Exploring the distribution of time to failure of bearing experimental data

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Abstract. Bearing failure degradation describes the probability of failure after survive a length of time. This paper explores the empirical distribution of time to failure and modeling of bearing failure degradation using vibrational experimental data. Kurtosis was used as a feature of vibrational data. The failure probability was estimated using actuarial method. Fitting to some time to failure distributions and bearing failure degradation models will be discussed as an illustration of the proposed method. The results of the study can be used to predict the percentage bearing failures for a certain time of period. The results of the proposed method can contribute to maintenance system of a mechanical system

1. Introduction
Reliability refers to the probability that a component will operate satisfactory for a certain length of time. Let T be a continuous random variable representing time to failure with probability density function f. The reliability function is given by R(t) = P(T > t). The degradation function h(t) = \frac{f(t)}{R(t)} describes how prone the unit is to failure after a length of time. It is only necessary to know one of the function h(t), f(t), R(t) in order to be able to deduce the other two. The degradation function is important because it has a direct physical interpretation, and information about the nature of the function is useful in selecting an appropriate model for time to failure. Rolling bearing is one of the most critical components in rotating machinery. Its state is related to the performance of the machinery. Vibration analysis is the frequently used method for fault diagnosis of rotating machinery. In order to extract useful features from original signal, a lot of effective signal extraction have proposed. To determine the vibration generated in a ball bearing, a model was created to find the equation that define its movement. Vibration data is one of the reliable information that represent the performance of machineries and widely used to define the health states of a system.

Caesarendra et al. presents a combined method of the probability approach and support vector machine to predict failure degradation based on simulated and experimental failure bearing data [1]. Caesarendra et al. proposes an application of relevance vector machine, logistic regression and autoregressive models to assess failure degradation based on run-to-failure bearing simulation [2]. Widodo and Ceaserendra reviews new developed techniques for machine degradation [3]. Kosasih et al. developed a combined low pass filter and adaptive line enhancer to predict bearing degradation in low
speed slewing bearing [4]. Caesarendra et al. proposes a sequential Monte Carlo to predict the machine degradation [5]. Qingzhong and Fulei proposes point contact theory to develop bearing degradation assessment [6].

The main objective of this work is the exploration of time to failure and degradation of bearing based on experimental data. An actuarial approach was used to estimate the unit probability of bearing failure. The degradation was explored using bearing vibration experimental data. The kurtosis was used to determined the time of failure of the bearing. The determination of time to failure of 12 bearing is the first part of the paper. The second part concern with the estimation of fault in unit time. The third part concerns with the estimation of bearing degradation using linear assumption.

2. Materials and methods
The vibration experimental data was generated from bearing test rig to produce run-to-failure The data was downloaded from the Prognostics Center of Excellence (PcoE), University of Cincinnati (Lee et al.) [7]. Vibrational signals was collected every 20 minutes by a data acquisition card. The data sampling rate was 20 kHZ and the data length was 20 480 points. The vibrational run-to-failure PcoE data consist of 3 datasets with 12 time-to-failure and 4 normal data; dataset 1 20480x8x2156, dataset 2 20480x4x984, dataset 3 20480x4x4448. Kurtosis calculated for each datasets produces an array of dimension 8x2156 for dataset 1, 4x984 for dataset 2, and 4x4448. Using threshold kurtois 20, dataset 1 produces 8 time-to-failure data, dataset 2 produces 4 time-to-failure, and dataset 3 produces 4 censored data since all the kurtosis are less than 20. Figure 1 shows the bearing vibration plot in time domain (measurement point). Kurtosis was calculated from this vibrational data and for dataset 1 produces 8 (4 bearing in horizontal and vertical direction) kurtosis plot as shown in figure 1. Using threshold 20, time-to-failure is determined as the first time the kurtois cut the threshold. Time-to-failure of bearings of three datasets along with the value of the kurtois is shown in figure 1.

![Figure 1. Vibrational plot; amplitude versus measurement points (20480). Kurtosis was calculated from 20480 amplitude of bearing vibration.](image)
3. Results and discussion
The main results are shown in table 1, table 2 and table 3. Table 1 shows the time to failure and kurtosis of 12 measurements of bearing vibration [1]. Table 2 shows the calculation of unit failure probability $q_t$ using the method of moments (London) [8]. Using exponential and linear assumption, the bearing failure degradation as function of unit failure probability is shown in figure 3. As expected, the bearing degradation increases as the time $t$ increases. The plot can be used to predict the time bearing failure given a certain failure degradation level. The proposed method can be used to develop a bearing failure degradation models using smoothing techniques. Some standard models such as Weibull, Gompertz, Pareto, etc can be fitted to the experimental data. Due to small data set the model fitting process will be investigated in the future research.

Table 1. Measurement Points (MP), minute, hour and day of time to failure of 12 bearing. Dataset 1 has 8 rows data corresponds to 4 bearings in horizontal and vertical direction.

| Bearing | MP  | Minute | Hour | Day  | Kurtosis |
|---------|-----|--------|------|------|----------|
| 1       | 1723| 34440  | 574.00| 23.92| 25.78    |
| 2       | 1468| 29340  | 489.00| 20.38| 62.55    |
| 3       | 1722| 34420  | 573.67| 23.90| 20.20    |
| 4       | 1747| 34920  | 582.00| 24.25| 21.94    |
| 5       | 1731| 34600  | 576.67| 24.03| 28.04    |
| 6       | 1732| 34620  | 577.00| 24.04| 25.38    |
| 7       | 1675| 33480  | 558.00| 23.25| 26.71    |
| 8       | 1682| 33620  | 560.33| 23.35| 32.61    |
| 9       | 974 | 19460  | 324.33| 13.51| 25.63    |
| 10      | 974 | 19460  | 324.33| 13.51| 28.67    |
| 11      | 974 | 19460  | 324.33| 13.51| 22.84    |
| 12      | 974 | 19460  | 324.33| 13.51| 28.67    |
| 13      | 4448| 88940  | 1482.33| 61.76| 3.32     |
| 14      | 4448| 88940  | 1482.33| 61.76| 3.563    |
| 15      | 4448| 88940  | 1482.33| 61.76| 3.285    |
| 16      | 4448| 88940  | 1482.33| 61.76| 3.51     |
Table 2. Computational $q_t$ using q-method, bearing failure degradation using exponential and linear assumption $h_{eksp} \left( t + \frac{1}{2} \right)$, $h_{linear} \left( t + \frac{1}{2} \right)$.

| i  | $t_i$ | $q_t$ | $h_{eksp} \left( t + \frac{1}{2} \right)$ | $h_{linear} \left( t + \frac{1}{2} \right)$ |
|----|------|-----|-------------------------------|-------------------------------|
| 1  | 13.51| 4   | 0.51                         | 2.04                          |
| 2  | 20.38| 1   | 1                            | 0.38                          |
| 3  | 23.25| 1   | 1                            | 0.25                          |
| 4  | 23.35| 1   | 1                            | 0.35                          |
| 5  | 23.90| 1   | 1                            | 0.90                          |
| 6  | 23.92| 1   | 1                            | 0.92                          |
| 7  | 24.03| 1   | 1                            | 0.03                          |
| 8  | 24.04| 1   | 1                            | 0.04                          |
| 9  | 24.25| 1   | 1                            | 0.25                          |
| 10 | 61.76| 1   | 1                            | 4.00                          |
|    |      |     | 262.39                       | 14.04                         |

Table 3. Failure probabilities $q_t$, bearing failure degradation using $h(t)$ exponential and uniform assumption $h_{eksp} \left( t + \frac{1}{2} \right)$, $h_{linear} \left( t + \frac{1}{2} \right)$.

| No | $t$ | $q_t$ | $h_{eksp} \left( t + \frac{1}{2} \right)$ | $h_{linear} \left( t + \frac{1}{2} \right)$ |
|----|----|------|-------------------------------|-------------------------------|
| 1  | 13 | .285 | .335                           | .332                           |
| 2  | 20 | .088 | .09198                         | .09191                         |
| 3  | 23 | .420 | .553                           | .539                           |
| 4  | 24 | .690 | 1.186                          | 1.064                          |
| 5  | 61 | 1.000| .000                           | 2.000                          |

Figure 3. Bearing failure degradation with linear assumption.

4. Conclusion
An actuarial approach was proposed in this article to estimate the bearing failure degradation using unit failure probability. The unit failure probability was estimated using the method of moment. Bearing
failure degradation was obtained from unit failure probability using exponential and uniform assumption. The results show that the proposed method can be used to predict the bearing failure degradation. Fitting a failure degradation is subject to future research.

References

[1] Caesarendra W, Widodo A and Yang B S 2011 Combination of Probability Approach and Support Vector Machine Towards Machine Health Prognostics Probabilistic Engineering Mechanics 26 165-173

[2] Caesarendra W, Widodo A, Thom P H, Yang B S and Setiawan J D 2011 Combined Probability Approach and Indirect Data-Driven Method for Bearing Degradation Prognostics IEEE Transaction on Reliability 60(1)

[3] Widodo A and Caesarendra W 2014 Summary of the Recent Development Techniques for Machine Health Prognosis Rotasi 16(1) 21-27

[4] Kosasih P B, Caesarendra W, Tieu K, Widodo A and Moodie C A S 2014 Degradation Trend Estimation and Prognosis of Low Speed Slewing Bearing Lifetime Applied Mechanics and Materials 493 343-348

[5] Caesarendra W, Niu G, and Yang B S 2010 Machine Condition Prognosis Based on Sequential Monte Carlo Method Expert System with Application 37 2412-2420

[6] Qingzhong H and Fulei C 2016 Bearing Performance Degradation Assessment Based on the Contact Stress and Deformation, 3rd International Conference on Mechatronics and Information Technology ICMIT Atlantis Press

[7] Lee J, Qiu H, Lin J and Rexnord Technical Service 2007 Bearing Data Set IMS (Cininati: University of Cinncinati NASA Ames Prognostics Data Repository NASA Ames Moffet Field)

[8] London D 1988 Survival Models and Their Estimation (Winsted, Connecticut: ACTEX Publications)