Remaining Useful Life Estimation of Mining Equipment – A Case Study

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To ensure the production/output and customer satisfaction in mining sector the estimation of Remaining Useful Life of mining machineries is a prime. In this paper we used the reliability analysis in order to estimate an optimal mining equipment repair/replacement policy by estimating their remaining useful life. The proportional hazard model was used in reliability analysis to be realistic and take the operational influencing factors in calculation. Methods are presented for calculating the conditional reliability function and computing the remaining useful life (RUL) as a function of the current conditions to guarantee the desired output. The model is applied in the hydraulic jack unit of LHD machine in an underground mine in Sweden. A Weibull proportional hazard model (PHM) with time-independent covariates was considered for the hazard function in an illustration of the proposed model. Presented results can be used, e.g. for developing of preventive maintenance plan or replacement intervals based on the conditional probability of failure or RUL.

Keywords: Remaining Useful Life (RUL), Proportional Hazard Model, Conditional Reliability Function, Weibull Distribution, LHD Machine

1.0 Introduction

The growth of reliability, availability and safety of a system is a determining factor in regard with the effectiveness of industrial performance. As a consequence, the high costs in maintaining complex equipment make it necessary to enhance maintenance support systems and changing traditional concepts like preventive and corrective strategies by new ones like prognostic. Prognostic is the estimation of time to failure and risk for one or more existing and future failure modes. Prognostic is also called the prediction of a system's lifetime as it is a process whose objective is to predict the RUL before a failure occurs given the current machine condition and past operation profile [11]. Therefore, the reliability estimation of equipment as well as its RUL is mandatory in maintenance optimization. [3]

Reliability of an individual unit during field use is important in many applications such as mining equipment. When the failure indication (degradation) has been detected, it is essential to estimate the RUL accurately for making a timely maintenance decision for failure avoidance. Likewise, more accurate reliability estimation is likely to result in accurate determining of the optimal inspection intervals, then minimizing the overall cost of the system. In recent years, RUL prediction in service has received increasing attention. It is important to assess the RUL of an asset while in use since it has impacts on the operational performance, planning of maintenance activities, spare parts provision and the profitability of the owner of an asset [5, 8, and 12].

With increasing mechanization and automation in mines, the importance of obtaining highly reliable operating systems has recently been recognized by the mining industry. From an economic point of view, high reliability is desirable to reduce the maintenance costs of the systems. Earlier, maintenance was never considered as a major problem in mines because the consequences of equipment failure were negligible. But the failure consequences of today’s capital intensive machines cannot be ignored particularly when the mineral prices are high. But nowadays RUL is recognized as a key feature in maintenance strategies, while the real prognostic systems are rare in industry, even in mining industry and it is a process whose objective is to predict the RUL before a failure occurs given the current machine condition and past operation profile, however the useful life is found variant depending on the actual operating conditions and characteristics of the environment such as temperature and pressure, humidity condition and corrosion rate, of course there are many uncertainties that might result in an inaccurate estimate of RUL as well. A central problem can be pointed out from this, the accuracy of a prognostic system is related to its ability to approximate and predict the degradation of equipment. However, in practice, choosing an efficient technique depends on classical constraints that limit the applicability of the tools: available data-knowledge experiences, dynamic and complexity of the system, implementation requirements (precision, computation time, etc.), and available monitoring devices. Moreover, implementing an adequate tool can be a non-trivial task as it can be difficult to provide effective models of dynamic systems.

In this paper we utilize reliability methods to estimate the mean residual life at any given time t. then first we explain some theoretical point then follow it up by case study and use of reliability methods in determining the RUL as well as the optimal operating condition and for this ,we consider the following complementary assumptions: (a) Best fit distribution for time to failure of mechanical components is Weibull distribution [7] and constant failure rate is considered for non-repairable components; (b) System reliability characteristics and factors for both the component and the whole system are required for reliability analysis and RUL estimation. Systems operating environmental factors such as dust, system temperature, operators' skills (known as covariates) are assumed influencing covariate in this context.

2.0 Proportional Hazard Model (PHM)

Cox's proportional hazard model [2] is a widely accepted semi-parametric model for analysis of failures with covariates. It has been successfully used for survival analyses in medical areas and reliability predictions in the presence of external influencing factors. The PHM is a complement to the set of tools use in reliability analysis and provides some particular advantageous features [7]. This model is classified as multiplicative and semi-parametric regression model considering covariates that assumes the hazard rate of a system/component is a product of baseline hazard rate $h_0(t)$, dependent on time only and a positive functional term $\psi(z, \alpha)$, basically independent of time, incorporating the effects of a number of covariates such as temperature, pressure and changes in design. Thus:

$$h(x,z) = h_0(x)\psi(z\alpha) \tag{1}$$

$$z\alpha = \sum_{i=1}^{n} z_i \alpha_i \tag{2}$$

Where *h(x, z)* is the hazard function, 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 which each covariate has on the hazard function; and $h_0(x)$ is the baseline hazard rate.

One of the advantages of the PH model is its capability of including time-dependent and independent covariates. Kalbfleisch and Prentice (1980) classified the covariates into two broad categories internal and external covariates. An internal covariate is the output of a stochastic process generated by the unit under study and usually is time dependent. It can be observed as long as the unit survives and is not censored. On the other hand, an external covariate which can be time independent in general could be one of stresses from the outside of the unit such as the ambient temperature. They are usually assumed to be fixed or have predetermined paths during the system's operation.

Therefore, the observed hazard rate of a system with respect to the exponential form of function, which includes the effects of covariates, may be given as:

$$\lambda(t,z) = \lambda_0(t)\exp(z\alpha) = \lambda_0(t)\exp(\sum_{i=1}^{n}\alpha_i z_i) \tag{3}$$

Weibull distribution is a widely used failure time distribution. In a special case, assuming the baseline hazard has the form of two-parameter Weibull yields:

$$\lambda(t,z) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp(\sum_{i=1}^{n} \alpha_i z_i) \tag{4}$$

Where, β > 0 and η > 0 are the shape and scale parameters of Weibull respectively. The model is referred to as the Weibull PH model. The corresponding reliability function conditional on the history of degradation features up to time t is:

$$R(t) = R_0(t)\exp(\sum_{i=1}^{n} \alpha_i z_i) \tag{5}$$

Where

$$R_0(t) = \exp\left[-\int_0^t \lambda_0(x)dx\right] = \exp\left[-\Lambda_0(t)\right] \tag{6}$$

, and $R_0(t)$ is the baseline reliability function dependent only on time.

3.0 Remaining Useful Life (RUL)

We intend to estimate the expected value of the remaining life of an item/component/system before it fails from an arbitrary time t_0. If $MTTF(t_0)$ represents the expected time to failure of an item aged t_0, Mathematically, $MTTF(t_0)$ can be expressed as [4]:

$$\mathrm{MTTF}(\mathrm{t}_0) = \int_{\mathrm{t}_0}^{\infty} (\mathrm{t} - \mathrm{t}_0)\, f(\mathrm{t}|\mathrm{t}_0)\mathrm{dt} \tag{7}$$

where the $f(\mathrm{t}|\mathrm{t}_0)$ is the density of the conditional probability of failure at time t, provided that the item has survived till time t_0. Thus,

$$f(t|t_0) = h(t) \times R(t \mid t_0) \tag{8}$$

where $R(t|t_0)$ is the conditional probability (reliability) that the item survives up to time t, given that it has been survived up to time t_0. Now, the above expression can be written as:

$$f(t|t_0) = h(t) \times \frac{R(t)}{R(t_0)} \tag{9}$$

Once the conditional reliability function is calculated, it is easy to define and calculate the remaining useful life (RUL) function. This function is usually defined as the conditional expected time to failure, given current working age, i.e. as e(t) = E(T − t|T > t) [1]. So, we can have the following equation for $MTTF(t_0)$ [11]:

$$\mathrm{MTTF}(\mathrm{t}_0) = \frac{\int_{\mathrm{t}_0}^{\infty} \mathrm{R(t)\,dt}}{\mathrm{R}(\mathrm{t}_0)} = \frac{\int_{0}^{\infty} \mathrm{R(t)\,dt} - \int_{0}^{t_0} \mathrm{R(t)\,dt}}{\mathrm{R}(\mathrm{t}_0)} = \frac{MTTF - \int_{0}^{t_0} \mathrm{R(t)\,dt}}{R(t_0)} \tag{10}$$

where MTTF is the mean time to failure of the studied item and can be calculated as:

$$MTTF = \eta \times \Gamma(1 + \frac{1}{\beta}) \tag{11}$$

and the Γ(.) is the Gamma function.

4.0 Model application: Case Study

The dominating machine for loading rock in an underground iron ore mine in Sweden is the load-haul-dump (LHD) machine, which is used to pick up ore or waste rock from the mining points and for dumping it into trucks or ore passes. An investigation of a fleet of LHD machines deployed at this mine shows that the hydraulic systems are most critical sub-systems. The lifting cylinder (jack) is a part of hydraulic system, which has been considered and studied in this paper (Figure 1).

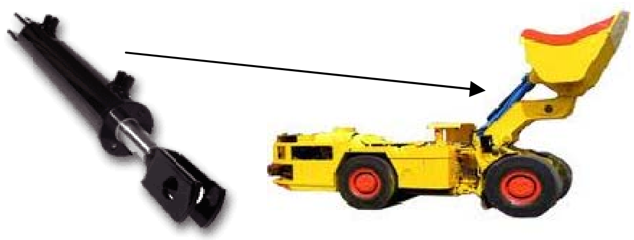

Figure 1 Hydraulic jack

The operation and maintenance cards for a fleet of LHD machines were collected and required information such as time to failure was obtained from the cards. Three T2500 (25 tone bucket) model machines that are working in the same condition with the same age were studied. With non-repairable assumption for hydraulic jacks some minor parts of it (such as gasket or seal), however, could be replaced in order to restore the failed jack in functional mode.

For the purpose of this study, the available information about the operating conditions of the hydraulic jack was determined and codified by a numeric value wherever required [9]. In this case the formulation of covariates (influencing factors except time) were carried out based on observation and the experience of operators and maintenance crew, and are as:

(a) Operator skill: this covariate refers to the operator's experience in driving, loading and hauling. It is denoted by OPSK.
(b) Maintenance crew skill: this factor affects the quality of service, repair and maintenance and the condition of jacks after service, and denoted by MCSK.
(c) Hydraulic oil quality: the indicator "HOILQ" which is used to denote the quality of hydraulic oil in the system.
(d) Hydraulic system temperature: this factor has influence on the viscosity of hydraulic oil and elasticity of rubber components in jack (such as seals and gaskets). For this covariate, the indicator "TEMP" is used to denote the condition.
(e) Environmental factors: This parameter indicates the effect of operating environmental factors such as existence of dust, chemical materials, etc. on the jack. This covariate is present the jack is exposed to corrosive conditions when the pollution and dust exist in the hydraulic oil and operating environment. Indicator "DUST" denotes this covariate.

The software SYSTAT, which is used for estimation of regression coefficients, uses a "step down procedure" where all the covariates are first considered together in the model.

Thus, covariates found to have no significant value were eliminated in the subsequent calculations. The corresponding estimates of α (regression coefficient) were obtained and were tested for their significance on the basis of t-statistics (the ratio of the estimated α to the standard error of the estimates) and/or p-value (obtained from the table of unit normal distribution). One minus the p-value for a covariate gave a measure of importance when we considered whether to retain any particular covariate in the model. By following the step down procedure we found that the effects of three covariates (DUST, OPSK and TEMP) were significant at the 10% p-value.

So, the best hazard rate model based on the PHM analysis can be defined as:

$$\lambda(t,z) = \lambda_0(t)\ \exp(-1.201\,OPSK - 1.425\,DUST - 0.748\,TEMP) \qquad (12)$$

Based on the results from trend test, the time to failure cannot be exponentially distributed and on the other hand it follows the power law process with shape parameter = 3 and scale parameter = 4500 hour (manufacturer recommendation). With this assumption the hazard rate is equal to:

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left(\sum_{j=1}^{n}\alpha_j z_j\right) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \times \exp(-1.201\,\mathrm{OPSK} - 1.425\,\mathrm{DUST} - 0.748\,\mathrm{TEMP}) \qquad (13)$$

We used the factorial design method to find out the value of conditional reliability in the different covariates existence situation (Table 1). Therefore, the estimated reliabilities were classified into eight categories. Table 1 shows the different combinations of existing covariates. The values of 1 and -1 for each covariate indicate the good (improving) and bad (deteriorating) condition respectively (for detail see [10].

Table 1 different covariates existence situation

Category	OPSK	DUST	TEMP
1	1	1	1
2	1	1	-1
3	1	-1	1
4	1	-1	-1
5	-1	1	1
6	-1	1	-1
7	-1	-1	1
8	-1	-1	-1

Table 2 represents the value of reliability function considering the effect of different covariates for different operating time. As it is seen the reliability decreases with the both increment of operating time (age) and number of negative influencing covariates. For instance at the age of 3000 (hrs) the reliability at the stage 1 which represents no negative covariates (good condition) is 99% whereas in the states 4 and 7 the reliability values decreases to 46% and 15% respectively where there are two negative influencing factors.

Table 2 Reliability function R(t) for Weibull PHM calculated for different states of covariates

Age (t)	R(t) at different stages of existing covariates and times							
	State 1	State 2	State 3	State 4	State 5	State 6	State 7	State 8
500	1,00	1,00	1,00	1,00	1,00	1,00	0,99	0,96
1000	1,00	1,00	0,99	0,97	1,00	0,98	0,93	0,73
2000	1,00	0,99	0,95	0,79	0,97	0,86	0,57	0,08
3000	0,99	0,96	0,84	0,46	0,89	0,60	0,15	0,00
4000	0,98	0,90	0,66	0,16	0,77	0,30	0,01	0,00
6000	0,92	0,69	0,25	0,00	0,41	0,02	0,00	0,00
8000	0,82	0,42	0,04	0,00	0,12	0,00	0,00	0,00
10000	0,69	0,18	0,00	0,00	0,02	0,00	0,00	0,00
12000	0,52	0,05	0,00	0,00	0,00	0,00	0,00	0,00
13000	0,44	0,02	0,00	0,00	0,00	0,00	0,00	0,00
15000	0,28	0,00	0,00	0,00	0,00	0,00	0,00	0,00

Figure 2 shows the reliability function values for different ages. It is obvious how the existence and state of covariates strongly affects the shape of reliability function.

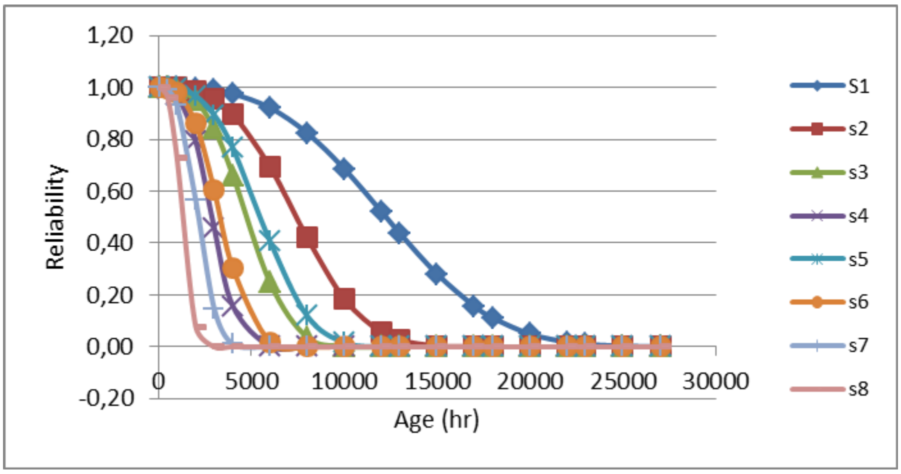

Figure 2 Reliability for Weibull PHM calculated in different states of covariates

Table 3 similar to Table 2 was obtained for any initial survival time and state of covariates. Table 3 shows the conditional reliability function values calculated for a given initial survival time (current working age) of 2000 (hrs) and different states of influencing parameters.

Table 3 Conditional reliability function for Weibull PHM calculated for initial survival time of 2000 (hrs) and different states of covariates

Age	CR	Covariates existing states							
		1	2	3	4	5	6	7	8
4000	R(2000|2000)	0,979	0,910	0,696	0,198	0,792	0,352	0,019	0,000
6000	R(4000|2000)	0,931	0,726	0,295	0,004	0,456	0,029	0,000	0,000
8000	R(6000|2000)	0,827	0,426	0,039	0,000	0,123	0,000	0,000	0,000
10000	R(8000|2000)	0,688	0,187	0,002	0,000	0,016	0,000	0,000	0,000
12000	R(10000|2000)	0,523	0,055	0,000	0,000	0,001	0,000	0,000	0,000

The conditional reliability function, i.e. the functions $R(t|2000,Z(x) = i) = P(T > t|T > 2000,Z(x) = i)$ for $i = 1, 2, 3, 4, 5, 6$ and $x > 2000$ is illustrated in Figure 3. It is obvious how the state of the covariates strongly affects the shape of and value of the reliability function. The situations are worst at the states 4 and 6 of influencing covariates where there is two negatively affected covariates.

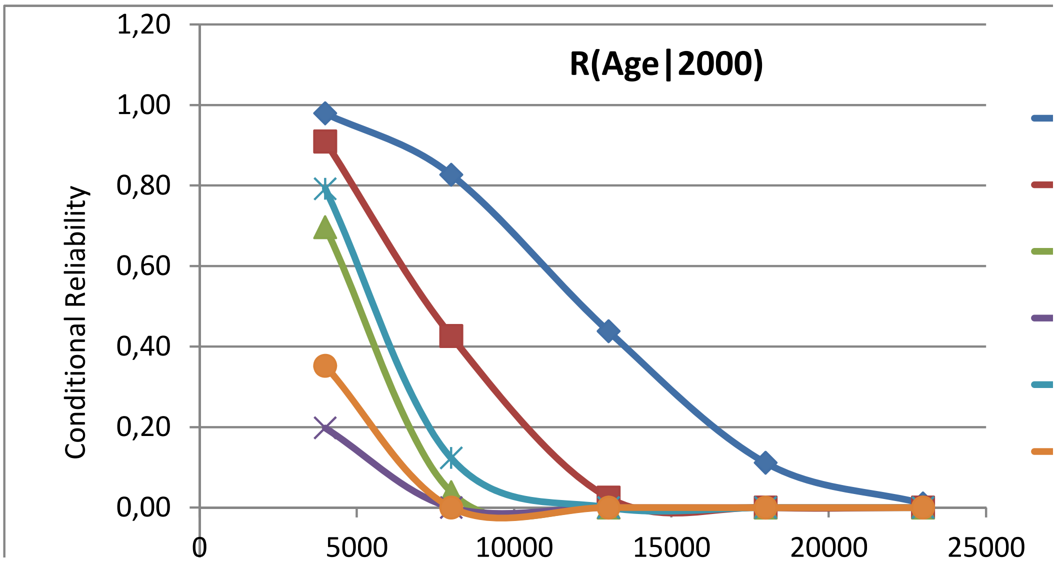

Figure 3 Conditional reliability function for Weibull PHM calculated for initial survival time of 2000 (hrs) and different states of covariates

The remaining expected life for some survival times and different states of existing covariates are presented in Table 4. It should be noted that with an increase of the intense of covariates the expected useful life decreases.

Table 4 Remaining expected useful life (hrs) for Weibull PHM calculated initial survival time t and different states of covariates

Age	Covariates existing states							
	1	2	3	4	5	6	7	8
1000	11361,24	6506,27	3821,50	1971,51	4572,32	2417,31	1257,94	522,51
2000	10389,79	5576,56	2969,94	1281,85	3689,59	1670,67	704,22	220,30
3000	9460,46	4740,48	2145,93	839,59	2947,04	1152,50	413,59	1943,23
4000	8585,84	4011,42	1759,75	566,62	2348,23	810,11	236,94	…
6000	7025,96	2867,39	1073,12	131,23	1511,32	429,89	…	…

The category eight of existing covariates in Table 4, where all covariates are in the worse condition (with negative impact), indicates the most harmful and unpractical situation. It's a risk alarm for operation in practice and therefore, it's attempted to avoid that circumstance. Meanwhile, as the expected RUL in this category for long time operation is unreliable and unrealistic, therefore we ignore to estimate and use the RUL for such condition.

In Figure 4, the RUL function is shown as a function of current working age and the state of covariates at that working age, i.e. the functions $e(t, i) = E(T - t|T > t, Z(t) = i)$, for i = 1, 2, 3, 4, 5 and t= 1000, 2000, 3000, 4000 and 6000 (hrs) are shown.

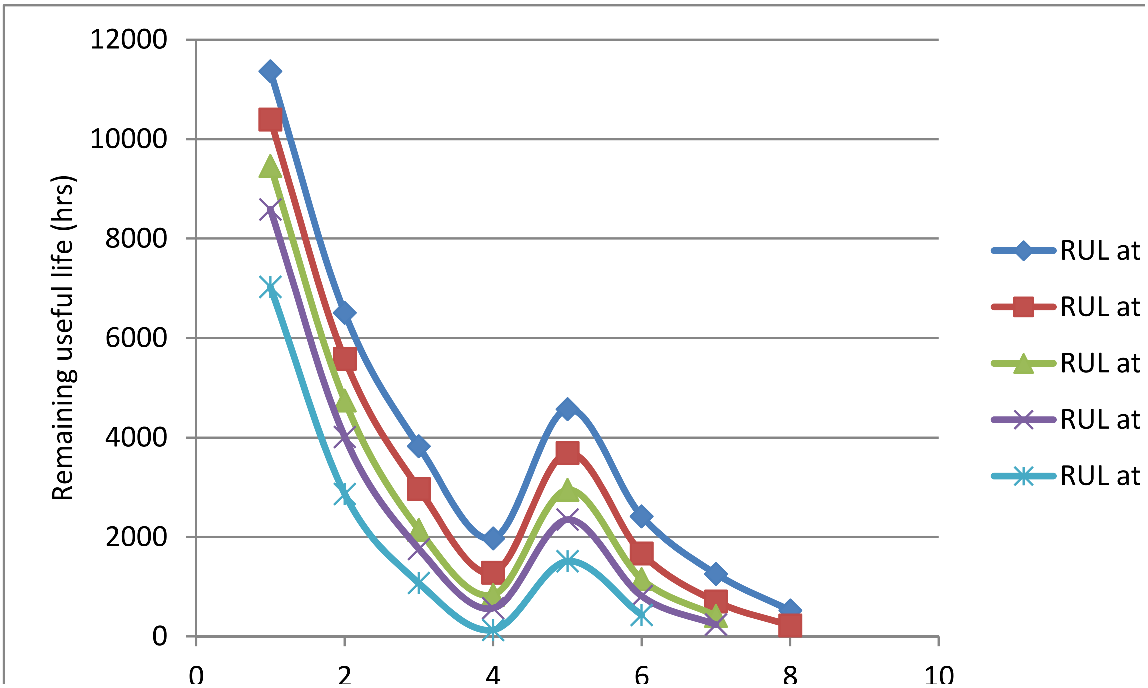

Figure 4 Remaining expected useful life for Weibull PHM calculated for different initial survival time t and different states of covariates.

As it's obvious in Figure 4, the remaining useful life increases at the state of the covariate 5, where there is only one covariate with negative influence and two with positive. In general, however, the remaining useful life of hydraulic jack decreases as the state of the covariates getting worse, which cause the reliability of system decline.

The remaining useful life of hydraulic jack launched in LHD can be roughly estimated by using the above mentioned graph for rapid evaluation of existing situation. This is an important issue and aspect for infield engineers to make decision on running the project and production.

5.0 Conclusions

In this paper, we introduced a model for estimation of remaining useful life (RUL) as a combination of a system hazard function affected by external influencing factors and conditional reliability function. To be realistic it is appropriate to include the external (e.g. environmental) condition monitoring (CM) process into reliability calculation. Theoretical and numerical methods for the calculation of the conditional reliability function for the RUL and its expected value, given the current age and history of the CM, were studied. A Weibull PHM with time-independent covariates was considered as a model for the hazard function in an illustration of the proposed model.

Field data from the hydraulic jack launched on a LHD were used in the application. The results represent a considerable difference between various situations of covariate presence. As the influencing parameters on system reliability getting worse the remaining useful life getting short. Presented results can be used, e.g. for planning of preventive maintenance based on the conditional probability of failure or RUL.

6.0 References

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