Degradation Modeling Analysis for Microrobots Flexure Hinges Using Intracorporeal Surgeries

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The new generation of instruments in the field of medical robotics aims to use devices that are less and less invasive for the patient. However, some of these microrobots are in underdevelopment and must undergo several tests in order to obtain the mandatory certifications to be used on patients. Indeed, one of the main tests to be validated is the accurate determination of their reliability and remaining useful life (RUL) in order to ensure optimal performance during the surgical procedure. This paper is focused on obtaining a degradation modeling for a microrobot dedicated to intracorporeal laser surgeries. For this purpose, simulated degradation data is collected from a four-bar complaint mechanism that fulfills the same behavior of a flexure hinge. For it, our work is based on the pillars of the Prognostics health and management (PHM). Knowing that a flexure hinge of the microrobot is a critical element and knowing that it is possible to have measures of the evolution of its performance and therefore of its degradation, we propose a data-driven degradation modeling by considering the normal life distribution in order to assess the reliability and the RUL. In conclusion, a data-driven model within the PHM study for lifetime estimation was presented.

Keywords: Data-driven, Degradation modeling, Remaining useful life, Reliability, Surgical microrobots, Flexure hinges.

1. Introduction

Surgeries using a laser as a scalpel brings several advantages as sealing off blood vessels and nerves reduces bleeding, swelling, scarring, pain, infection, and the length of the recovery period. However, a laser as a scalpel is uniquely used in surgical interventions in areas as ophthalmology, dermatology, and a few other vocal folds, always with the laser source placed outside the human body. Between 2012 and 2015, the European FP7 project μRALP proposed to develop a system to place a miniature robotic laser scalpel inside the human body see Fig. 1.

This relative progress to the existing technology was possible thanks to the creation of a teleoperated surgical system based on a microrobot as an end-effector and an adjustable laryngoscope to insert the microrobot and cameras inside the patient's body and in this way to treat diseases inside the human body using a laser as scalpel. Nevertheless, this microrobot which is used to drive the laser beam inside the human body must undergo several tests, mainly to determine its useful lifetime and ensure an optimal performance during the surgical procedure. Prognostics health and management (PHM) approach incorporates many assessment skills from the observation all the way to the decision phase, including the analysis phase. Thus, a PHM approach is presented precisely to determine the lifetime of the microrobot which is a necessity to the certifications to get access to the commercialization.

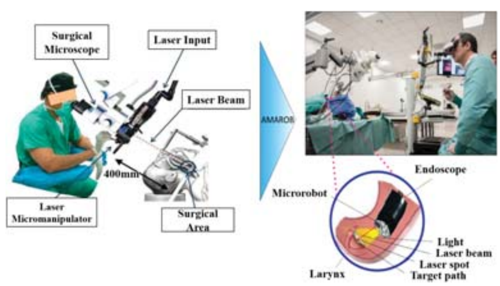

Fig. 1. Concept of μRALP project.

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PHM approach has been studied to increase the reliability, availability, safety, maintainability, logistics of the systems in order to minimize the maintenance cost of engineering assets, see (Atamuradov et al. (2017); Das et al. (2011)). A key pillar of the PHM is the prognostics, which enables the RUL estimation of the systems by taking into account their current health state and their future operating (Khelif et al. (2017)).

In order to estimate the RUL of the systems, there are several prognostics methodologies and techniques (Okoh et al. (2014)). They are classified into four groups: Experienced-based approaches are based on the distribution of events records of a population of an identical item, can be implemented when historical repair and failure data are available, and not consider the failure indication to predict the life. Model-based approaches usually used mathematical dynamic models, this can be physics-based models and statistical models, for example, the Crack growth modeling. Knowledge-based approaches usually are solved by human specialists, for example, expert systems, and fuzzy logic systems, and they have been used for fault diagnostics. Data-driven approaches are based upon statistical and learning techniques, for example, multivariate statistical methods, neural networks, Bayesian networks, and Hidden Markov models (Gorjian et al. (2010))

This work is based on a data-driven approach since thanks to the growth of sensor technology this has become the main approach in the domain of RUL estimation. Degradation data contain valuable information about the performance of systems. It even provides more information than the traditional failure times. For that reason, the reliability assessment of the systems using degradation data has become a crucial approach to evaluate the reliability and to estimate the RUL of a complex system. Moreover, the degradation data can be analyzed before failure occurs and provides reliable estimations of the systems.

Probabilistic methods use a large quantity of data of failure that, according to the information that these provide, allow selecting a probabilistic distribution that demonstrates the life cycle of the system through a life distribution.

According to ReliaSoft (2015), the term life distributions is used to describe the collection of statistical probability distributions that we use in reliability engineering and life data analysis. A statistical distribution is fully described by its probability density function (pdf) and its cumulative distribution function (cdf). The pdf represents the relative frequency of failure times as a function of time while the cdf is used to measure the probability that the item in question will fail before the associated time value, and is also called unreliability. These life distributions are selected according to the given data-set. Each dataset provides valuable information and the analyst must choose the most appropriate one using a goodness-of-fit-test. As it was mentioned already above, the probabilistic distributions demonstrate the behavior of a system during its life cycle, thus it is important to explain that most failures of the system are caused by the degradation of material and devices that occur throughout this cycle.

Failures occur when the degradation measure reaches a critical failure level making the systems inoperable as designed (Huairui Guo (2015)), within the specified conditions and specified time (Ming Zhang (2017)). The degradation can not be physically measured, but it is possible to have measures of the evolution of the product's performance and therefore of its degradation see (Escobar et al. (2003)). If the physics of the model is unknown, the statistical approach can be used to find a degradation model that can best fit a given data set. We here propose a data-driven degradation modeling by considering some usual life distributions in order to assess the reliability and the RUL of the flexure hinges, having as a base the PHM concepts.

This paper is organized as follows. Section 2 presents a review of a microrobot dedicated to intracorporeal surgeries and a short explanation of the proposed mechanism to collect the simulated degradation data. Section 3 deals with the methodology of the pillars of the PHM where the associated steps are explained as well as the life distributions for reliability and RUL prediction. In Section 4, the experiments and results for the computation are explained. Finally, Section 5 provides the conclusion of this work.

2. Microrobot Dedicated to Intracorporeal Surgeries review

In this section, a synthesis of the microrobot dedicated to intracorporeal surgeries is presented, where the consecutive parts and the function of the flexure hinges for better compression of this study are explained. Moreover, the design of the sample to data collection is explained which will show the behavior of a single flexure hinge.

2.1. *Microrobot Analysis*

A microrobot with a parallel kinematics structure destined to perform laser microsurgery on vocal folds was created and tested in laboratory conditions in FEMTO-ST Institute, this is shown in Fig. 2. Smart Composite Microstructure (SCM) fabrication technique was used to fabricate this microrobot. The SCM technique was chosen to create passive hinges which are combined in some parts with piezoelectric cantilevers actuators and in other parts simply left free in order to generate the displacement. The flexure hinges are made of polyimide and yield a relatively high range of rotations (Lescano (2015)). However, these hinges

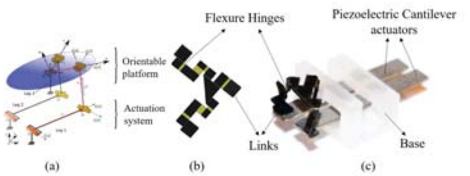

Fig. 2. Microrobot dedicated to intracorporeal surgeries, (a) Parallel Kinematic structure made with SCM technique, (c) microrobot assembly.

can cause complex deformations or failures in the product which can affect the reliability of the microrobot, hence these joints are considered the critical element of the microrobot. The reliability of the microrobot can be evaluated with the information that provides the degradation data as well as estimating the RUL since through this data its performance is known.

Nevertheless, the parallel structure of the microrobot is complex to be analyzed since this integrates many flexure hinges and in order to identify the flexure hinge that causes the failure, an in-depth analysis of the mechanism must be made. Thus, a mechanism design was proposed to collect the degradation data, this mechanism design will be explained in Section 2.2.

2.2. *Four-Bar Compliant Mechanism Design and obtaining data*

The proposed four-bar complaint mechanism shown in Fig. 3 was used as a sample to collect the simulated degradation data. This sample design performs the same movements of the flexure hinges of the microrobot.

The mechanism design of the sample was based

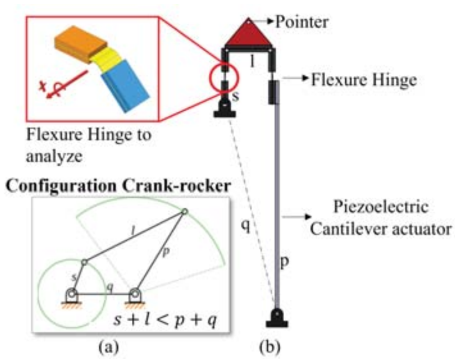

Fig. 3. Four-bar mechanism, (a) Crank-rocker configuration of a four-bar mechanism and (b) Crank-rocker configuration of a four-bar compliant mechanism.

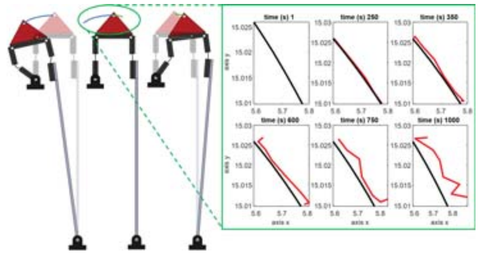

Fig. 4. Bending motion simulation of a flexure hinge and path collection.

on Grashof's law and a crank-rocker configuration equal to $s + l < p + q$ was selected in order to obtain a large flexion angle in the flexure hinge to be analyzed, where s, l, p, and q are the links of the mechanism.

When simulating the bending motion of the flexure hinge in SolidWorks® Software, x and y coordinates are obtained during its operating cycle. These data save the information degradation evolution over time. To observe this evolution, a path that represents the collected past health state is considered as a reference, in which the design conditions are not modified during the simulation.

To obtain the current health path of the flexure hinge, simulations are carried out for 10 samples and the flexure hinge spring constant is modified, which represents a design condition when simulating a compliant mechanism.

The purpose of modifying the value of this parameter is to try to show in the simulation that each sample has different mechanical characteristics even if they look similar, since these may vary due to various factors at the time of manufacture, however, these variations take very small values.

Fig. 4 shows a comparison between the past health collected, represented by the black line, with the current health, represented by the red line, where the evolution of the degradation over time is observed. The analysis of these paths is presented in Section 4.

3. Methodology

We now come to present the proposed methodology for flexure hinge degradation modeling with the PHM. In this work, we will focus on the data-driven approach since we will use a data set collected from simulations that shown how a

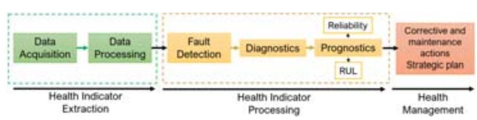

Fig. 5. PHM Pillars.

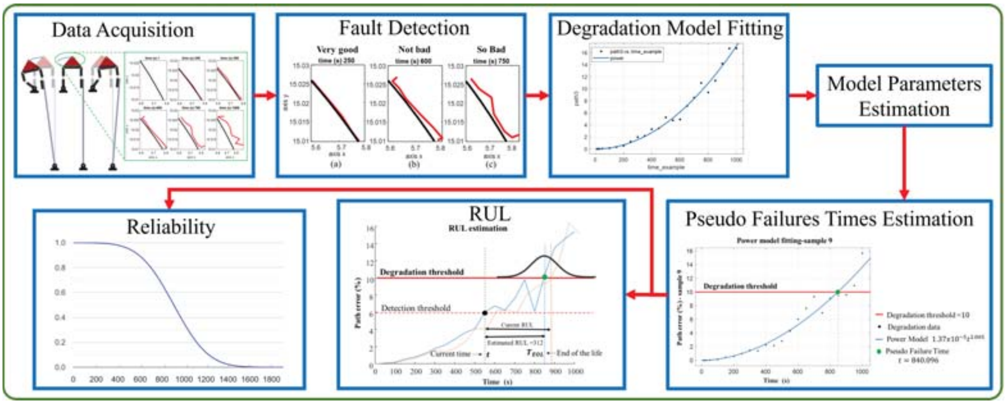

Fig. 6. Steps of the proposed methodology.

flexure hinge is degraded over time. Recall that PHM usually has 6 pillars see Fig. 5 that collectively enables us to understand the behavior of the system. These pillars involve the next steps: data acquisition, data processing, fault detection, diagnostics, prognostics, and decision support.

Data acquisition is the first step of the PHM, this provides access to the digitized sensors or transducers data that are collected from the systems in order to perform diagnostic and prognostics. In order to get error-free data and better interpretation of the behavior of the system, the second step is the data processing, since sometimes the collected data involve noises that could confuse the interpretation of the behavior of the systems. Thus, the data must be submitted to cleaning, evaluation, and selection of the main features in order to get valuable information as the health state of the systems. As for the faults' detection, it is dedicated to comparing the input data with expected values in order to detect strange behaviors or anomalies taking account of the functioning conditions (Thurston (2001)). Diagnostic enables us to evaluate and detects the root cause of the failures from the moment that these are identified. The fault detection can provide useful information for the diagnostic models, moreover to enable us to get better precision with a reduction of the inactivity time and a reduction in the operation costs of the system (Bailey et al. (2015)).

Prognostics namely RUL estimation is known as the prediction of the useful life of a system and also can be defined as a mean of probability, i.e., as a way of quantifying the possibility that a machine will fail, or to know the time when the machine can fail Dragomir et al. (2009). RUL refers to the time left before observing a failure given the current machine age and condition, and the past operation profile. It is given by

$$RUL(t) = T_{EOL} - t, \tag{1}$$

where T_{EOL} is the failure time to a predefined degradation threshold and t is the current time.

Fig. 6 shows an algorithm about our proposed methodology in order to evaluate the reliability and estimate the RUL of the system. The first step consists of collecting the data as described in Section 2.2. Then, we go through the fault detection part, the degradation modeling, and the reliability and RUL estimation.

The main aim of developing a statistical model for the degradation data is to identify a model for the degradation paths. The shape of the paths can take different forms depending on the degradation process as a function of the variable measuring lifetime of a unit (Meeker et al. (2011)).

As mentioned earlier, this study is focused on analyzing degradation data, thus statistical methods can be used to find a model that can best fit a given data set. Therefore, it is considered important to present the basic degradation models commonly used: linear, exponential, logarithmic, and power (Huairui Guo (2015)) listed below:

- Linear model: $D(t) = a \times t + b$
- Exponential model: $D(t) = b \times e^{a \times t}$
- Power model: $D(t) = b \times t^a$
- Logarithmic model: $D(t) = a \ln(t) + b$

where $D(t)$ is an index representing the degradation, a and b are the model parameters, a represents the slope of the curve and b represents the intercept (at time =1), and t is the time. These four models are ranked according to the sum of the square of error (SSE) defined by

$$SSE = \sum_{i=1}^{m} SSE_i = \sum_{i=1}^{m} \sum_{j=1}^{n_i} (D_{ij} - \hat{D}_{ij})^2, \tag{2}$$

where m is the number of units, n_i is the number of observations, D_{ij} is the past degradation value collected and $\hat{D}_{ij}$ is the predicted degradation. SSE essentially measures the variation of modelling errors and is the sum of the squared differences between each observation and its group's mean. The model with a smaller SSE is considered better than a model with a larger SSE (Huairui Guo (2015)).

Moreover, in order to know if the model fits well the given data also is recommended to verify the square of the correlation coefficient (R^2) between the observed degradation value and the predicted value. R^2 reflects the goodness-of-fit of a model to the variable that it intends to explain. It is important to know that the result of the coefficient of determination oscillates between 0 and 1. The closer its value is to 1, the greater the fit of the model to the variable that we are trying to explain.

The RUL estimation and the reliability evaluation through the life data that are extracted from the degradation modeling are considered as the most central concepts in PHM, for their evaluation life distributions are used. A life distribution is a collection of failure data or life data and is presented graphically as a graph of the number of failures as a function of time. There are many life distributions as Normal, Exponential, Lognormal, and Weibull distributions that can be used to model the reliability of the system, that is, to determine with a certain degree of confidence the probability that a system can survive for a set time while operating correctly, and that also allows estimating in terms of probability the time left from the current time to the failure time or degradation threshold known as RUL.

In our study will explain in more detail the Normal distribution since this one was the most appropriate for the computed pseudo failure time data, which refer to the times that reach a preset degradation threshold.

According to Pham (2006) the Normal distribution is used to describe mechanism systems where the failure is the product of the wear-out effect or a result of the accumulation of small and random mechanical damage. This distribution has two parameters, μ that represent the mean of the population, and σ , the standard deviation of the population. The spread of the normal distribution is determined by the standard deviation of its pseudo failure data. The Normal distribution takes the well-known bell shape and is described by the probability density function $f(t)$ and cumulative density function $F(t)$ given by

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{t-\mu}{\sigma})^2} \quad (3)$$

and

$$F(t) = \int_{-\infty}^{t} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{s-\mu}{\sigma})^2} ds, \quad (4)$$

where μ is the mean value, σ is the standard deviation, $f(t)$ indicates the relative frequency of failures at any time t and $F(t)$ gives the probability that a system will fail at or before t.

The reliability function is defined by

$$R(t) = \int_{t}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{s-\mu}{\sigma})^2} ds. \quad (5)$$

Based on the above proposed methodology, we will show the statistical and probabilistic methods and techniques applied to the experimental results in order to estimate the reliability and the RUL of the flexure hinges.

4. Experimental Results

We now come to show the experimental results. When the microrobot performs the activities for which it was designed, the flexure hinges are subjected to loading and unloading cycles repeatedly during their operating cycle, this phenomenon leads to the degradation of the material. Therefore, when the flexure hinges of the microrobot perform the bending motions in optimal conditions can be obtained the graph of its path during this operating time through the use of sensors, then as it occurs the degradation of this path can change drastically.

In Section 2.2 it was explained how the path was obtained for each sample through simulations, now we will explain what these paths show. Fig. 4 shows the path of sample 9 during 6 different times to know the health of the bending hinges over time, where the black line represents a good state of health of the system, that is, that the hinge of bending is working properly within the specified conditions and the specified time, and the red line represents the degradation of the bending hinge, that is, it shows the reduction of its reliability, and from this figure, three different

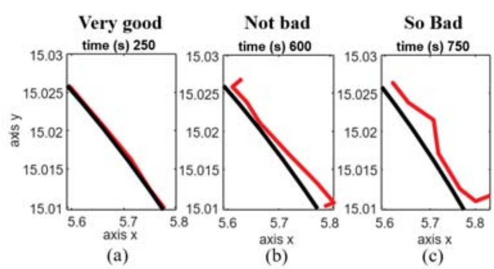

Fig. 7. Failures and anomalies detection, (a) Failures at 250 seconds, (b) Failures at 600 seconds, and (c) Failures at 750 seconds.

Table 1. Simulated degradation data for the flexure hinges over time.

t	$S1$	S2	S3	S4	S5	S6	S7	S8	S9	S10
10	6.2e^{-4}	3e^{-3}	5e^{-3}	0.029	3e^{-3}	3.7e^{-3}	2e^{-3}	3e^{-3}	3.6e^{-3}	3.2e^{-3}
100	0.05	0.27	0.184	0.135	0.183	0.17	0.14	0.21	0.15	0.14
200	0.26	0.92	0.858	0.702	0.757	0.76	0.78	0.78	0.7	0.536
300	0.41	1.89	1.778	2.028	1.987	1.84	1.12	1.76	1.04	1.52
400	0.86	3.69	4.817	3.36	3.665	2.80	2.24	2.86	1.79	4.23
500	1.17	4.25	4.260	4.21	4.722	3.91	3.89	4.61	3.91	3.87
600	2.06	5.55	9.417	4.767	6.12	7.75	4.35	5.42	6.14	5.67
700	2.2	12.35	15.72	6.59	8.054	9.15	3.80	8.05	6.58	8.32
800	3.16	10.94	18.12	11.30	13.39	11.71	8.01	11.87	11.18	9.57
900	3.91	16.17	16.17	14.82	16.29	11.59	8.56	12.61	13.58	18.42
1000	5.66	24.32	26.03	12.27	13.54	19.44	14.21	20.13	11.12	18.66

health states were identified during three instances of time shown in Fig. 7: when there is no failure as very good at 250 seconds, when a soft failure appears as not bad at 600 seconds, and when the failure occurs as bad at 750 seconds.

As the reference x and y coordinates of 1 operating cycle change with respect to the x and y coordinates of n cycles number, it is deduced that the flexure hinge has reached the degradation. Taking into account these parameters and making a statistical comparison between the reference x and y coordinates, the number of cycles in which the flexure hinge stops fulfilling the specified requirements can be estimated.

The collection of these degradation data is essential for PHM methodologies since it allows us to predict and prevent failures in flexure hinges thanks to the valuable information on the health state provided by these data.

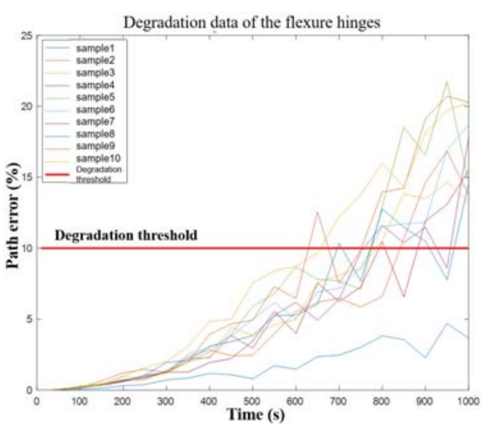

Fig. 8. Degradation path error corresponding to 10 samples.

To perform the degradation analysis, once the initial path is obtained, a greater number of operating cycles is simulated in the MATLAB® Software and random numbers are used in order to obtain a change in the path according to the number of cycles of the simulation, then a percentage error between the initial path and the path to cycle n is calculated to represent the degradation data. The degradation data are shown in Table 1 and correspond to a change in the percentage of the error in the path vs time. The number of cycles was transformed in time for a better interpretation of the data. The degradation curves corresponding to the 10 samples are shown in Fig. 8, where the x-axis represents the time in seconds, the y-axis the change in the percentage of the path error, and the horizontal line is the degradation threshold value, this line is considered as the indicator of failures of the flexure hinge and maximum acceptable error is 10%. When the change in the percentage of the path error exceeds a set degradation threshold, it can be considered that the flexure hinge is no longer suitable for future operations.

Once we get the degradation data set shown in Table 1, the basic degradation models presented in Section 3 are used in order to fit the data.

In the Table 2 is shown the result of fitting

Table 2. Sum squares of error (SSE) and square of the correlation coefficient (R^2).

Model	Rank	SSE	R^2
Linear	3	58.36	0.91
Exponential	2	21.18	0.96
Power	1	10.23	0.98

the given degradation data using three basic models: linear, exponential, and power, considering its rank, the SSE, and the R^2.

On the one hand, considering its ranking, the power model got the highest rank for each sample, since the values of the SSE of each sample proved to be the smaller values, and on the other hand, according to the computed values of the R^2 of the power model of each sample, these values were the closest to 1, which shows the predicted values are close to the observed values. According to the results of the Table 2, the power model is considered the model that best fits the given data.

4.1. ***Reliability Estimation***

In order to estimate the reliability of the system, the simple approach called pseudo failure time is used, since when fitting the degradation model is known its parameters a and b, therefore, when knowing the degradation threshold can be computed the pseudo failure time for each sample.

Table 3 provides the parameters a and b obtained for each sample as well as their pseudo failure times. If we replace these parameters in the power model $D(t) = b \times t^a$ and we replace $D(t)$ by the degradation threshold 10, then pseudo failure times can be easily calculated by solving t from the power model.

For example, the parameters a and b for sample 9 are 2.005 and 1.37×10^{-5}, respectively. When replacing these values in the power model and taking $D(t) = 10$, the pseudo failure time $t = 840.096$ is obtained, this is shown in Fig. 9.

Once life or pseudo failure time data set are available (see Table 3), the life distributions mentioned in Section 3 are used to estimate the reliability of the flexure hinge at any time. In order to select the life distributions that most accurately fit

Table 3. Power model parameters and pseudo failure time corresponding to each sample.

Samples	Parameter a	Parameter b	Pseudo Failure Time
1	1.984	6.077e^{-6}	1359.01
2	1.988	2.324e^{-5}	682.158
3	1.96	3.018e^{-5}	655.34
4	1.971	1.979e^{-5}	782.954
5	1.98	2.064e^{-5}	743.633
6	1.994	1.736e^{-5}	774.269
7	1.988	1.479e^{-5}	1224.45
8	1.993	1.7e^{-5}	785.069
9	2.005	1.37e^{-5}	840.096
10	2.001	1.662e^{-5}	773.108

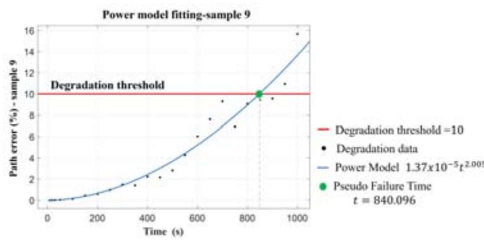

Fig. 9. Power model fitting for sample 9 and its pseudo failure time.

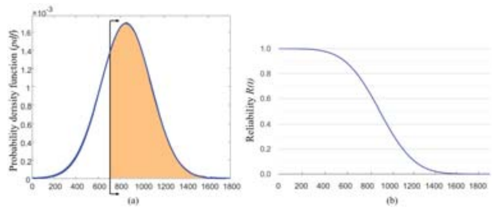

Fig. 10. Normal Distribution. (a) Probability density distribution at $t = 700$ seconds, and (b) reliability function at $t = 700$ seconds.

the given data set, the chi-square test was evaluated.

The computed Normal distribution parameters were $\mu = 862.009$ and $\sigma = 234.686$, then replacing these parameters in (5) and with a determined time value we can compute the reliability of the flexure hinge at any time.

For example Fig. 10 shown the reliability for sample 9 at time $t = 700$ is $R(700) = 0.76$ represented by the orange area. This indicates 76% of reliability at 700 seconds. In other words, the probability that the flexure hinge will not fail is high and the probability of failure represents 24%. When knowing the life distribution that fits the pseudo failure times, the reliability at any time can be calculated.

4.2. ***RUL Estimation***

The current RUL and predicted RUL are shown in Fig. 11 these are represented by its probability density function *pdf*. Estimated RUL is computed from the point where the degradation was detected, this represents the current time t, in this time we can define a detection threshold value until the time T_{EOL} that represents the maximum degradation condition. The RUL for sample 9 is equal to 312 seconds, and it was computed by (1) considering the current time $t = 550$ and the failure time $T_{EOL} = 862.009$. In this way, different RULs can be estimated, their precision depends on the amount of data available, the higher data amount their precision increases.

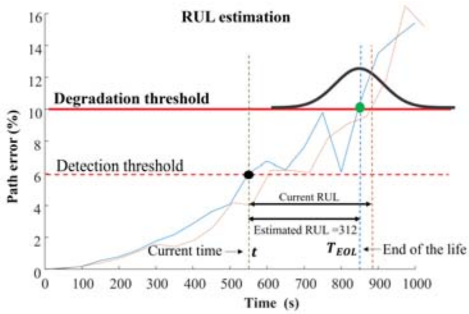

Fig. 11. Illustration of current RUL and estimated RUL where the orange and blue lines refer to the current and the predicted degradation, respectively.

5. Conclusion

An analysis of the basic degradation models within the PHM study for lifetime estimation was for the first time presented of the flexure hinges of a microrobot dedicated to intracorporeal surgeries.

The proposed approach is based on the flexure hinge simulated degradation data and some basic probabilistic and statistical tools that allowed fitting properly a degradation model and choose the adapted life distribution for the failure times, being the adapted Normal Distribution. The selection of the life distribution allowed us to predict the reliability at any time and be able to estimate the RUL.

This work opens a window for future studies on real degradation analysis when the tests are carried out with the proposed sample, as well as involving more advanced approaches in order to estimate the RUL.

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