influenced by different factors such as the operational environment, maintenance policy, operator skill, etc. However, in most reliability-based spare parts provision (RSPP) studies, the effect of these influence factors has not been considered. Hence, the statistical approach selected for reliability performance analysis must be able to handle the effect of these factors. One of the important models for reliability analysis by considering risk factors is the proportional hazard model (PHM), which has received less attention in the field of spare parts provisioning. Thus, this paper aims to demonstrate the application of the available reliability models with covariates in the field of spare part predictions using a case study. The proposed approach was evaluated with data from the system of fleet loading of the Jajarm Bauxite mine in Iran. The outputs represent a significant difference in spare parts forecasting and inventory management when considering covariates.

Keywords: Spare part; Reliability; Proportional hazard model; Jajarm Bauxite mine.

1. Introduction

It is evident that there is no such system without failure, and it is impossible to design a system without failure. Therefore, it is necessary to adopt appropriate and well-scheduled activities regarding support and spare parts to ensure the desired level of availability throughout the system's life [1]. However, spare parts provisioning is a complex problem and requires an accurate analysis of many factors that may affect the required number of spare parts.

The availability of spare parts is an important factor that can increase the system's performance and effectiveness. The downtime of a failed system can be significantly reduced if all spare parts needed for the repair are immediately available. On the other hand, if spare parts are not immediately available, their waiting time can cause costly production losses. Moreover, overstocking unnecessary spare parts or the obsolescence of too many stored units can lead to huge losses due to investment costs. Hence, as an important part of product support activity, accurate spare parts prediction has to be considered seriously in the design and operation phases [2, 3]. Spare parts prediction and optimization is a complex problem and requires identifying all influence factors and selecting an appropriate model for

quantifying their effect on the required number of spare parts. Some of the important influence factors are the operational conditions, including climatic conditions (temperature, wind, snow, dust, ice, etc.), the skill of the operator and maintenance crew, the history of the repair activities carried out on the machine, etc., [4, 5].

All production systems typically need maintenance and the installation of spare parts, performed regularly to ensure product reliability. Whereas for increasing the performance of the production system, keeping spare parts of critical components should be carefully considered because it causes to enhance system efficiency and prevent unplanned stoppages. In this way, the performance indexes such as availability, reliability, and maintainability of the product are important and have a vast influence on product support.

The first step in the reliability-based spare parts provision is to identify the item's reliability performance and failure rate. After that, the number of required spare parts and the probability of spare part availability can be estimated [6]. However, to have an effective prediction, any factors that influence the reliability and performance of the item must be considered. The reliability performance of an item can be influenced by different factors such as the operational environment, geographical location, design material, maintenance history, operator

and crew skill, etc., [7, 8]. The factors that may influence the reliability performance of an item are referred to as covariates. Ignoring such covariates may lead to wrong results in reliability performance analysis and, consequently, in spare parts provisioning [8–10].

Kumar presented a concept for developing a service delivery strategy for industrial products with a special reference to mining systems in 2003. In this work, some factors that influence service delivery strategy are studied, and suggested approaches for service delivery strategy building to reduce these gaps, which would help reach customer satisfaction and fulfill operational commitments [11]. Ghodrati and Kumar, for the first time, discussed the required spare parts (hydraulic seal of hydraulic jacks of open pit loaders) based on product design characteristics and operating environment for conventional and functional products [12]. In 2004, S. Kumar studied the various sides of spares and service management from a maintenance, repair, and operations point of view [13]. Ghodrati and Kumar 2005 focused on the reliability and hazard rate of hydraulic brake pumps used in mining loaders and how to calculate required spare part requirements based on influencing factors [14]. These researchers also determine the number of required spare hydraulic jacks concerning the effect of the external factors, except time, on the reliability characteristics of components through the proportional hazard model [15]. Ghodrati 2007 attempted to analyze the risk of ignoring the effects of operating environment factors on the output of a process in the form of system downtime and loss of production by fault tree analysis and event tree analysis [16]. Ghodrati et al. proposed a mathematical model for spare parts prediction at the component level for the bucket lifting cylinder of the loader in the Swedish mining industry [17]. These researchers 2012 studied the influence of operating environmental factors on the failure rate of the wheel loader's brake pads data obtained from an open-pit iron ore mine in Iran for three years. The spares management software (SMS) was used [18]. Barabadi et al. presented the application of PHM to spare parts provision and demonstrated electricity meters in the power distribution system in Jajarm, Iran [19]. Recently, Barabadi et al. demonstrated the application of RRMC for the provision of spare parts for drill bits in the Jajarm Bauxite Mine, Iran [20]. In 2015-2018, Ali Nouri Qarahasanlou demonstrated the application of the Cox regression method for mining fleet and spare tire analysis of dump trucks in Sungun mine, Iran [21–28].

In statistical approaches for reliability modeling, the required number of spare parts is calculated based on the reliability performance of the item. Hence, to quantify the effect of operational conditions on the required number of spare parts, their effects should be quantified on the reliability performance of the item. However, in most of the available studies, operating time is the only variable, and operational conditions have not been considered as variables [1], [29–33]. Therefore, there is a lack of implementation of RRMC, such as the proportional hazard model for spare part predictions.

The proportional hazard model (PHM) is a valuable statistical procedure to estimate the reliability performance and failure rate of an item subjected to covariates. The main assumption in PHM is that the effect of covariates is time-independent; therefore, this model is not applicable for estimating the item spare parts in the presence of time-dependent covariates. The time-dependency of covariates, such as ambient temperature, can directly affect inventory management and spare part planning. Therefore, any method used for spare parts provision must be able to handle the time-dependency of the ambient temperature.

The literature review firstly shows a shortage of application of reliability models with covariates for spare part predictions. This paper aims to show the application of RRMC for the provision of spare parts for bucket teeth in Jajarm Bauxite Mine, Iran. Bucket teeth are among the important parts of the crane shovels, and any shortage of these items can lead to the stoppage of production in the mine. The operational conditions in a mine are more severe than in most other industries. It is believed that the operational conditions influence the reliability characteristics of the Bucket teeth in Jajarm Bauxite Mine. Hence, it is important to investigate this subject and accurately estimate the number of spare parts needed, considering the effect of operational conditions, to reduce downtime.

Moreover, because different types of bucket teeth can be used for the loading process, it is important to find the most cost-effective one to minimize the cost of the loading process. Considering the operating conditions, the bucket teeth' reliability can provide essential information for such a type of cost analysis. The rest of this paper is organized as follows: In Sections 2, 3, and 4, the basic concept and methodology for spare parts prediction using RRMC and RSPP are discussed. In Section 5, the application of this methodology is demonstrated by a case study. Furthermore, this section shows how an appropriate RRMC can be found for specific data sets. Finally, Section 6 provides the conclusions.

2. Reliability analysis considering Covariates Effects

The RRMC can be broadly categorized into two main groups: parametric and non-parametric models. In the parametric method, such as the family of accelerated failure time models, the lifetime of a system is assumed to have a specific distribution, such as lognormal. However, if the historical data does not follow the selected distribution and the assumptions about the parametric method are incorrect, parametric methods may be misleading. On the other hand, in the non-parametric method, such as the proportional hazard models family, no specified distribution is assumed for the lifetime of a system [30–33]. Reliability models have been developed based on the method suggested by Kaplan and Meier [29] and Nelson [31]. A major contribution to the concept of

non-parametric models for modeling the effects of covariates is the proportional hazard model (PHM) suggested by Cox [32]. In general, the basic theory of these non-parametric models is to build the baseline hazard function using historical failure data and the covariate function using covariate data. The baseline hazard function is the hazard rate that an item will experience when the effect of the covariates is equal to zero. The covariate function shows how the baseline hazard model will change due to the covariates' effect. Figure 1 shows the most available RRMC [33–35]. In these Models, the number of failures of the item in a specific period can be calculated after identifying the distribution of failure data using the appropriate model. Finally, the required number of spare parts can be calculated using an existing model such as Birth and Death or Palm's Theorem and other factors such as expected preventive maintenance frequency and repair rate for the repairable items [6]. This continuous procedure needs to be updated by upcoming historical data.

The PHM model is based on the proportional assumption (PH assumption) that the covariates are time-independent variables, which means that the ratio of any two hazard rates is constant concerning time [36].

The effects of covariates were made by the method known as the proportional hazard model (PHM), which is suggested by Cox [36, 37]. In PHM, the hazard rate 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 covariates. The generalized form of PHM that is most commonly used is written as [32]:

$$\lambda(t,z) = \lambda_0(t)\psi(z,\alpha) \tag{1}$$

The common form of the PHM is log-linear, expressed as the following equation [15], [16]:

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

The reliability influenced by the covariates is given as [12]:

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

Where $\lambda(t,z)$, and $R(t,z)$ are the hazard and reliability functions, respectively; $z\alpha = \sum_{i=1}^{n} z_i\alpha_i$; α (column vector) is the unknown parameter of the model or regression coefficient of the corresponding n covariates (z) (row vector consisting of the covariate parameters), indicating the degree of influence of each covariate on the hazard function; and $\lambda_0(t)$ and $R_0(t)$ are the baseline failure rate and baseline reliability, respectively.

As mentioned earlier, in the PHM, the proportional assumption (PH assumption) is that the covariates are time-independent variables, so the ratio of any two hazard rates is constant concerning time [36].
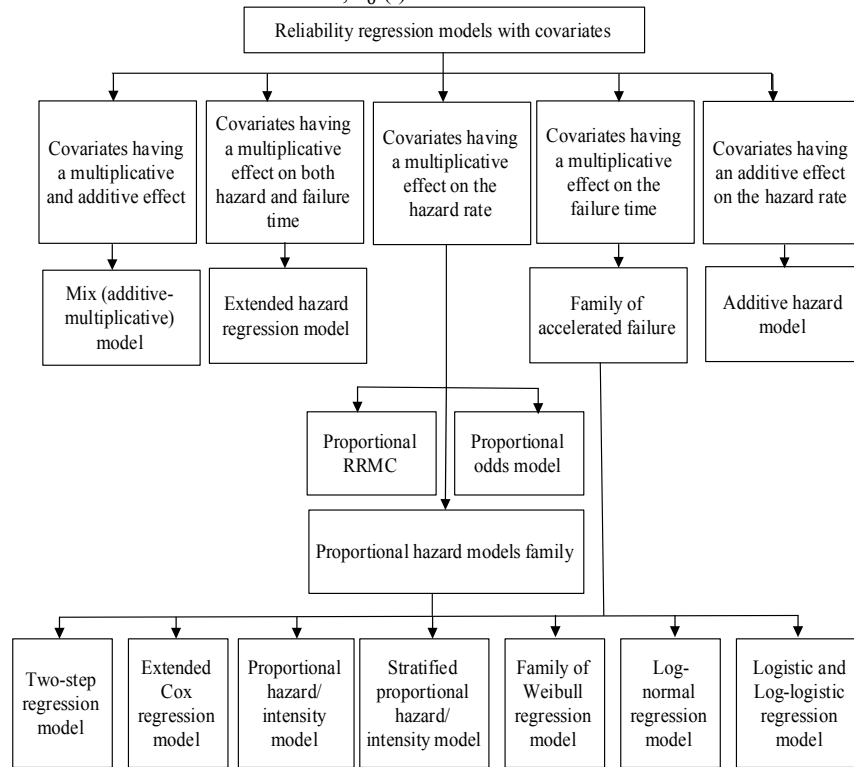

Figure 1. Reliability regression models with covariates [38]

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 involving time-dependent variables have been used most widely in PH assumption evaluations [37]. There are two general approaches to checking the time-dependency of covariates i) graphical procedure and ii) goodness-of-fit testing procedure [32]. The developed graphical procedure can generally be categorized into three main groups i) cumulative hazards plots, ii) average hazards plots, and iii) residual plots [8]. For example, in the cumulative hazard plots, the data will be categorized based on the different covariate levels that will be checked for time dependency. Hence, if the assumption of PH is justified, then the logarithm plots of the estimated cumulative baseline hazard rates against time for defined categories should be shifted by an additive constant coefficient of covariates. In the other world, they should be approximately parallel and separated, corresponding to the different values of the covariates. Departure from parallelism of the above plots for different categories may suggest that z_r is a time-dependent covariate. For a review of other graphical approaches, see [8], [39], [40]. Similar to the cumulative baseline hazard rate, a Log-log Kaplan-Meier curve over different (combinations of) categories of variables can be used to check the assumption of PH. A log-log reliability curve is simply a transformation of an estimated reliability curve that results from taking the natural log of an estimated survival probability twice. If we use PHM models and the estimated log–log reliability curves for defined categories on the same graph were plotted, the two plots would be approximately parallel [8]. 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:

$$e_i = -H_0(t_i)\exp(\eta_r z_r) \tag{4}$$

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 [8], [41].

When the covariate is time-dependent, the component will have different failure rates based on the different values of time-dependent covariates. In this situation, the stratified Cox regression method can be used for data analysis [4]. The "stratified Cox model" is an extension of the PHM that allows for control by "stratification" of a predictor that does not satisfy the PH assumption. In this model, when there are n levels for the time-dependent covariates, each level is defined as a stratum. Under this circumstance, historical data will be grouped in different strata. Then, for each stratum, separate baseline reliability functions are computed, while the regression coefficients for all strata are equal. The hazard rate using the stratification approach can be written as follows in the sth stratum [15, 36]:

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

Covariates influence the component reliability in the sth stratum [12]:

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

Where $\lambda_s(t,z)$, and $R_s(t,z)$: are the hazard and reliability functions in the sth stratum, $z\alpha = \sum_{i=1}^{n} z_i \alpha_i$, and α (column vector) is the unknown parameter of the model or regression coefficient of the corresponding n covariates (z) (row vector consisting of the covariate parameters), indicating the degree of influence that each covariate has on the hazard function. $\lambda_{0s}(t)$ and $R_{0s}(t)$ are the baseline failure rate and baseline reliability in the sth stratum. As with the original stratified Cox regression method, the model has two unknown components: the regression parameter α and the baseline failure function $\lambda_{0s}(t)$ for each stratum. The baseline failure functions for r remain completely unrelated in the different strata. If the "s" subscript suffix in Eqs. 5 and 6 are removed, PHM and reliability functions will be achieved [15, 16].

According to PHM, the hazard rate of an item is the product of a baseline hazard rate, $\lambda_0(t)$ that depends on time only, and a positive function, which describes how the hazard rate changes as a function of covariates as:

$$\lambda(t;z) = \lambda_0(t)\exp\left[\sum_{i=1}^{p_1} \eta_i z_i\right] \tag{7}$$

Where z_i, i=1,2,…,n, are the covariates associated with the item and η_i, i=1,2,…,n, are the model's regression parameters defining the effects of each covariate. An estimate of the η_i parameters can be obtained by maximization of the partial likelihood function [5]. The baseline hazard rate represents the hazard rate an item will experience when all covariates are equal to zero. PHM in the form of Eq.1 can only handle time-independent covariates. In the presence of time-dependent covariates, the extension of PHM or Stratification approach can be used. According to the extension of PHM, the hazard rate of an item can be calculated as follows:

$$\lambda(t;z;z(t)) = \lambda_0(t)\exp\left[\sum_{i=1}^{p_1} \eta_i z_i + \sum_{j=1}^{p_2} \delta_j z_i(t)\right] \tag{8}$$

Where η_i and δ_j are column vectors consisting of the regression parameters, z_i is a time-independent covariate and $z_j(t)$, is a time-dependent covariate, p_1 is the number of time-independent covariates and p_2 is the number of time-dependent covariates. The method of maximum likelihood can be applied for the estimation of η_i and δ_j. The reliability function in the presence of time-dependent and time-independent covariates is given by:

$$R(t;z;z(t)) = R_0(t)\exp\left[\sum_{i=1}^{p_1} \eta_i z_i + \sum_{j=1}^{p_2} \delta_j z_i(t)\right] \tag{9}$$

3. Reliability-based Spare Part Provision considering Covariates

RSPP is one of the popular mathematical models used in spare parts provisioning based on renewal theory. The renewal process model provides a way to describe the rate of occurrence of events (in our case, the number of failures) over time. Because non-repairable components are discarded, it is reasonable to assume that the number of spare parts required equals the number of failures. The renewal process can be used whenever the failure rate is not constant. Whenever the failure rate is constant, we use the homogeneous Poisson process as a special renewal process case to forecast spares' demands. It is important to note that the above statement is valid only for non-repairable spares (components) [15]. Suppose the operation time (and planning horizon) of the machine in which part (component) is installed is quite long, and several replacements must be made during this period. In that case, the average number of failures in time t, E[N(t)] = M(t) will stabilize to the asymptotic value of the function as [17, 42]:

$$M(t) = E\left[N(t)\right] = \frac{t}{\bar{T}} + \frac{\zeta^2 - 1}{2} \qquad (10)$$

Where ζ denotes the coefficient of variation of the time to failure and is defined as [17]:

$$\zeta = \frac{\sigma(T)}{\bar{T}} \qquad (11)$$

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 [17], [42]. If the time of planning horizon (t) is large, then N(t) in Eq. 10 Is approximately normally distributed (based on a central limit theorem) with mean = $\overline{N(t)}$. The approximated number of spares (N_t) needed during the period of planning horizon with a probability of shortage = $1 - p$ is given by [17], [42]:

$$N_t = \frac{t}{\bar{T}} + \frac{\zeta^2 - 1}{2} + \zeta\sqrt{\frac{t}{\bar{T}}}\Phi^{-1}(p) \qquad (12)$$

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. There is no problem in determining the t and p ,but for ζ needs to obtain the reliable distribution of the failure data of components. As mentioned before, PHM or SCRM has been used for the model time dataset to incorporate the effects of covariates. The problem originates here that determining $\bar{T}$ and $\sigma(T)$ for PHM is no easy task. Thus we need to apply changes in the parameter of best fit classic distributions (e.g., Exponential, Weibull, Lognormal, etc.) in the reliability baseline function for considering the covariates. As mentioned previously, a major part of the research based on RSPP (about all of them) used just two Exponential and Weibull distributions instead of the best-fit one. Therefore, in this study, we try to fix it.

4. Spare parts inventory management

The main objective of any inventory management system is to achieve an appropriate spare part level with a minimum inventory investment and managerial costs, which can be achieved, for instance, directly by saving on ordering costs by ordering more than what is needed. An inadequate level causes unacceptably long downtime; an unreasonably high-level causes blocked capital cost in inventory [20]. To achieve balance in inventory management, the economic order quantity (EOQ) can be used and is the lot size that minimizes the total inventory cost, concerning both holding and ordering concerning the elimination of shortages, and can be calculated as [42]:

$$EOQ = \sqrt{\frac{2DS}{H}} \qquad (13)$$

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).

For the "continuous review system" as inventory position controlling and management, we need to calculate the "reorder point (ReP)". The "reorder point" is [12]:

$$ReP = d \times L + \overline{\sigma_D \times \sqrt{L}\Phi}\left(\frac{p}{2}\right) \qquad (14)$$

where d: is average demand, L: is lead time, $\Phi_{(p/2)}$: is the confidence level of cycle service and σ_D: is the number of standard deviations from the mean and calculated as [12]:

$$\sigma_D = \sqrt{\frac{t}{\bar{T}}} \qquad (15)$$

5. Case study

Except for preventive maintenance activities, spare parts for maintenance tasks are usually required at random intervals. Hence, due to the uncertainty about the failure time, the number of spare parts can be modeled using the illustrated probability distribution. The methodology is based on four main tasks (Figure 2):

1. Establishing the context
2. Data collection, identification and formulation of covariates.
3. Identification of the model of failure data considering covariate effects.
4. Calculation of the required number of spare parts.
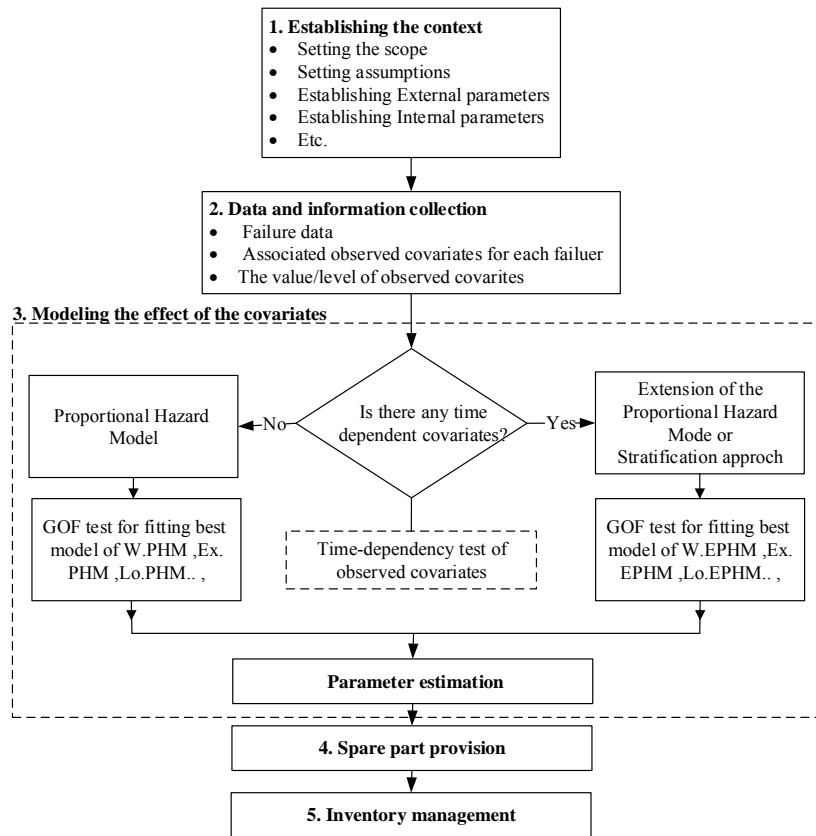5. Inventory management

Figure 2. A methodology for calculating the required numbers of spare parts considering the effect of covariates

5.1 Establishing the context

The case study refers to the failure data of the crane shovel bucket teeth ($m = 5$) from the Kaj-Mahya company 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 the Shemshak formation. The bauxite layer is not of even thickness and consistent quality. Generally, 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 2, the failure data and associated observed covariates should be collected at the first stage. For this aim, the observed covariates should be identified. Table 1 shows the selected observed covariates. As this table shows, six covariates are identified, which may affect the reliability of the crane shovel bucket teeth. The number in the branches in Table 1 is used to nominate (formulate) the covariates. For example, crane shovels are working in three 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 covariates for the loaders

Covariate	Covariate level	Covariate	Covariate 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 Covariate		Kaolin Bauxite [3]
Temperature (z_t)	Continuous Covariate		Chile Bauxite [4]
System ID (Crane shovels number) (z_{id})	DT.1 (1) to DT4 (4)		Tailings [5]
			Dolomite [6]

To formulate the covariates, 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 covariates is shown in **Table 2**. The "Status" shows the event type as a censored failure with "0" and complete failure as "1".

Table 2. A sample of failure data and their associated covariates

No.	TBF(Hs)	Status	z_{wf}	z_{rk}	z_{id}	z_t	z_p
1	408	1	2	1	1	22	53
2	422	1	2	5	1	19	28
3	447	1	1	6	1	8	57
4	212	1	1	6	1	14	32

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. The P(PH) is used to evaluate that variable's PH assumption. 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 tested variable does not satisfy this assumption [43]. Thus, a more objective decision provide by a statistical test than a graphical approach.

Table 3 is illustrated the mean value and the statistical GOF test outcomes of influence covariates for teeth data.

Table 3. Statistical test approach results for PH assumption

	Covariates	Rock type	temperature	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 constant.						

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 covariates are time-independent, log minus log survival plot (LML) or log cumulative failure plot versus time graphs for the different selected values of covariates yield parallel curves. To check the time-dependency of the covariate effect on equipment performance, collected data on mine equipment were stratified based on rock types and system ID. The results show that the plotted curves are parallel

for five types using LML and log cumulative failure plots. For example, Figure 3 shows the results of such analysis for teeth in rock types and system ID. Thus, according to Figure 2, the PHM can be used to assess the covariates of the teeth.

According to the methodology steps in Figure 2 on the left side of the algorithm (step 3), the GOF test needs to fit the best baseline function for data. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) can be used to find the best fit distribution for the baseline hazard rate [44]. The candidate distribution with the smallest AIC and BIC value is the best fit distribution to model the baseline hazard rate [45–47]. The AIC and BIC procedures are applied to select the best fit distribution for the baseline hazard rate under two different ways for model estimation (complete and backward stepwise) with different distributions (Weibull, Exponential, Lognormal, and Log-Logistic). As a result, 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 teeth data's reliability. Table 4 shows the values of the AIC and BIC for the different nominated distributions for the baseline hazard rate with the same covariates.
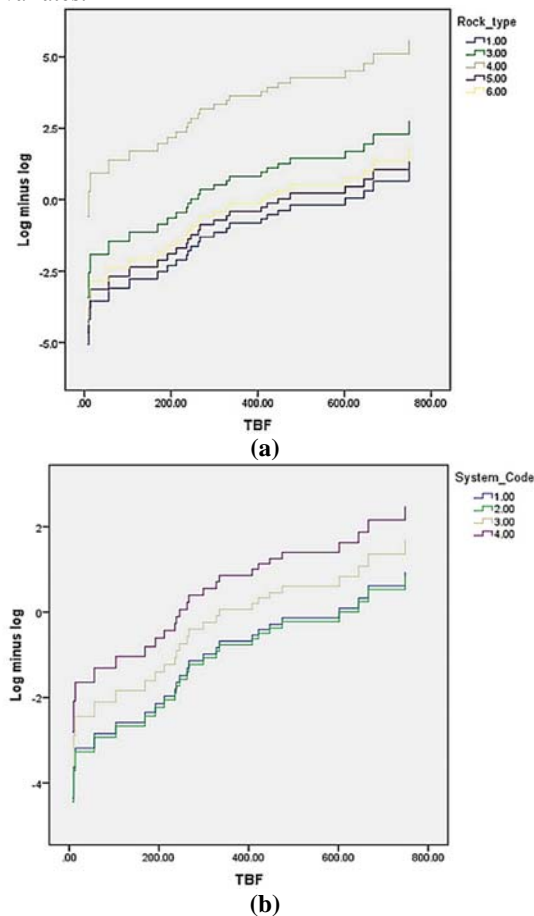

(a)

(b)

Figure 3. The Log minus log graph for the time between crane shovels based on rock kind **(a)** and system ID **(b)**

Table 4. Goodness of fit of different reliability models

Model	AIC	BIC
Weibull Model - Estimation stepwise	349.77	354.259
Weibull Model - Estimation complete	359.469	369.944
Exponential Model - Estimation complete	357.74	368.215
Lognormal Model - Estimation stepwise	425.314	425.314
Lognormal Model - Estimation complete	403.838	414.313
Log-Logistic Model - Estimation stepwise	356.132	362.118
Log-Logistic Model - Estimation complete	360.922	371.397

In stepwise methods, the score statistic is used to select variables for the model. In this study, corresponding estimates of α are obtained by a backward stepwise method and tested for their significance based on the Wald statistic (P-value). 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 covariate, Temperature $(\mathbf{z_t})$", is found significant at the 10% level. The estimates of α (coefficient of covariate) and parameters of two parameters of Weibull baseline distribution (Shape and Scale) are listed in Table 5.

Table 5. Estimation of reliability baseline parameters and covariate coefficient

Distribution	Parameter	Estimate	Standard Error	Z	p-Value
Weibull	Shape	1.34	0.23	5.904	0
	Scale	238.77	123.30	1.94	0.05
	Temperature ($\mathbf{z_t}$)	0.03	0.03	0.97	0.33
Exponential	Lambda	229.38	693.29	0.33	0.74

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

$$R(t,z) = \left(exp\left(-\frac{t}{238.766} \right)^{1.344} \right)^{exp\left(0.031 z_t \right)} \qquad (16)$$

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 4. The results show the teeth in hot weather are less reliable than those in other weather conditions. As can be seen, their reliability reaches about 58% after about 100 h of operation. There is a 93% and a 95% chance that teeth will work without failure for 24 h in normal and cold

weather, respectively. The results can help engineers and managers make decisions about operation planning, maintenance strategy, sales contract negotiations, spare parts management, etc.

5.4 Spare part-provision
According to the existing literature, if the distribution of the baseline hazard rate of an item is Weibull, the covariates effect only changes the distribution's scale parameter, and the shape parameter remains unchanged.
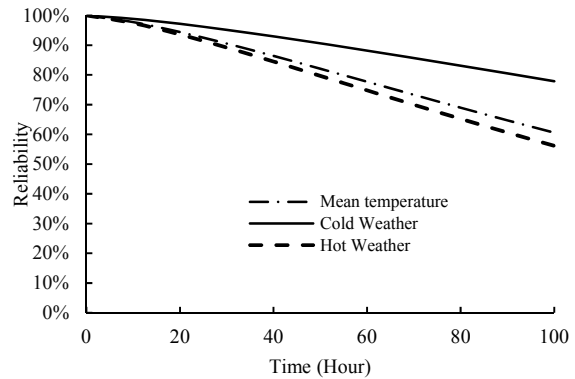

Figure 4. Comparison of reliability performance of teeth in normal, cold, and hot weather

Therefore, the shape parameter (β) and scale parameter (η), of the Weibull distribution considering the effect of covariates are defined by [15, 17, 42]:

$$\begin{cases} \beta = \beta_0 \\ \eta = \eta_0 \left[exp\left(\sum_{i=1}^{n} z_i \alpha_i \right) \right]^{-\frac{1}{\beta_0}} \end{cases} \qquad (17)$$

The $\bar{T}_s$ and $\sigma_s(T)$ of the Weibull distribution and the Power Low Process (PLP) can be calculated based on the shape and scale parameter, expressed as [15], [17], [42]:

$$\bar{T}_s = \eta_s \Gamma\left(1 + \frac{1}{\beta_s} \right) \qquad (18)$$

$$\sigma_s(T) = \eta_s \sqrt{ \Gamma\left(1 + \frac{2}{\beta_s} \right) - \Gamma^2\left(1 + \frac{1}{\beta_s} \right) } \qquad (19)$$

The number of required spare parts for teeth is calculated using Eq.s 18 and 19 for considering the effect of covariate and without them of operation with the probability of storage equal to 95%. The results of the analysis for five years show in Table 6. In this table, spare parts consumption for the next 1 to 5 years has been calculated with considering the effects of covariates (z_t=0 in Eq.16) and without considering the effects of covariates (z_t= mean value of temperature in Eq.16). For example, in the next two years, parts consumption will be approximately 41 unit with the effect of the covariates in mind and 29 without it.

Table 6. Spare part-provision based on WPHM

Next year number	Spare part-provision	
	with covariates	without covariates
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 covariates. In addition,

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 five days
- The cycle service confidence level is 95%

For more explanation and to show the effect of temperature covariates in the analyses, the required spare parts are calculated by Eq.16 with z_t= mean value of cold and hot weather temperature. The Table 7 provides the number of spare parts provisions in next 5 years considering the influence factor. For example, in the next two years, parts consumption in cold weather will be approximately 25 in mind and 45 in hot weather. As the Table shows, there is a big difference between cold and hot weather spare part required that is about in hot weather two times bigger than a cold one.

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

Year	spare part provision	
	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

The economic order quantity (EQO) and reorder point (ReP) concerning annual demand rates in different scenarios are calculated in Table 8 for considering and ignoring the condition. The table showed that, considering the covariate effect for one year, whenever the inventory position reaches 6.56 units/teeth, we should order 3.04. However, ignoring the covariate, the EOQ and RP of teeth for one year are equal to 5.6 and 2.51, respectively. In comparison, the EOQ and RP 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 machine-process management, in this case, the loaders.

Table 8. Economic order quantity

Year	With covariates		Without covariates	
	EOQ	Reorder point (RP)	EOQ	Reorder point (RP)
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 significantly influence the required number of spare parts. Hence, any method used for spare parts provision must be able to quantify such effects. The reliability-based spare part provision considering the effect of covariates, can be used to quantify the effect of the operational environment. In these methods, the operational environment can be considered a covariate. Then 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 properly defining the covariates for spare parts provision to quantify the effect of influence factors. However, it is necessary to examine the historical data to find an appropriate model that fits the data more appropriately. The results of the reliability analysis of the teeth in the Jajarm mine using WPHM show that the reliability of a part in cold weather is higher than in other conditions.

The noticeable difference in spare parts estimation is caused by considering and neglecting the temperature effect. Moreover, the temperature significantly affects the teeth' reliability characteristics and, consequently, the required number of spare parts. The analysis shows that spare parts consumption for the next 1 to 5 years has, with and without considering the effects of covariates, almost 38 percent (37.14%, 38.36%, 39.00%, 39.41%, and 39.71%, respectively). This difference in the consumption of spare parts for hot and cold weather is almost 42% 42.36%, 43.25%, 43.71%, 44.00%, and 44.21%, respectively). The economic order quantity almost 18 percentage (17.11%, 17.63%, 17.90%, 18.07% and 18.20% respectively) and reorder point calculation show an almost 22% (21.04%, 21.60%, 22.01%, 22.35% and 22.63% respectively) difference between the two cases. For future studies, the influence of intangible factors can be considered. Also, using new approaches such as machine learning, data mining, and deep learning will provide estimation power and, as a result, more correct decisions for management if there is a sufficient data bank.

7. References

[1] G. Lanza, S. Niggeschmidt, and P. Werner, "Optimization of preventive maintenance and spare part provision for machine tools based on variable operational conditions," CIRP Ann., vol. 58, no. 1, pp. 429–432, 2009.

[2] W. Van Jaarsveld and R. Dekker, "Spare parts stock control for redundant systems using reliability centered maintenance data," Reliab. Eng. Syst. Saf., vol. 96, no. 11, pp. 1576–1586, 2011.

[3] M. Marseguerra and E. Zio, "Optimizing maintenance and repair policies via a combination of genetic algorithms and Monte Carlo simulation," Reliab. Eng. Syst. Saf., vol. 68, no. 1, pp. 69–83, 2000.

[4] A. Barabadi, "Reliability and Spare Parts Provision Considering Operational Environment: A Case Study.," Int. J. Perform. Eng., vol. 8, no. 5, 2012.

[5] B. Ghodrati, "Weibull and Exponential Renewal Models in Spare Parts Estimation: A Comparison," Int. J. Perform. Eng., vol. 2, no. 2, p. 135, 2006.

[6] U. D. Kumar, J. Crocker, J. Knezevic, and M. El-Haram, Reliability, Maintenance and Logistic Support: - A Life

[7] L. Xie, J. Zhou, Y. Wang, and X. Wang, "Load-strength order statistics interference models for system reliability evaluation," Int. J. Perform. Eng., vol. 1, no. 1, p. 23, 2005.

[8] D. Kumar and B. Klefsjö, "Proportional hazards model: a review," Reliab. Eng. Syst. Saf., vol. 44, no. 2, pp. 177–188, 1994.

[9] A. Barabadi, J. Barabady, and T. Markeset, "Application of accelerated failure model for the oil and gas industry in Arctic region," 2010, pp. 2244–2248.

[10] D. Louit, R. Pascual, D. Banjevic, and A. K. Jardine, "Condition-based spares ordering for critical components," Mech. Syst. Signal Process., vol. 25, no. 5, pp. 1837–1848, 2011.

[11] U. Kumar, "Service delivery strategy for mining systems," Appl. Comput. Oper. Res. Miner. Ind. South Afr. Inst. Min. Metall., pp. 43–48, 2003.

[12] B. Ghodrati, U. Kumar, and D. Kumar, "Product support logistics based on product design characteristics and operating environment," presented at the Annual International Logistics Conference and Exhibition: 12/08/2003-14/08/2003, 2003.

[13] S. Kumar, "Spare Parts Management–An IT Automation Perspective," Domain Competency Group Infosys Technol. Ltd., 2004.

[14] B. Ghodrati and U. Kumar, "Operating environment-based spare parts forecasting and logistics: a case study," Int. J. Logist. Res. Appl., vol. 8, no. 2, pp. 95–105, 2005, doi: 10.1080/13675560512331338189.

[15] B. Ghodrati and U. Kumar, "Reliability and operating environment-based spare parts estimation approach: a case study in Kiruna Mine, Sweden," J. Qual. Maint. Eng., vol. 11, no. 2, pp. 169–184, 2005.

[16] B. Ghodrati, P.-A. Akersten, and U. Kumar, "Spare parts estimation and risk assessment conducted at Choghart Iron Ore Mine: A case study," J. Qual. Maint. Eng., vol. 13, no. 4, pp. 353–363, 2007.

[17] B. Ghodrati, D. Banjevic, and A. K. Jardine, "Developing effective spare parts estimations results in improved system availability," 2010, pp. 1–6.

[18] B. Ghodrati, D. Benjevic, and A. Jardine, "Product support improvement by considering system operating environment: A case study on spare parts procurement," Int. J. Qual. Reliab. Manag., vol. 29, no. 4, pp. 436–450, Apr. 2012, doi: 10.1108/02656711211224875.

[19] A. Barabadi, B. Ghodrati, J. Barabady, and T. Markeset, "Reliability and spare parts estimation taking into consideration the operational environment—a case study," 2012, pp. 1924–1929.

[20] A. Barabadi, J. Barabady, and T. Markeset, "Application of reliability models with covariates in spare part prediction and optimization–a case study," Reliab. Eng. Syst. Saf., vol. 123, pp. 1–7, 2014.

[21] N. G. Ali, K. Reza, A. Mohammad, and M. Ashkan, "Reliability Analysis of Conveyor Belt System of Crushing Department," in CIVILICA, 2015, vol. 01. Accessed: Jan. 29, 2017. [Online]. Available: http://www.civilica.com/Paper-RSTCONF01-RSTCONF01_115=Reliability-Analysis-of-Conveyor-Belt-System-of-Crushing-Department.html

[22] A. Nouri Gharahasanlou, M. Ataei, R. Khalokakaie, and A. Barabadi, "Normalised availability importance measures for complex systems," Int. J. Min. Reclam. Environ., pp. 1–14, 2016.

[23] A. Nouri Gharahasanlou, R. Khalokakaie, M. Khalokakaie, and A. Mokhtarei, "Reliability Analysis of Conveyor Belt System of Crushing Department," J. Appl. Environ. Biol. Sci.-TextRoad Publ., vol. 5, pp. 349–357, 2015.

[24] A. Nouri Qarahasanlou, "Production Assurance of Mining Fleet Based on Dependability and Risk Factor (Case Study: Sungun Copper Mine)," PhD Thesis in Mineral Exploita, Shahrood University of Technology Faculty of Mining, Petroleum & Geophysics, Iran, Shahrood, 2017.

[25] A. Nouri Qarahasanlou, M. Ataei, R. Khalokakaie, B. Ghodrati, and R. Jafarei, "Tire demand planning based on reliability and operating environment," Int J. Min. Geo-Eng., vol. 50, no. 2, pp. 239–248, Dec. 2016, doi: 10.22059/ijmge.2016.59875.

[26] A. Nouri Qarahasanlou, R. Khalokakaie, M. Ataei, and M. Mokhberdoran, "Spare Parts Provision," J. Anal. Numer. Methods Min. Eng., vol. 0, no. 0, Dec. 2016, Accessed: Jan. 04, 2017. [Online]. Available: http://anm.yazd.ac.ir/article_857.html

[27] A. Nouri Qarahasanlou, M. Ataei, R. Khaolukakaie, B. Ghodrati, and M. Mokhberdoran, "Maintainability measure based on operating environment, a case study: Sungun copper mine," J. Min. Environ., 2016.

[28] A. Nouri Qarahasanlou, A. Mokhtarei, A. Khodayarei, and M. Ataei, "Fault tree analysis of failure cause of crushing plant and mixing bed hall at Khoy cement factory in Iran," Case Stud. Eng. Fail. Anal., vol. 2, no. 1, pp. 33–38, 2014, doi: 10.1016/j.csefa.2013.12.006.

[29] E. L. Kaplan and P. Meier, "Non-parametric estimation from incomplete observations," J. Am. Stat. Assoc., vol. 53, no. 282, pp. 457–481, 1958.

[30] A. Barabadi, J. Barabady, and T. Markeset, "A methodology for throughput capacity analysis of a production facility considering environment condition," Reliab. Eng. Syst. Saf., vol. 96, no. 12, pp. 1637–1646, 2011, doi: 10.1016/j.ress.2011.09.001.

[31] W. Nelson, "Hazard plotting for incomplete failure data," J. Qual. Technol., vol. 1, no. 1, pp. 27–52, 1969.

[32] D. R. Cox, "Regression models and life-tables," J. R. Stat. Soc. Ser. B Methodol., pp. 187–220, 1972.

[33] D. Kumar and U. Westberg, "Some reliability models for analyzing the effect of operating conditions," Int. J. Reliab. Qual. Saf. Eng., vol. 4, no. 02, pp. 133–148, 1997.

[34] A. K. Sheikh, F. L. Callom, and S. G. Mustafa, "Strategies in spare parts management using a reliability engineering approach," Eng. Costs Prod. Econ., vol. 21, no. 1, pp. 51–57, 1991.

[35] N. Gorjian, L. Ma, M. Mittinty, P. Yarlagadda, and Y. Sun, "A review on reliability models with covariates," Eng. Asset Lifecycle Manag., pp. 385–397, 2010.

[36] A. Barabadi, J. Barabady, and T. Markeset, "Maintainability analysis considering time-dependent and time-independent covariates," Reliab. Eng. Syst. Saf., vol. 96, no. 1, pp. 210–217, 2011.

[37] D. G. Kleinbaum, Survival analysis. Springer, 2011.

[38] A. Barabadi, "Reliability Analysis of Offshore Production Facilities Under Arctic Conditions Using Reliability Data From Other Areas," J. Offshore Mech. Arct. Eng., vol. 136, no. 2, p. 021601, 2014, doi: 10.1115/1.4026240.

[39] S. W. Lagakos, "The graphical evaluation of explanatory variables in proportional hazard regression models," Biometrika, vol. 68, no. 1, pp. 93–98, Apr. 1981, doi: 10.1093/biomet/68.1.93.

[40] R. J. Gray, "Some Diagnostic Methods for Cox Regression Models Through Hazard Smoothing," Biometrics, vol. 46, no. 1, pp. 93–102, 1990, doi: 10.2307/2531633.

[41] D. R. Cox, "A note on the graphical analysis of survival data," Biometrika, vol. 66, no. 1, pp. 188–190, Apr. 1979, doi: 10.1093/biomet/66.1.188.

[42] B. Ghodrati, "Reliability and operating environment based spare parts planning," Doctoral Thesis, Luleå University of Technology, Sweden, 2005.

[43] D. G. Kleinbaum and M. Klein, "Survival Analysis: A Self-Learning Text," Springer Sci. Bus. Media, 2012.

[44] E. T. Lee and J. Wang, Statistical Methods for Survival Data Analysis. John Wiley & Sons, 2003.

[45] A. Garmabaki, A. Ahmadi, J. Block, H. Pham, and U. Kumar, "A reliability decision framework for multiple repairable units," Reliab. Eng. Syst. Saf., vol. 150, pp. 78–88, 2016, doi: 10.1016/j.ress.2016.01.020.

[46] J. F. Lawless, "Regression methods for Poisson process data," J. Am. Stat. Assoc., vol. 82, no. 399, pp. 808–815, 1987.

[47] M. J. Brewer, A. Butler, and S. L. Cooksley, "The relative performance of AIC, AICC and BIC in the presence of unobserved heterogeneity," Methods Ecol. Evol., vol. 7, no. 6, pp. 679–692, 2016.