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REMAINING LIFE TIME PREDICTION OF BEARINGS USING K-STAR ALGORITHM – A STATISTICAL APPROACH

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Abstract

The role of bearings is significant in reducing the down time of all rotating machineries. The increasing trend of bearing failures in recent times has triggered the need and importance of deployment of condition monitoring. There are multiple factors associated to a bearing failure while it is in operation. Hence, a predictive strategy is required to evaluate the current state of the bearings in operation. In past, predictive models with regression techniques were widely used for bearing lifetime estimations. The Objective of this paper is to estimate the remaining useful life of bearings through a machine learning approach. The ultimate objective of this study is to strengthen the predictive maintenance. The present study was done using classification approach following the concepts of machine learning and a predictive model was built to calculate the residual lifetime of bearings in operation. Vibration signals were acquired on a continuous basis from an experiment wherein the bearings are made to run till it fails naturally. It should be noted that the experiment was carried out with new bearings at pre-defined load and speed conditions until the bearing fails on its own. In the present work, statistical features were deployed and feature selection process was carried out using J48 decision tree and selected features were used to develop the prognostic model. The K-Star classification algorithm, a supervised machine learning technique is made use of in building a predictive model to estimate the lifetime of bearings. The performance of classifier was cross validated with distinct data. The result shows that the K-Star classification model gives 98.56% classification accuracy with selected features.

Keywords: Remaining useful Life, K-Star algorithm, Statistical methods.

Nomenclatures

I	Infinite set of instances
n	Statistical sample size
P	Set of all prefix codes
s	Statistical standard deviation
T	Finite set of transformations on I
x, y	Statistical sample means

Abbreviations

DAQ	Data Acquisition
FP Rate	False positive Rate
K*	K-Star algorithm
RUL	Remaining Useful Life
TP Rate	True Positive Rate

1. Introduction

Bearings play vital role in rotatory machineries and find its applications in many automotive and industrial applications. Bearing lifetime prediction seeks importance in industrial applications as it directly affects the overall reliability metrics. Hence, preventive measures have to be taken to avoid the downtimes.

There has been numerous studies done on fault diagnosis of bearings which are based on natural faults and simulated faults like wear of inner race, outer race cage faults, roller defects, etc. In past, the experiments were conducted at accelerated conditions so that less time is consumed. In the present study, experiment was carried out at pre-defined load and speed conditions. However, the results of accelerated test conditions differ from the experiments run at defined test conditions matching to the real time applications.

The raw vibration signals were attained from brand new bearing on a continuous basis mounted on the experimental set-up till it gets damaged naturally. The acquired signals were grouped into 5 different categories based on the health state of the bearings, viz stage 1 to stage 5 respectively. Stage 1 includes the signals which are acquired from the brand new bearing immediately at the start of the experiment. Signals which are acquired over 1000 hours of running the bearing at defined load and speed were placed on stage 2. Stage 3 and 4 include the signals after 1250 and 1500 hours respectively. Signals belonging to final stages of the bearing were placed at stage 5.

Regression technique is the most common predictive method in condition monitoring of the bearing. The present study was carried out using a classification technique and in real time environment. For the general maintenance purpose, it is enough to know the state of bearing either it is safe state or damaged state. The remaining lifetime of bearing was diagnosed using a predictive model built. With the collected signals 12 statistical features were extracted. Subsequently, feature selection process was carried out to identify the best contributing feature combinations through decision tree techniques. Further, the prognostic model was built using K-Star classification technique following supervised learning approach with the selected descriptive statistical features. The classification accuracy thus attained and the performance of the classifier is discussed in the later sections.

Experience based prognostic methods were used in building the predictive model. Real time historical data such as maintenance data, manufacturing data like breakdown, scrap are collected over a period of time. The principles for estimating the useful life of bearings at defined conditions were already detailed in the earlier studies [1-3]. The basic reliability functions were used in this method and it's easy to use. However, the results from experience based prognostic methods were accurate when compared to other predictive methods.

Data driven methods were used in the estimation of the residual lifetime of bearings. The study was carried out with the signals which are acquired with sensors, accelerometers, etc. Later the system degradation is monitored with the use of these signals. A predictive model was built using Artificial Neural Network, spall propagation and statistical method. The built model was successful in diagnosing the lifetime of bearings additionally; the model accommodates to variable condition and quickly responds to the change in environment. However, the results were precise and do not suit to all real time applications [4, 5].

Prognosis focuses on assessing the remaining the useful lifetime of bearing. The prognosis can be carried out in two different methods, direct method for fracture mechanical [6-8] and statistical method for vibration signals [9].

In all rotatory machineries, bearings are categorised as a critical component as it directly impacts the performance of the asset. In general, bearing maintenance can be categorized into prognosis and diagnosis. Diagnosis refers to the identification of the faults. Bearing diagnosis were widely deployed across following the major unique approaches namely use of artificial neural network [5, 10] in fault diagnosis, condition monitoring techniques using vibration analysis [11-13] and life predictions and degradation studies using statistical methods [14, 15].

Apart from the vibration signals, acoustic signals collected from the bearings were used to assess the remaining useful lifetime. The defects in rolling element bearing were identified through statistical parameter estimation using sound pressure and vibration signals. It is evident from the paper that the effectiveness of diagnosis is at its best with both vibration and acoustic signals than the beat function parameters [16].

The results of vibration and acoustic monitoring studies conducted on the multistage gearbox with normal operating conditions and as well with simulated faulty conditions were assessed. It can be concluded from the paper, that acoustic conditional monitoring will be suitable in real-time applications [17].

Acoustic signals were used in diagnosing the defects in the bearing of the fan using summarized dot pattern method. The proposed model detects the defects in bearing through the diagrammatic representation [18]. In the above works [16-18] sound signals from the bearings were used in predicting the bearing lifetime. However, the current effort details out the use of vibration signals in diagnosing the residual life of bearings.

Alternatively, the bearing life predictions were also done using stress based fatigue method based on degradation theories. It is extremely challenging to construct such a predictive model as degradation phenomenon is in-consistent over the period of time. Hence, such complex model is difficult in real-time applications [19].

In general, bearing maintenance is crucial as it directly impacts the overall performance of the machineries. Hence, fault diagnosis of bearings was primarily focused areas in the last few decades. Machine learning approaches were deployed for better diagnosis. Muralidharan et al. [20-23] have detailed the deployment of machine learning tools for fault diagnosis. Due to want of resources, manpower and money it is extremely challenging to accumulate the data on a fixed defined duration. The present work is coined based on classification technique and successful prognostic model was developed to estimate the residual life of bearing. Decision tree is a tree used for feature selection and prognostic model was built using K-Star algorithm. The performance of the classifier is discussed in results and discussion.

2. Experimental Set-up and Procedure

The ultimate aim of the study is to assess the residual life of the bearings at a defined state while under operations. To accomplish this task, a bearing test rig is required to continuously monitor the bearing for its entire life period. In general, due to time limitations bearing life studies are done at accelerated conditions to expedite and simulate the fault conditions. Moreover, predicting the life of bearings through fault diagnosis was primarily adopted method in past. This study is built upon the limitations of the previous experimental studies done in the bearing life predictions and the uniqueness of the new approach is adopted for conducting this experiments. The experiments conducted on these bearings were simulated to real time environments by selecting the rated load and speed conditions similar to that of the application wherein the bearing is deployed. In addition to that the experiments were conducted based on run-to-failure approach, meaning the bearings were tested on the experimental set-up until it fails naturally on its own. This approach is different from the accelerated life tests wherein the conditions are accelerated and it does not reveal the real time scenarios. This approach will help to get closer to the real time environment. As said this also is one of the challenges that were put forward while building this experiment.

The experimental set-up as shown in Fig. 1 was built keeping these factors in mind. The set-up consists of a self-lubricated ball bearing which is put to life test, a motor, accelerometer and a DAQ card for data acquisition. The selected bearing is a ball bearing type with 25mm bore diameter which is commonly used in low load carrying applications like conveyors, special machine tools, etc. These bearing are mounted on to a suitable housing. These bearings are self-lubricated type bearings and however, solid grease is used as an additional lubricant while fitting the bearing in the housing. The housing is a split type which will ensure ease maintenance during operation at defined intervals. The split housing is mounted on the simple steel structure which is in-turn placed on a damper sheets to arrest the vibrations during operation.

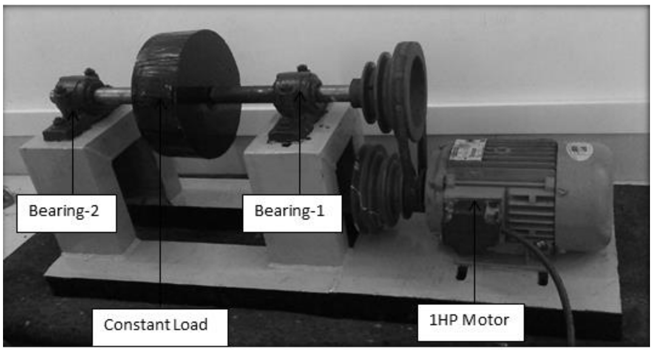

Fig. 1. Experimental setup.

The bearings are connected to each other with a shaft mounted with a stepped pulley on drive end. A dead weight with a constant load of 0.2kN is welded to the shaft between the bearings. This weight acts as a radial load to the bearings on either side. The pulley on the shaft is connected to the motor through a belt drive. A 1HP 3Phase induction motor is used on this experiment for continuous operation. The transmitted speed from the motor to the drive end of the shaft is checked by the tachometer. The 5-step pulley ensures that the speed can be varied to 05 increments. However this experiment runs on constant load 0.2 kN and speed of 1300 rpm as equivalent to the real time application. The vibration signals are acquired through accelerometer which is positioned on top of the housing wherein the bearing is mounted. This accelerometer is mounted to the housing by adhesive type bonding and appropriate actions are taken that the mounting surface and accelerometer surfaces are parallel to each other. There are enough studies done and proved to substantiate the placement of the accelerometer on the housing for vibration measurement of the bearings. The vibration signals are transferred to lab VIEW software loaded on to the personal computer through a DAQ card. The amplitude of the vibration signals is supervised on a regular basis for assessing the current health state of the bearings. The amplitude is small and smooth when the bearing is at the initial stages or it is newly mounted. The amplitude increases in due course of time as the bearing tends to wear. Hence the degradation phenomena can be monitored from the signals as shown in Figs. 2. Thus, vibration signal proves out to be the most reliable condition monitoring technique for life predictions in bearings. The differences in signals, thus acquired for the bearings in multiple stages can be seen in Figs. 2(a), (b), (c), (d) and (e) respectively. The following were the parameters chosen for data acquisition.

Sample length: 1024

Sampling frequency: As per Nyquist theorem, sampling frequency for this experiment was derived out is 24 kHz

Number of samples: 200 samples for every 08 hours of running were collected for the entire life period of bearings under operation.

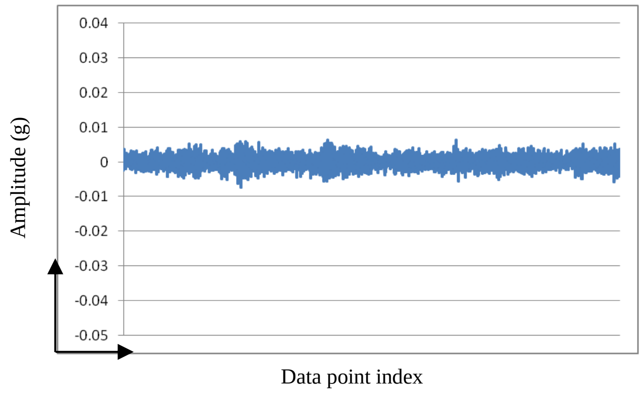

Fig. 2. (a) Stage-1: Vibration signals at start of experiment.

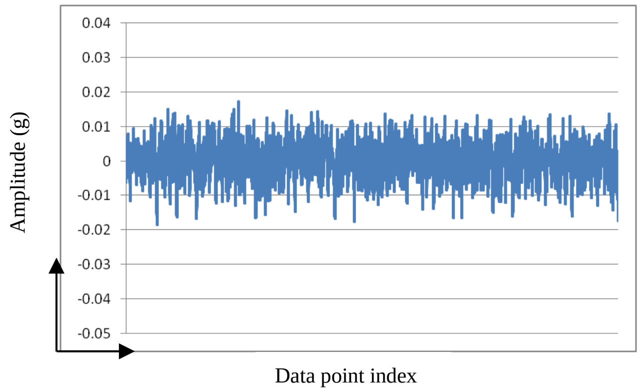

Fig. 2. (b) Stage-2: Vibration signals after 1000 hours of running.

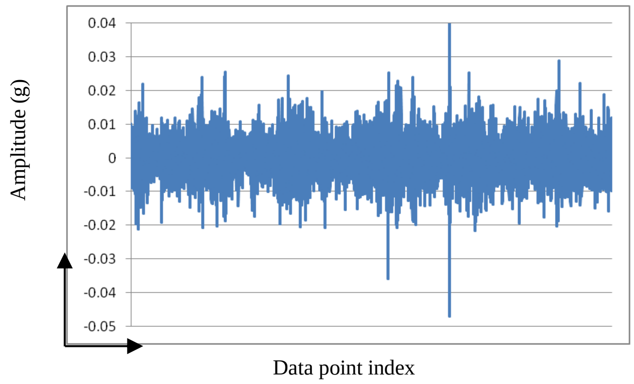

Fig. 2. (c) Stage-3: Vibration signals after 1250 hours of running.

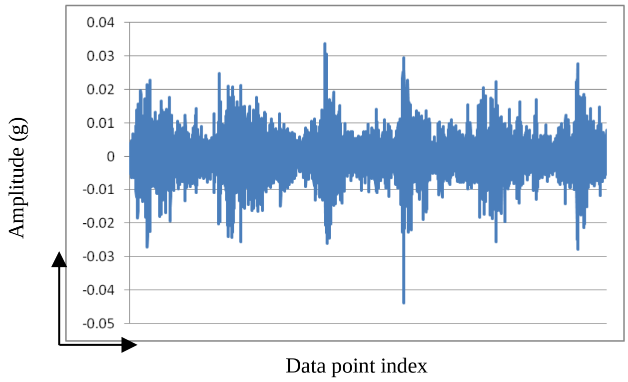

Fig. 2. (d) Stage-4: Vibration signals after 1500 hours of running.

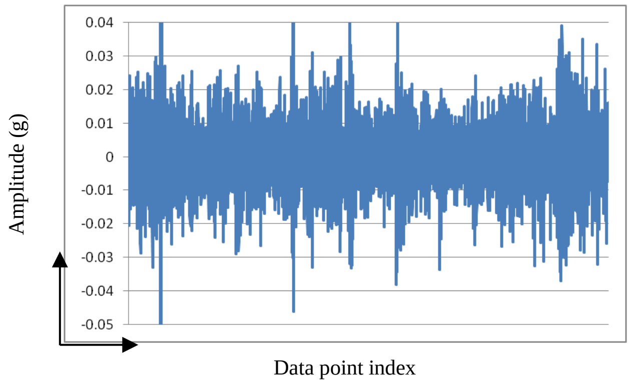

Fig. 2. (e) Stage-5: Vibration signals at 1800 hours during final stages.

3. Feature Description

Descriptive statistics is deployed in this paper for statistical analysis on life predictions. This feature summarizes out the available data in much simplest form. Descriptive statistics comprises of 12 basic features such as standard deviation, mean, mode, median, range, sum, minimum, maximum, sample variance, standard error, kurtosis and skewness which are referred as "statistical features" in this paper. These features are discussed in detail by Jegadeeshwaran and Sugumaran [24].

(a) Standard error: In statistics and regression, standard error refers to the measure of error in the predictions. *x* and *y* denotes the sample means and '*n*' denotes the sample size in the predictions.

$$\sqrt{\frac{1}{n-2}\left[\sum(y-\bar{y})^2-\frac{\left[\sum(x-\bar{x})(y-\bar{y})\right]^2}{(x-\bar{x})^2}\right]} \tag{1}$$

(b) Standard deviation: This is a measure to quantify the spread of the variation in the datasets. The standard deviation in statistics is computed with the below formula.

$$\sqrt{\frac{\sum x^2-\left(\sum x\right)^2}{n(n-1)}} \tag{2}$$

(c) Sample variance: It is the variance derived from the sample population. It becomes highly complex to compute variance for a big population and hence a sample is derived for the entire population. The below formula was used for computation of sample variance.

$$=\frac{\sum x^2-\left(\sum x\right)^2}{n(n-1)} \tag{3}$$

(d) Kurtosis: Kurtosis measures the spikiness of the signals. In statistics, the flatness of the distribution is measured with relative to normal distribution. With reference to this study, kurtosis is mainly used to measure the peaks of the signals. The formula to compute kurtosis is provided below where “s” denotes the standard deviation of the given sample.

$$=\left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^4\right\}-\frac{3(n-1)^2}{(n-2)(n-3)} \tag{4}$$

(e) Skewness: It describes the amount of unevenness of a probability distribution surrounding its mean. The value of skewness can be positive or negative. The below formula was used to compute skewness in statistics.

$$\frac{n}{n-1}\sum\left(\frac{x_i-\bar{x}}{s}\right)^3 \tag{5}$$

(f) Range: In statistics and arithmetic, range refers to the difference between largest and smallest values in the given entire population.

(g) Minimum value: The minimum most value in the given entire population. In this study the minimum value of the signal points is benchmarked to the standards to find the abnormalities in the overall vibration signals.

(h) Maximum value: The maximum value in the given entire population. In this study, similar to minimum value, maximum value is also bench marked to the standards to figure out the abnormalities in the overall vibration signals.

(i) Sum: It refers to the arithmetic sum of all values in the given entire population.

4. Feature Selection Process

The current paper is laid out on the foundation of feature selection process that was carried out through J48 decision tree as detailed by Satishkumar and Sugumaran [25]. Classification accuracy and performances of classifiers can be improved through feature selection. Decision tree gives structural information and a set of "if-then" rules can be formed. By merely looking the tree structure one can identify the top contributing features. The attributes which are all on the top of a tree are the best ones and bottom of the tree are the least contributing features. Feature selection process was done with the extracted 12 statistical features as standard deviation, maximum, sum, skewness, kurtosis, range, mode, median, mean, standard error, variance and minimum and the best ones among them were selected for further process. This process ensures that the classification accuracy is not affected due to the non- contributing features in the data set.

5. Feature Classification Process

K-Star algorithm is used as classifier using Instance Based Learning. In general, data may come with noise and unwanted attribute which may affect the overall performance. Hence, feature classification seeks importance in artificial intelligence. Many research scholars used different methodologies as required for the nature of data. Some well-known methodologies include Instance Based Learner IB1-IB5 [26, 27] andID3, which uses decision tree for feature classification [28, 29]. It can be found from the above models, the classification accuracy was high for the predictive model built. However, these instances based learning algorithms fails to handle data with missing values and real valued attribute. Hence, a unified approach is much needed to handle these problems. In the present paper, K-Star classification algorithm was used for feature classification process.

Description of K-Star Algorithm:

Let *I*: infinite set of instances;

T a finite set of transformations on *I*;

P set of all prefix codes from *T** which are determined by σ(the stop symbol)

Members of T* uniquely define a transformation on

$$I : \bar{t}\,(a) = t_n\,(t_{n-1})(\ldots\, t_1(a)\ldots))\ where\ \bar{t} = t_1 \ldots.\ t_n \tag{6}$$

A probability function p is defined on T*.It satisfies the following properties:

$$0 \leq \frac{p(\bar{t}u)}{p(t)} \leq 1 \tag{7}$$

$$\sum u\ \ p(\bar{t}u)\ =\ p(\bar{t}) \tag{8}$$

$$p(\Lambda) = 1 \tag{9}$$

as a consequence, it satisfies the following

$$\sum_{\bar{t}\,\in\,p} p(\,\bar{t}) = 1 \tag{10}$$

The probability function $P*$ is defined as probability of all paths from instance a to instance b

$$\text{P* (b |a)} \sum \bar{t}\ \in p :\ \bar{t}(a) = b\text{P}(\bar{t}) \tag{11}$$

$$\sum_b P\ *\ (b|a) = 1 \tag{12}$$

$$0 \leq \text{P*(b|a)} = 1 \tag{13}$$

The K* function is then defined as

$$K^*(b|a) = -\log_2 P*(b|a) \tag{14}$$

The advantage in the present approach is that both symbolic attributes and real attributes can be dealt with the same framework. The detailed explanation on the classifier can be found at [30].

6. Results and Discussions

The bearings were tested on the experimental set-up with defined load and speed conditions. Vibration signals were taken from the brand new bearing on a continual basis till the bearing gets damaged naturally. The current work focuses on developing a prognostic model to diagnose the current state of bearing. Descriptive statistical features were deployed in this current study. The raw vibration signals picked-up from the experiments were transformed into features in the feature extraction process and followed by feature selection process was carried out as detailed in section 4. The vibration signals acquired from the bearings mounted on the experiment was grouped into degradation stages viz stage 1 to stage 5 respectively. The signals collected while start of the experiment with a new bearing was placed on stage 1 and similarly signals after 1000 and 1250 hours and 1500 hours of running were placed at stage 2, stage 3 and stage 4 respectively. The signals during the final stages were grouped in stage 5. Totally 12 features were present and it should be noted that all features may not contribute equally towards the effective classification. Hence, parameters are to be optimized in order to attain better results.

Table 1. Impact of number of features on classification accuracy.

Number of features	**Classification accuracy (%)**
1	79.20
2	80.72
3	92.24
4	94.60
5	94.00
6	93.80
7	**98.56**
8	98.52
9	98.16
10	98.28
11	98.40
12	98.16

Table 1 shows the impact of selection of statistical features in classification accuracy. Feature selection was done through decision tree and ordered. It should be noted that out of 12 features, 7 features such as kurtosis, mode, skewness, standard deviation, range, sum and maximum were found to be most contributing for the end results.

Table 2. Results of K-Star classification - Detailed accuracy by class.

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	1	0	1	1	1	1	Stage-1
	0.968	0.01	0.960	0.968	0.964	0.999	Stage-2
	0.960	0.008	0.968	0.960	0.964	0.999	Stage-3
	1	0	1	1	1	1	Stage-4
	1	0	1	1	1	1	Stage-5
Weighted Average	0.986	0.004	0.986	0.986	0.986	1	

Stage-1: New; Stage-2:1000hrs; Stage-3:1250hrs; Stage-4:1500hrs; Stage-5:1800hrs.

Table 2 presents detailed accuracy by class. For an ideal system True Positive rate (TP Rate) should be close to 1 and the False Positive rate (FP Rate) should be nearer to 0. In the present work TP rate and FP rate equal to 1 and 0 respectively, which indicated the predictive model built is an ideal one.

Table 3 presents the results of K-Star classification in the form of confusion matrix. This matrix illuminates the accuracy of the solution to the classification problem. The correctly classified instances can be found at diagonal elements. The first component in the row denoted as “category a” indicates the number of elements that belongs to “stage-1”. It is evident that all 500 elements belong “stage-1” is correctly as “stage-1” and there are no misclassification in stage 1. In the second row, second element indicates the instances that belong to “stage-2”.

Table 3. Confusion matrix for K-Star.

Category	a	b	c	d	E	
a	500	0	0	0	0	a=stage-1
b	0	484	16	0	0	b=stage-2
c	0	20	480	0	0	c=stage-3
d	0	0	0	500	0	d=stage-4
e	0	0	0	0	500	e=stage-5

Out of total 500 instances in the category “a”, 484 instances were correctly classified and 16 instances that belong to “stage-2” is misclassified as “stage-3”. Similarly, in all other rows leading diagonal elements indicates correctly classified instances. Stage 4 and stage 5 has no misclassified instances. The error is very minimal and can be applied to many practical applications.

7. Conclusion

Bearings are critical components in rotatory machineries as its failure directly affects its overall reliability metric. In the current study, vibration signals were attained from the experiments on a continuous basis till the bearing fails naturally. It is highly challenging to collect a huge dataset at regular intervals. A supervised machine learning approach was followed in this study. The extracted statistical features from the acquired signals were used as input for further process in the classification problem. The best contributing features with more information gain were selected through decision tree techniques. This process is referred to feature selection process and followed by feature classification process was done with K* (K Star) classifier. It can be found from the building and testing of classifier that the predictive model yields 98.56% accuracy which can be applied to many real time applications. Additionally, the number of misclassifications was very minimal and thus, a predictive model using the K* (K Star) classifier for assessing the remaining useful life of bearings proves out to be effective. This approach can be horizontally deployed for all other critical applications to assess and predict the state of the components.

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