RUL prediction of Ball Bearings

AI in Manufacturing Course Project

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Problem definition

Inefficient industrial bearing maintenance results in costly downtime. We seek a solution that utilizes vibration data analysis to proactively predict and prevent failures, thereby enhancing equipment longevity and streamlining maintenance practices.

Problems to solve

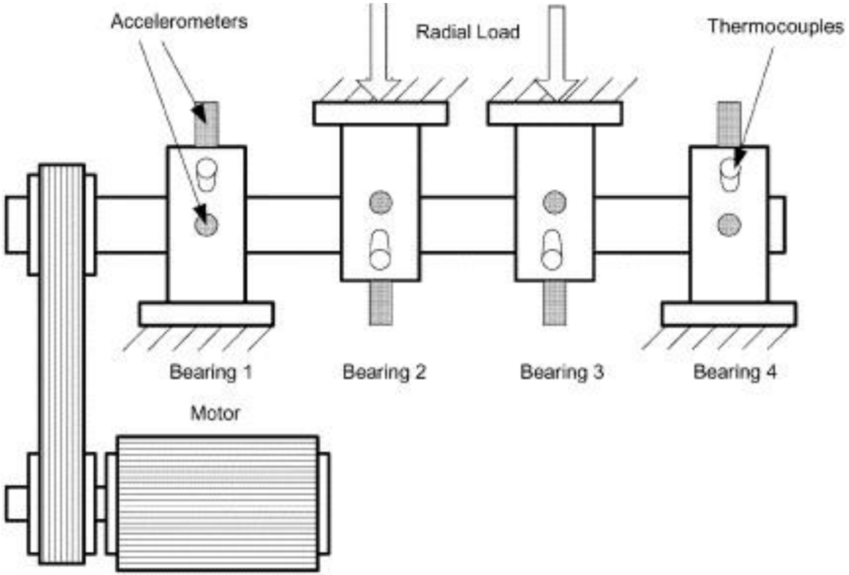
1. Identify early signs of bearing deterioration and degradation in vibration data.
2. Predict the remaining useful life (RUL) of industrial bearings based on their current condition.

Project objective

The aim of this project is to develop a predictive maintenance model for industrial bearings using vibration data analysis.

Data Source

Four bearings were installed on a shaft. The rotation speed was kept constant at 2000 RPM by an AC motor coupled to the shaft via rub belts. A radial load of 6000 lbs is applied onto the shaft and bearing by a spring mechanism. All bearings are force lubricated. Rexnord ZA-2115 double row bearings were installed on the shaft as shown in Figure . PCB 353B33 High Sensitivity Quartz ICP accelerometers were installed on the bearing housing (two accelerometers for each bearing [x- and y-axes] for data set 1, one accelerometer for each bearing for data sets 2 and 3).

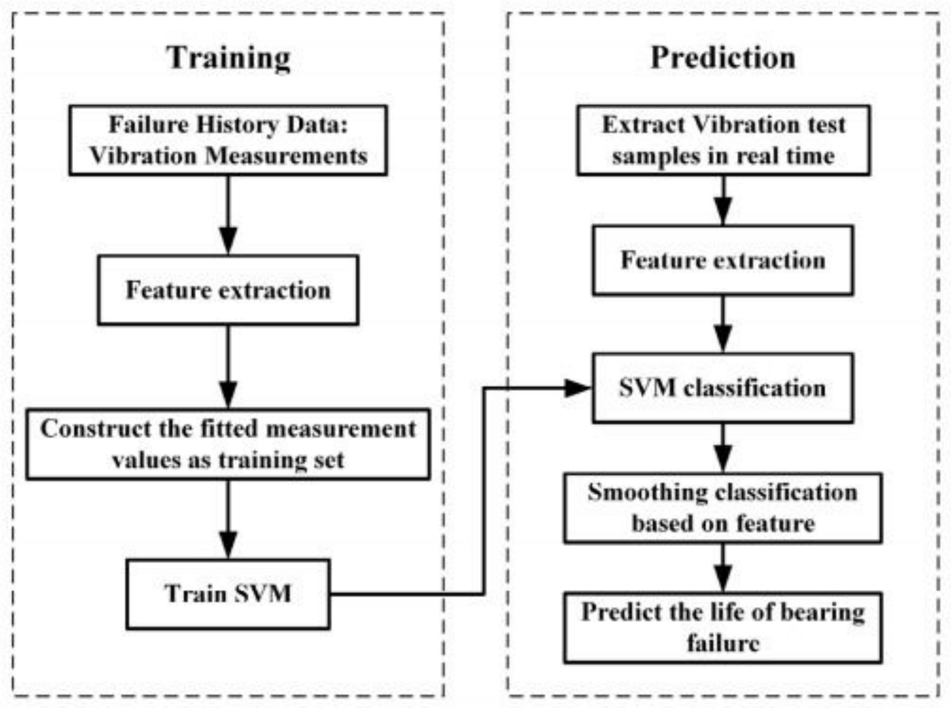


Hai Qiu, Jay Lee, Jing Lin, Gang Yu, Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics, Journal of Sound and Vibration, Volume 289, Issues 4–5, 2006,

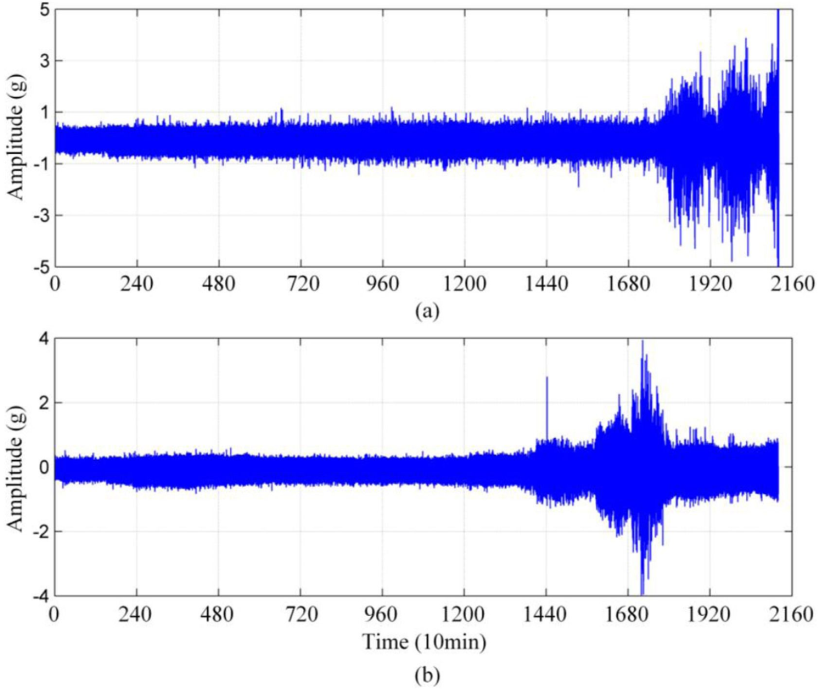
Introduction to the dataset

- Regarding the PHM Challenge, data representing 3 different loads were considered (rotating speed and load force).
- The challenge datasets were characterized by a small amount of training data and a high variability in experiment durations (from 1h to 7h).
- Theoretical framework (L10, BPFI, BPFE, etc.) mismatches the experimental observations.

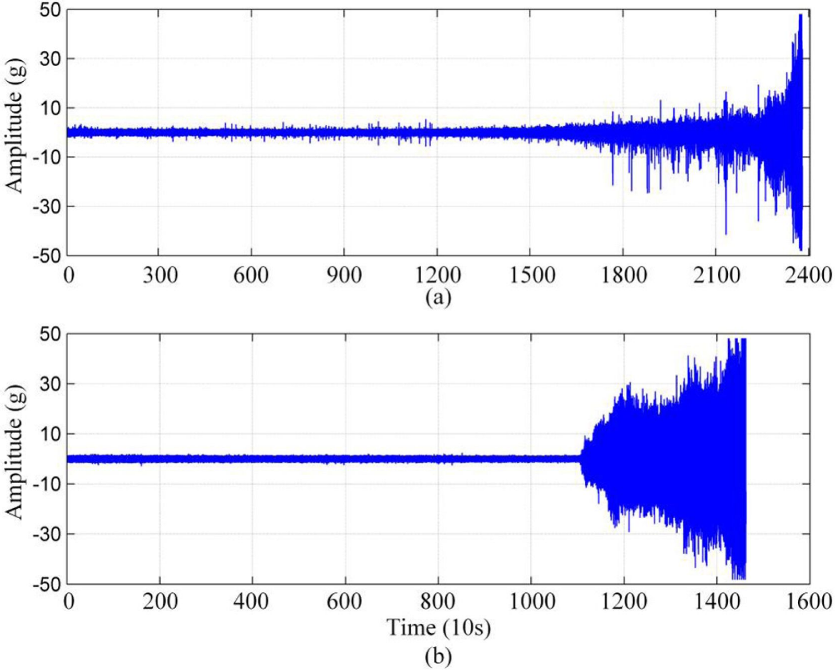
Methodology



Visualizing the Dataset



Run-to-failure vibration signals of bearing 3 of testing 1 (a) and bearing 4 of testing 1 (b)



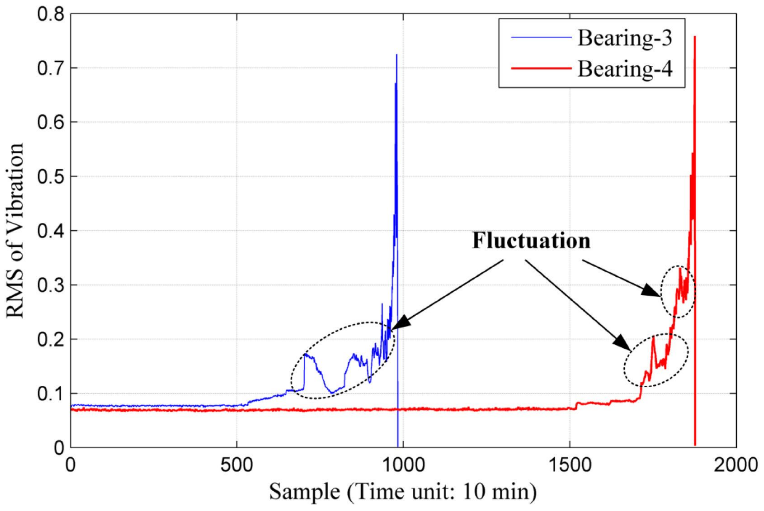
Run-to-failure vibration signals of bearing 3 and 4 (a, b) under first operating conditions

Exploring feature extraction options

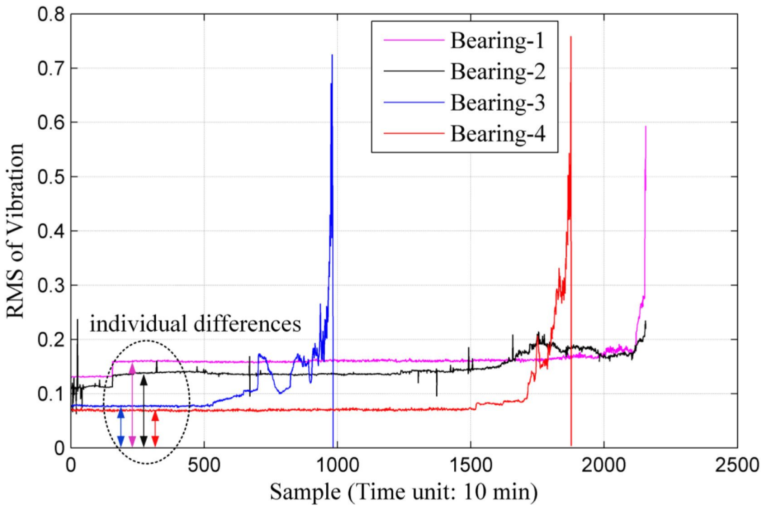
Based on dataset visualisation it can be inferred that RMS increases as degradation increases

However there are 2 major shortcomings of using RMS as a feature

1. Spurious fluctuations
2. Differences in stable stage for different bearings under the exact same operating conditions

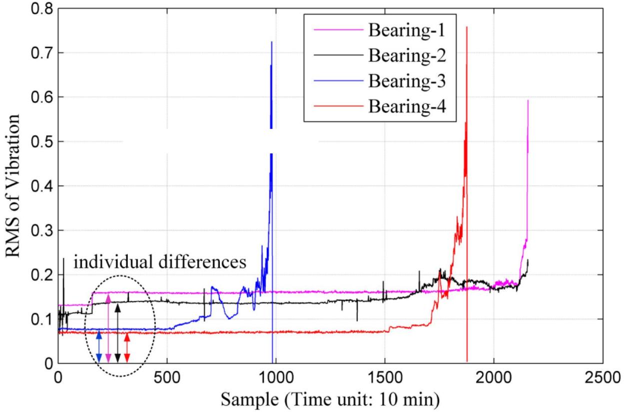


Spurious fluctuations in rms measurements

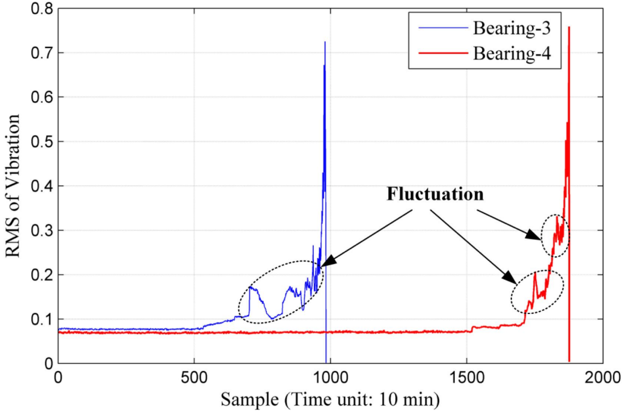


Differences in stable stage for different bearings under the same operating conditions

Extracted feature 1 - RRMS



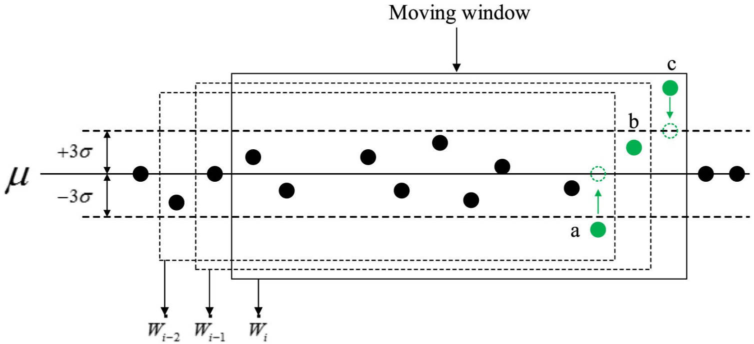
Differences in stable stage for different bearings under the same operating conditions



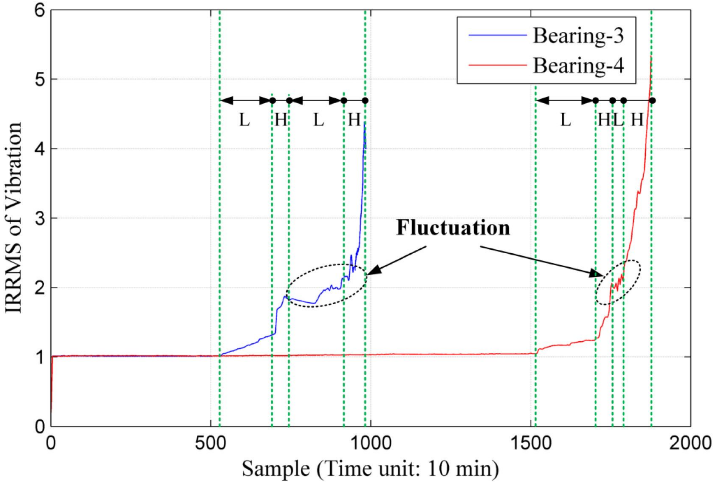
Spurious fluctuations in rms measurements

- When the small cracks on race were formed and propagating, the RMS started to increase.
- When the edges of small cracks were smoothing by the continuous rolling contact and the RMS was decreasing
- As the damaged area of bearing race spread broader, the RMS rose again.
- Sometimes, sensor noise and vibration from other parts of the machine can also cause fluctuation

Extracted Feature 2 - IRRMS



Schematic diagram of feature processing after eliminated local tendency.



RRMS measurement of bearings.

The procedures of the IRRMS implementation are explained as follows:

- Set initial sliding window (window length = 30), each IRRMS(*i*) in this window set to the mean of RRMS values in this window;
- Moving the sliding window forward with one step to calculate the IRRMS of new points in this window;
- Moving the sliding window forward again and recalculate the IRRMS for the new points in this window.

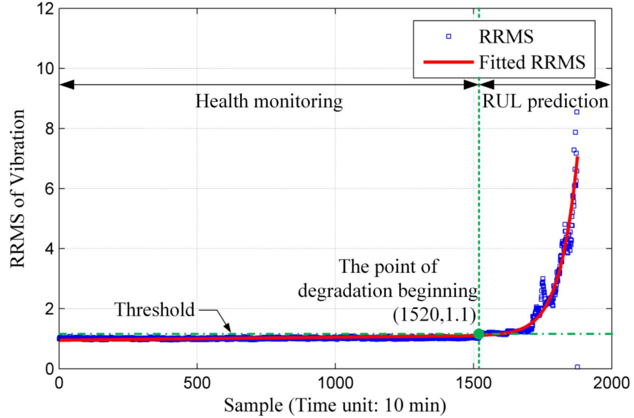
Feature Fitting

Given below is the exponential degradation model used for fitting:

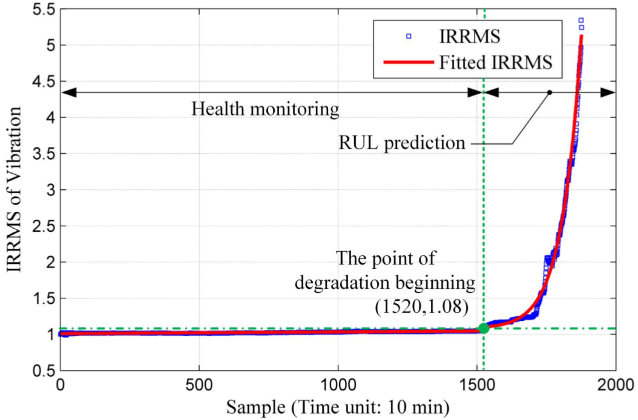
$$\lambda(t) = Y + Mt^{\beta}$$

RRMS = 1.1 denotes the threshold of degeneration beginning. The actual fitting model is given below:

$$\begin{cases} y = kt + b, & y < 1.1 \\ y = Y + Mt^{\beta}, & y \geq 1.1 \end{cases}$$

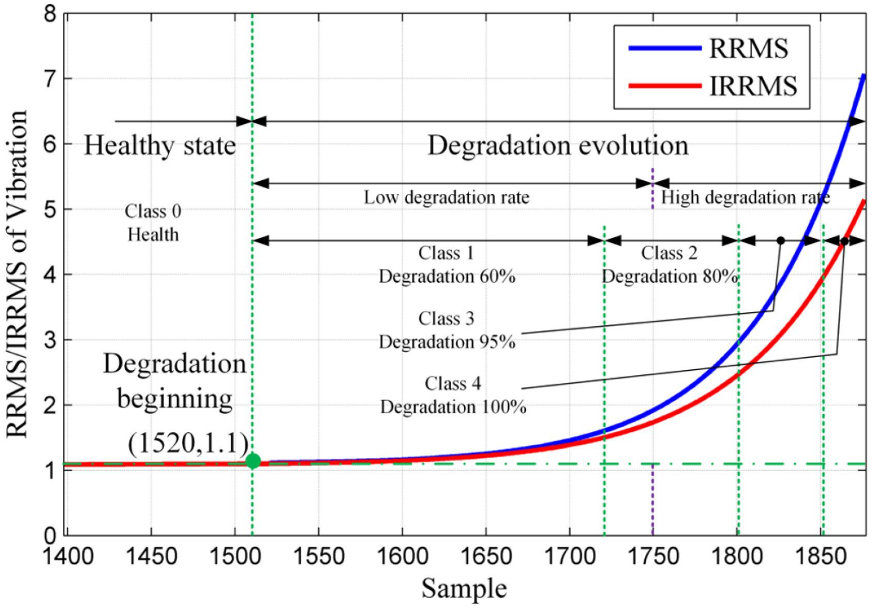


Fitted RRMS measurement of Bearing-4.



Fitted IRRMS measurement of Bearing-4.

Usage of SVM Classifier



Usage of SVM classifier

- Input of SVM is IRRMS and RRMS
- While the output is categorization into different degradation classifications
- Based of industrial standards we have used RRMS = 7 as the failure threshold
- Classification accuracy obtained is 98.88%

Use classes for different degradation states:

- Class 0: Healthy state
- Class 1: Degradation till 60%
- Class 2: Degradation 60-80%
- Class 3: Degradation 80-95%
- Class 4: Degradation 95-100%

Degradation starts when RRMS = 1.1

SVM Training

SVM input: $I = [RRMS(i), IRRMS(i)],$

SVM Output: *The number of classes (L),*

where class 1 represents the healthy state of bearing and the remaining classes represent different degradation stage of bearing, is used as output data.

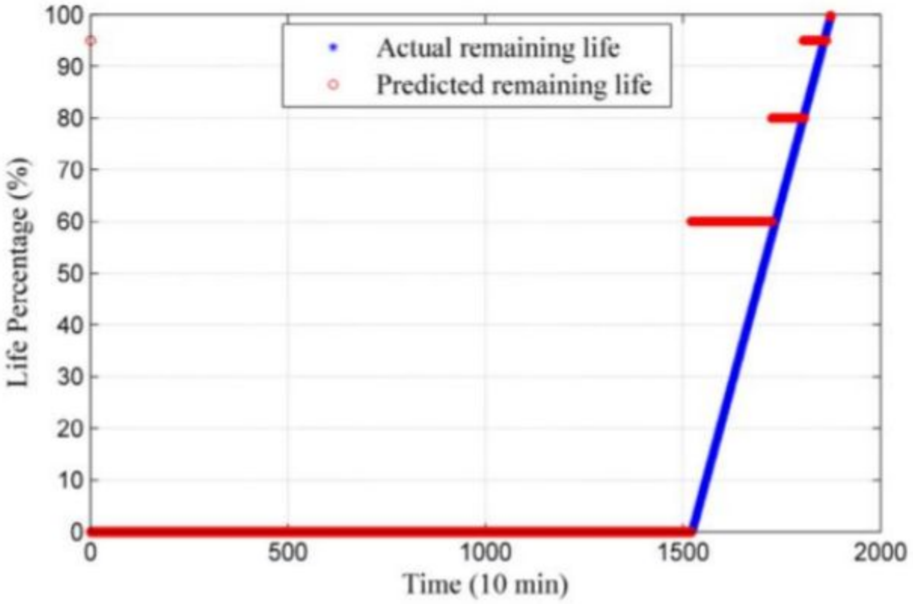
SVM training:

- The kernel function of SVM is **Radial Basis Function (RBF)**, be-cause it can handle the nonlinear relationship between features and labels.
- Cross-validation and Grid-search are applied on the parameters (the parameter γ of RBF function and penalty parameter C)optimization of the SVM model.)
- After the best parameter was found, we used the whole training set to train the SVMclassifier and generate the final classifier.

Hybrid Degradation tracking model

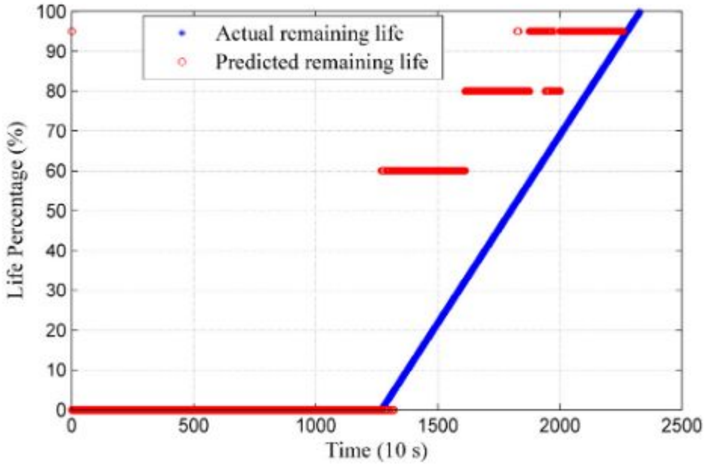
SVM classifier gives discrete values for degradation (ie, 60%, 80%, 95% or 100%) according to the classes we defined earlier.

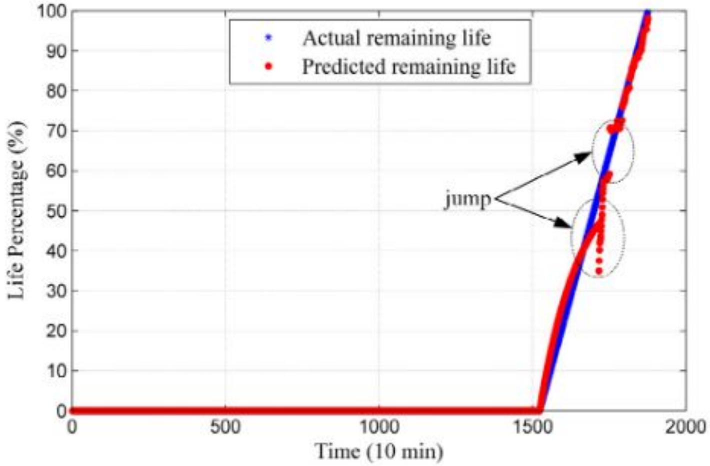
In order to get more accurate RUL%, we need to get continuous values instead of discrete values.



We use 2 different algorithms to smoothen the results given by the SVM classifier.

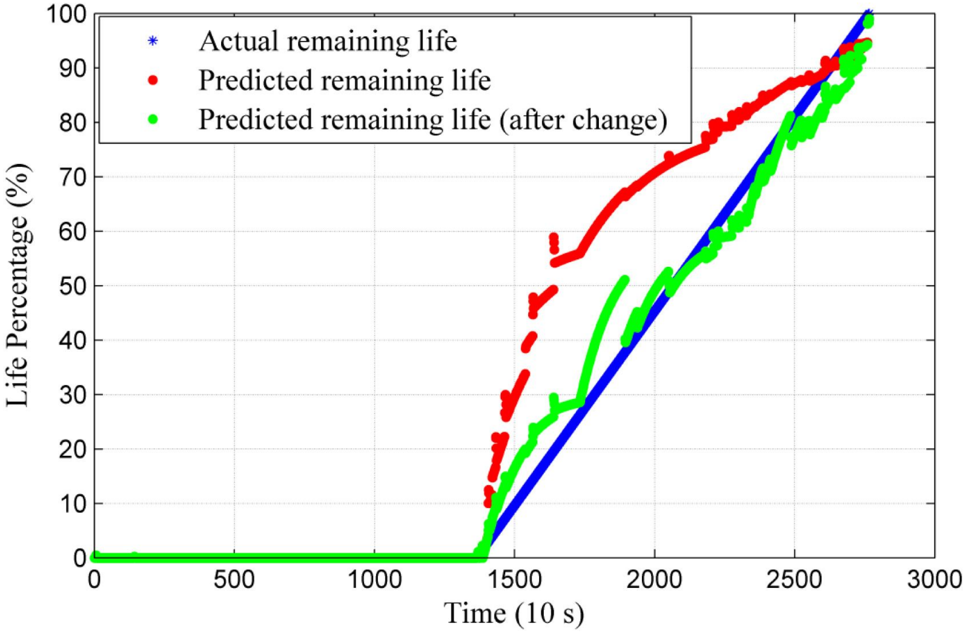
We use 2 different algorithms based on the zone defined by the SVM (LDR/HDR) to smoothen the results given by the SVM classifier which results in the observed jump





Result

Predictor obtained after hyperparameter tuning with 92.99% accuracy



Accuracy improves on smoothening function hyperparameter tuning

Future Scope

As future works, the raw vibration signals should be filtered by some suitable methods before extracting features. This step can separate bearing fault signals from loud heavy noises and other background masking signals, which can further improve the robustness of the proposed approach. Besides, the initial value ($IRRMS_{initial}$) and terminated value ($IRRMS_{termination}$) for each class based on degradation index need to be determined accurately by statistical analysis of more whole-life bearing test data. To guarantee the accuracy and generalization of classification, the classification method employing on bearing degradation stage needs further research, such as XGboost, decision tree, extreme learning machine.

Github Repository link of the Project

https://github.com/gobalee/prediction-of-RUL-of-bearings

Thank you.