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RESEARCH PAPER

Remaining Useful Life Estimation In the Presence of Given Shocks

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ABSTRACT

In a system, prediction of remaining useful service time (RUL) is a significant and practical issue. Operational environment of an equipment changes regarding stresses and shocks. These random environmental factors accelerate system deterioration by affecting on the level or rate of degradation path. The present study provides an operational guideline to anticipate the RUL of a system with general degradation path after receiving shocks which only affect on the degradation level. Exact estimation of the shock arrival times and measuring the magnitudes of future shocks to investigate shock effects on RUL is almost impossible in the real world and laborious in practice, consequently, a new procedure based on total defect size monitored in the constant inspection periods and Accelerated Factor (AF) is proposed to analyze RUL of the system. A Micro-Electro-Mechanical system (MEMS) is used as an example and the results indicate the applicability of the suggested method.

KEYWORDS: *Remaining useful life; Degradation process; General path; Accelerated degradation; Random shock; Accelerated factor.*

1. Introduction

In the past decade, many types of research have been done on prognostics and health management (PHM) in both academic and industrial communities, such as electronics, energy industry, aeronautics and aerospace, manufacturing, automotive industry, nuclear plants, and fleet-industrial maintenance. Generally, PHM is a discipline to evaluate the system reliability during its actual life cycle conditions to anticipate the breakdown time and decrease the system risk. PHM is comprised of two sections, prognostics and health management. In the prognostics, the RUL of a system is predicted based on available health condition data. And in the health management, the correct way of doing management activities is concerned [1].

RUL estimation is a guideline for successive management including inspection schedule, maintenance, replacement, and spare parts ordering. The RUL of a system is the time between the current time and the end of the useful life, that is, $t_f - t_c | t_f > t_c$. Where t_f is the downtime and t_c is the current time. Condition monitoring data are the basis of the RUL estimation results. [2]. Collecting failure data is increasingly expensive specially for expensive or highly reliable systems. Progress of signal processing and feature extraction methods has made condition monitoring (CM)- applying dedicated sensors- present a considerable amount of real-time information about the system's state of health. The CM data or degradation data present adequate health information. Evaluation of the reliability and prediction of the RUL of deteriorating systems, caused CM data to be used instead of conventional lifetime data. Based on the concept of the first hitting time (FHT), the system's lifetime is defined as the time in which degradation path passes the threshold. And the RUL is the period of time between current time and the first time that $D \geq D_{\max}$ [3]. Apart from gradual degradation, shock degradation is another kind of degradation where the damage is accumulated and abruptly resulting in a shift and discontinuity in the degradation curve. After a shock, the gradual degradation is accelerated at different rate. Material-dependent model

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parameters will be static if the material does not change, so degradation curves after and before arriving a shock are parallel [4]. After arriving each shock, the path moves toward the left, and the slope of the path is constant (Fig. 1).

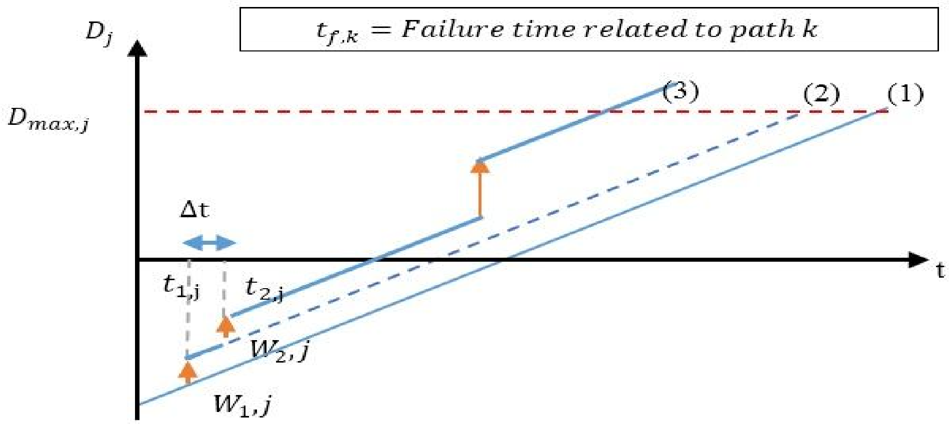

Fig. 1. Degradation path of system j in the presence of shocks.

[4] proposed a procedure for predicting RUL to explain two elements, the uncertainty in defect initiation time and the shock in the degradation. [3] reviewed recent extensions related to the procedures for degradation data modeling and RUL predicting regarding Wiener-process. [2] provided a survey on methods of degradation modeling and RUL prediction focused on the heterogeneity of the systems. In [5], four reliability models considering different stochastic processes and two types of shock effect on degradation path were developed. [6] estimated RUL for partially observed linear stochastic degrading systems with survival measurements. It excluded the probability of failure before the current monitoring time and regarded both impacts of the multisource variability and surviving degradation path on the RUL prediction. [7] applied a data driven prognostic method considering nonlinear autoregressive neural network with exogenous inputs compounded with wavelet-filter technique to estimate the RUL of bearings. Changes of distribution and feature due different operating conditions, fault modes and noise, made [8] propose a new data-driven approach for domain adaptation in prognostics using Long Short-Term Neural Networks. A new procedure based on machine learning was proposed by [9] in which the failure of machines in continuous production line was predicted. Normalization and principle component analysis were used in preprocessing step. Also it applied interpolation and grid search to optimize parameter. Multilayer perception neural network is utilized to build the model. In [10], Mont Carlo Dropout and gated recurrent Unit are used to model the uncertainty of RUL prediction and avoid overfitting phenomenon. [11] suggested a method considering transformer model to predict RUL. In this method, greater weight was given to characteristics of main time stages through self-attention mechanism. In [12], a long-short term memory neural network integrates a novel particle least square regarding a genetic algorithm. Firstly, the parameters are analyzed. then genetic algorithm searches optimal coefficients of the function. Then the RUL is predicted. [13] introduced an integrated deep learning method with convolutional neural networks and long short-term memory networks to learn the latent features and predict RUL value with deep survival model based on the discrete Weibull distribution. Systems subject to competing failures and their RUL estimation are considered in [14], [15] and [16]. A quick change in stress may lead to a significant shock. In [17] a degradation model in a dynamic environment focusing on effective shocks was presented to estimate RUL.

[18] predicted RUL of rotating machinery considering optimal degradation indicator. [19] considered uncertainties related to the component deterioration trend and failure threshold in RUL prediction, and compared two lifetime models on an application regarding the deterioration of choke valves used in offshore oil platforms. In [20], for RUL predicting, a degradation model

was presented regarding continuous degradation processes with recoverable shock damages. A new degradation-shock model subjected to a hidden degradation state was presented in [21]. In their research, a Kalman filter is modified with optimal prediction. A correct reliability assessment needs a correct analysis of models which calculate AF [22]. RUL estimation concerning AF has been done in these researches: [23] evaluated the reliability and RUL of electronic and detonating parts by considering accelerated life testing (ALT). ALT and assessment of performance in an accelerated environment are testing plans that accelerate the aging of the product. [24] reviewed the basics of these testing methods and their relations with statistical methods to estimate and predict the reliability and reliability growth. Underhill cracking is a failure process of organic packages during thermal cycling which then results in solder joint failure. [25] prepared the applicability of the thermal fatigue fracture behavior (dependent on temperature) to a material level acceleration factors to aid material selection and package lifetime predictions. A new method for calculating the acceleration factors was presented in [22].

Shocks accelerate degradation process and affect on failure time. RUL subject to shocks can be estimated based on AF. AF is determined based on simulation of lifetime under given shocks and normal situations (Eq. 1). After receiving any shock, degradation path is driven to the left slightly equal to Δt. That is, the system fails at Δt sooner.

In this research, a new method considering AF is presented to evaluate the RUL of system under general degradation path and random shocks. Here, based on mathematical relation between historical shock magnitudes and defect size monitored in each inspection time, life time in stressful situation is obtained.

The framework of this paper is as follows: The theoretical basis of the research is depicted in Sec. 2. Section 3 consists of the proposed method. In Sec. 4, a case study is presented as an example. Section 5, is allocated to results and discussion.

2. Research Basis

Scale-accelerated failure-time (SAFT) model is a simple, commonly used model utilized to identify the effects of variables on lifetime. This model is generally specified as the accelerated failure time model (Eq. 1) [26]. Regarding this model, normal lifetime characteristics are obtained based on stressful situation characteristics. AF is calculated based on phisical models or as follows [27] [28]:

$$AF = \frac{t_o}{t_s} \tag{1}$$

In a maintenance system, the defect size of *m* system can be measured in each inspection time. A curve is fitted to the mean of these data in each time, $\mu(t)$. This curve is degradation path. System degradation level in each time is obtained through degradation path (that can be linear, exponential, power, etc.). In this research, a degradation system which follows a general path process is considered (Eq. 2):

$$X_j(t) = a + bt, \tag{2}$$

Where a and $b \sim N(\mu, \sigma^2)$. Consider a system subject to shocks occur randomly during the time, with the specified magnitude W_{ij}. The damages of these shocks are modeled by a cumulative shock model. Assume that shock damage magnitudes are mutually independent and commonly distributed with no dependency on the state of the system. In this system, degradation level in each time is obtained as Eq. 3:

$$D_j(t) = \sum_{i=1}^{\infty} W_{ij} + X_j(t), \tag{3}$$

Where $\sum_{i=1}^{\infty} W_{ij}$ is the aggregation of the shock magnitudes affecting on the system j until t.

Fig. 1 exhibits the total degradation level versus time for a linear degradation path by noticing the shocks.

By adjusting the translational movement of degradation path, uncertainty in RUL prediction is decreased and effect of shock on the degradation is captured as well. After arriving each shock, the path moves to the left and slope of the path is constant [4].

Registration of the future shock magnitude and prediction of exact arrival time are difficult in practice and need special tools. Due to translation of the path after affecting a shock is Δt, it can be said that the system failed as equal as Δt sooner. So the reliability and RUL of the system change. According to Fig. 1, Δt, that is the time between two consecutive shocks, can be converted to the size of the crack length increase.

3. The Proposed Method

In order to introduce the proposed method a list of abrivation and notations presented in table 1.

Tab. 1. Abbreviation and notations

	Abbreviations		
AF	Accelerated Factor	RUL	Remaining Useful Lifetime
ALT	Accelerated life testing	PHM	Prognostics and health management
D	Degradation	CM	Condition monitoring
FHT	First hitting time	SAFT	Scale-accelerated failure-time
MEMS	Micro-Electro-Mechanical System		
	Notations		
$D_{max} = H$	Critical level of Degradation	$\boldsymbol{\mu(t)}$	Mean of defect sizes at time t
$X(t)$	Random variable representing degradation value at time t in the absence of shock	$\mathbf{D(t)}$	Random variable expressing overall degradation value at time t in the presence of shock
t_s	Lifetime of system in the stressful situations (in the presence of shocks)	$\mathbf{t_o}$	Lifetime of system in the absence of shocks
t_f	Failure time	t	Time of system
T	Inspection period	t_0	Initial degradation time (burn in time)
$\boldsymbol{T_i}$	ith inspection time	$\boldsymbol{t_{i,j}}$	Arrival time of ith sock on jth system
$W_{i,j}$	Magnitude of i^{th} shock on System	m	Number of system under test
i	$i = 1, 2, 3, \ldots$ Index of shock	j	j=1,…,m Index of system
$Mean_{RUL_o}$	Mean of RUL under normal situation	$\mathbf{Mean_{RUL_S}}$	Mean of RUL under stressful situation
$RUL_s(t)$	RUL of system under stressful situation	$\mathbf{RUL_o(t)}$	RUL of system under normal situation

In a maintenance system, inspection periods can be constant or variable. So the health monitoring of the system occurs at the specified times. In an inspection time, the change of defect size is measurable.

To reach t_s, calculation of total Δt or $\sum \Delta t_i$ is necessary.

As shown in Fig. 2, degradation path is general, *D*=*b*t, and b is the slope of the path and its relation with shock magnitude and between arrival time is according to Eq. 4**:**

$$b = \frac{w_{ij}}{\Delta t_i} \quad or \;\; \Delta t_i = \frac{w_{ij}}{b}, \tag{4}$$

Eq. 5 shows an example for the third shock on the system j, as highlighted in Fig. 2 in bold dashed curve:

$$\Delta t_3 = \frac{w_{3j}}{b}, \tag{5}$$

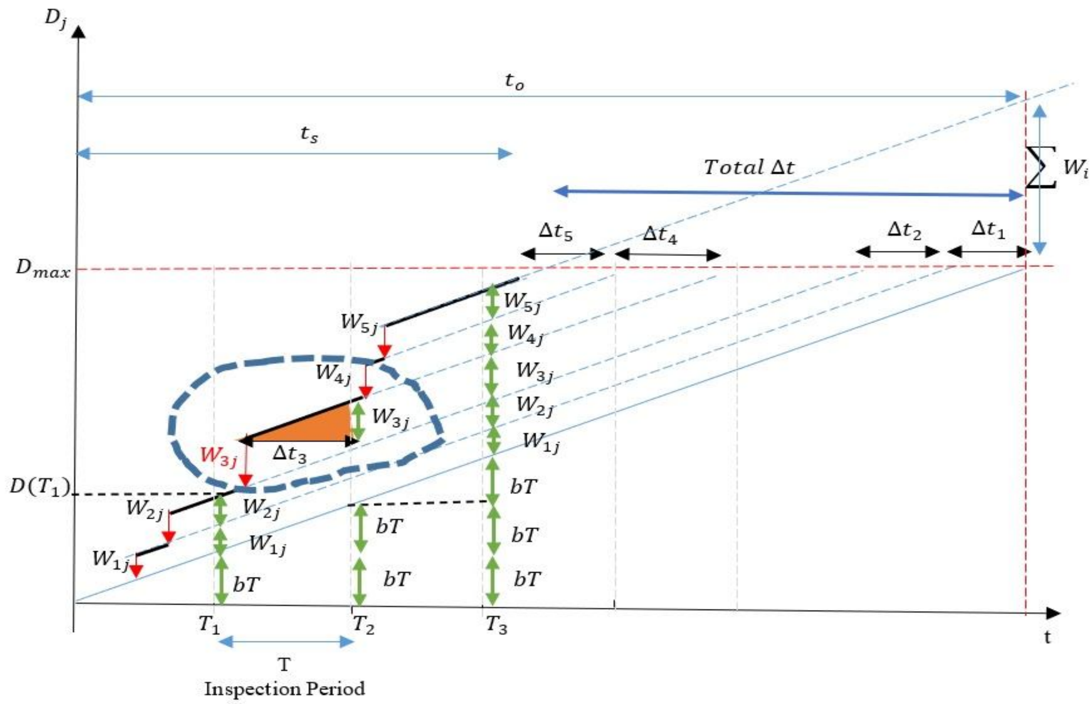

Fig. 2. Degradation path under shock. Lifetime under stressful (t_s) and normal situations (t_o)

Translation of the degradation path from initiation of degradation until T_2 (Fig. 2) is calculated as:

$$\sum \Delta t_i = \frac{W_{1j}}{b} + \ldots + \frac{W_{ij}}{b} = \frac{1}{b}\left(\sum W_{ij}\right)$$

$$or, \sum \Delta t_i = \frac{\sum W_{ij}}{b}, \tag{6}$$

It means that the change of normal life after arriving shocks is equal to $\sum \Delta t_i$, that gives t_s;

$$t_s = t_o - \sum \Delta t_i, \tag{7}$$

Based on (7), Eq. (1) is converted to (8):

$$AF = \frac{t_o}{t_s} = \frac{t_o}{(t_o - \sum \Delta t_i)} = \frac{t_o}{(t_o - \frac{\sum W_{ij}}{b})}, \tag{8}$$

In which, t_o is life time in normal situations.
The estimation of arrival times and following that, measuring the magnitudes of coming shocks are laborious in practice. As Fig. 2 depicts, increase of degradation level in the first inspection time, after first two shocks (which have affected on the system before first inspection time), is as follows;

$$D(T_1) = W_{1j} + W_{2j} + bT, \tag{9}$$

Based on Eq. (9), total D at inspection time T_n is equal to:

$$\text{Total } D \text{ at inspection time } T_n = D(T_n) = \sum W_{ij} + nbT \tag{10}$$

Generally, according to the equation (10), shock magnitude is returned to degradation level. So total shock magnitude until T_n is calculated as follows:

$$\sum W_{ij} = D(T_n) - nbT, \tag{11}$$

Based on (11), Eq. (8) is converted to (12):

$$AF_t = \frac{t_o}{(t_o - \frac{\sum W_{ij}}{b})} = \frac{t_o}{(t_o - (D(T_n) - nbT))}, \tag{12}$$

As Eq. 12 demonstrates, AF value is obtained based on t_o, total defect size at time T_n, and duration between two inspection time (T) which is constant. Advantage of this procedure is that all of these parameters are easier for accounting rather than accessing shock magnitudes.

4. Case Study

Consider a MEMS with a micro engine exposed to wear degradation [29]. A main failure process in MEMS is wear degradation. Failure analysis and reliability assessment are important issues for

MEMS devices, in which rubbing surfaces are unavoidable [29].

Visible wear on rubbing surfaces often effects on either size of micro engines, or their pin joints. Wear or removal of material from solid surfaces is a result of mechanical actions. Wear degradation is based on the mechanical and chemical properties of the bodies in contact and also the pressure and interfacial velocity under which the bodies make contact [29].

Let $X(t;B)$ depicts the actual degradation curve over time *t*, where B is a vector of model coefficients. Wear degradation model of MEMS is built regarding physical theory to quantify the functional relationship between the wear level, $X(t;B)$, and the number of revolutions to breakdown, t. Let *r* is the radius of the pin joint (depicted in Fig. 3), *c*, the coefficient related to wear and hardness of the material, and *F*, the force between the contacting surfaces, the linear degradation curve, $X(t;r,c,F)$, is shown in Fig. 4, and can be expressed as (13):

$$X(t;r,c,F) = 2\pi rcFt, \tag{13}$$

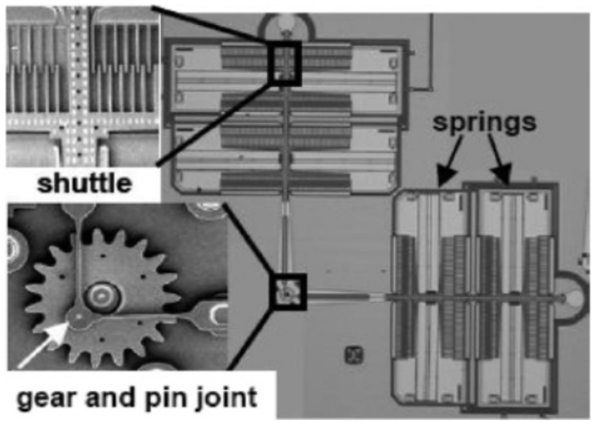

Fig. 3. Scanning electron microscopy image of a micro engine [29]

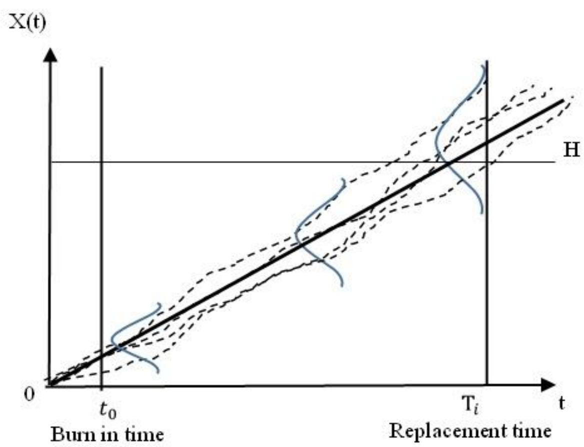

Fig. 4. Linear wear degradation path and Normal failure distribution of defect size data in each time [21]

Suppose that the coefficient is $3 \times 10^{-4} \frac{\mu m^2}{N}$, the mean value of the radius is $1.5 \frac{\mu m}{N}$, and the nominal value of the force applied between rubbing surfaces is $3 \times 10^{-6} N$. Degradation path in normal situation is as follows:

$$X(t) = 27 \times 10^{-10} t, \tag{14}$$

The initial wear level of the material after the completion of manufacturing is supposed to be zero, i.e., $X(0) = 0$. The micro engine experiences soft failures when the wear level arrives a critical level, H which is $0.00125 \mu m^3$. Table 2 denotes wear degradation level of 30 sample collected over 23 Inspection time.

Tab. 2. Defect size data (wear volume) of 30 sample collected over 23 inspection time

Inspection Time (Number of revolutions)	Sample No.				
	1	2	...	29	30
150000	0.0004302	0.000315		0.00021	0.0003
490000	0.0013099	0.001215		0.001341	0.001348
500000	0.0013449	0.001355		0.001505	0.001436

Data of each sample over 23 inspection times follow linear path with parameters p_1 and p_2. Table 3 shows p_1 and p_2 values for each sample. Each linear path shows the wear path related to each sample reaches critical wear level in special time that is called failure time of that sample. This value is obtained as (15):

$$t_f = \frac{H-p_2}{p_1}, \tag{15}$$

Tab. 3. Estimation of parameters $\mathbf{P_1}$ and $\mathbf{P_2}$

Main Degradation path	Degradation path parameters	Sample No.					Mean
		1	2	...	29	30	
$\boldsymbol{D(t) = p_1 t + p_2}$	p_1	2.79E-09	2.50E-09		3.15E-09	2.92E-09	2.72E-09
	p_2	-4.78E-05	7.17E-05		-0.00015	-9.66E-05	-9.29E-06

Failure time of each sample is shown in Table 4.

Tab. 4. Failure time of each sample

	Sample No.					Statistics	
	1	2	...	29	30	Mean	Standard Deviation
failure time	4.65E+05	4.72E+05	…	4.44E+05	4.61E+05	4.63E+05	9640.01

Distribution fitted on each data is Normal with parameters $N(4.63E+05, 9.29299E+07)$. RUL in time t means remaining useful time of system from t until failure time. That is:

$$RUL(t) = t_f - t, \tag{16}$$

Based on Eq. (16), RUL of each sample is calculated in each inspection time. In each time, there are 30 RUL data. Normal distribution is fitted to RUL values in each inspection time. The parameters are shown in Tab. 5.

Assume that the random shocks impact the system based on a homogeneous Poisson process with rate parameter 100000, $T \sim Exp(10^{-6})$. Shock magnitudes follow a Normal distribution with parameters $W \sim N(42 \times 10^{-12}, 10^{-8})$. As Fig. 5 displays, after arriving third shock, degradation path transports from 1 to 3 and failure time changes from $t_{f,1}$ to $t_{f,3}$.

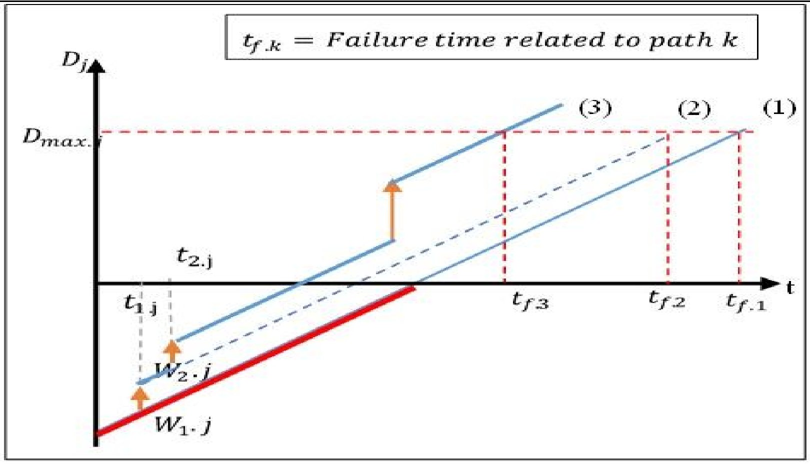

Fig. 5. Failure times of degradation path after and before arriving shocks are $t_{f.1}$ and $t_{f.2}$, respectively.

Mean of failure time of 30 sample under test in similar situations is 462963 but this value in mentioned stressful environment is equal to 454947.

Mean of Accelerated factor based on 30 sample is AF= 1.017616. Consequently, based on (1) we have:

$$RUL_o(t) = AF \times RUL_s(t), \quad (17)$$

RUL_s in each time for each sample is calculated according to (17) and RUL data. Table 5 shows parameters of RUL_s distribution that is Normal in each time.

Tab. 5. Mean and standard deviation of RUL_o and RUL_s in each time

Statistics	Time						
	410000	430000	450000	…	460000	470000	480000
$\mathbf{Mean}_{RUL_o}$	52913.2	32913.2	13114.8		5246.97	1305.83	392.867
$\boldsymbol{Var}_{\cdot RUL_o}$	91565761	91579158.09	84892636.2		52161761.7	16562865.1	4630329.3
$\boldsymbol{Std}_{\cdot RUL_o}$	9569	9569.7	9213.72		7222.31	4069.75	2151.82
$\mathbf{Mean}_{RUL_s}$	52028.7	32363.3	12693		2869.17	-6966.93	-16799.7
$\boldsymbol{Var}_{\cdot RUL_s}$	88543100	88824500	88484100		88730000	88446900	8846880
$\boldsymbol{Std}_{\cdot RUL_s}$	9409.74	9424.67	9406.6		9419.66	9404.62	9405.78

As can be seen from Tab. 5, mean and std. of remaining time in the presence of given shock decrease. Figures 6 and 7. display distributions of RUL_o and RUL_s during the time.

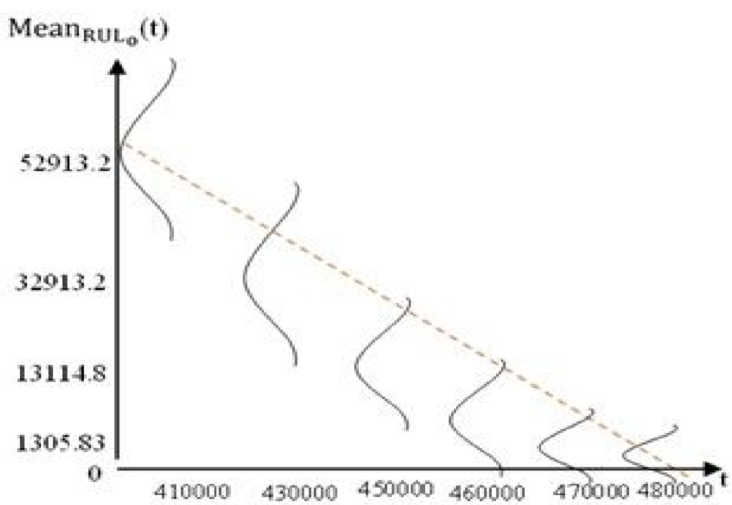

Fig. 6. Distribution of RUL_o during the time

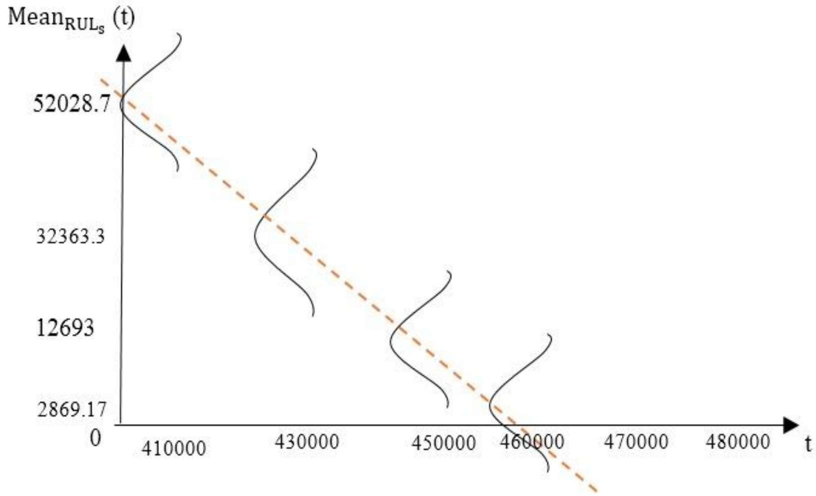

Fig. 7. Distribution of RUL_s during the time

5. Conclusion

Accurately predicting the Remaining useful service life of MEMS is of great importance for setting up a maintenance schedule and decreasing maintenance cost. This paper presents a forecasting method of the Micro-Electro-Mechanical-System RUL in the presence of shocks and degradation based on AF and a mathematical model. Defect size of 30 MEMS was collected during 23 inspection times. The defect size data of each system describe degradation path that is linear with parameters a and b with distributions $a \sim N(272E-09, 6.36047E-20)$ and $b \sim N(-9.29E-06, 1.08E-08)$, respectively. In situations without shock, this path reaches critical value at time t_f. This time is failure time with distribution $t_f \sim N(4.63E+0.5, 1.08E-08)$. Considering this time, RUL_o is accountable in each inspection time. RUL_o of 30 systems in each inspection time follows Normal distribution with different parameters for each time.

Based on AF and its relation with RUL_o and RUL_s, RUL_s values in each time and their distributions are obtained. Advantage of this procedure is that all of the required parameters are easier to access practically rather than measuring the future shock magnitudes. In addition, more extensive analyses can be done regarding RUL distribution characteristics such as skewness and kurtosis of the distribution.

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