PREDICTION OF BEARING REMNANT LIFE

By

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ABSTRACT

The predictions of the remaining useful life (RUL) of bearings are important in the conditioned maintenance industry. Hence, this project aimed to propose a prediction algorithm for bearing based on experimental results. In this project, a data driven prognostic technique based support vector machine regression (SVR) is employed for the RUL estimation of bearing. The acoustic signal is generated from the test rig experiment and collected by an acoustic emission sensor.

The raw signal was processed by Matlab to remove background noises and 6 time-domain variables such as mean, RMS, Peak to peak, Crest factor, Kurtosis and skewness are extracted from the normalized signals. The suitable variables are selected manually by comparing the trend curve presented in each teat results instead of cross validation method. Then the two variables are trained in proposed algorithm and compared in terms of the prediction error and accuracy. The error of the bearing RUL prediction and the overall prediction accuracy is calculated. The error of bearing RUL is small however the overall accuracy of the proposed model is not satisfy. Further works to improve the current project are required.

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APPROVAL SHEET

This dissertation/thesis entitled "**PREDICTION OF BEARING REMNANT LIFE"** was prepared by **LEE KONGTING** and submitted as partial fulfillment of the requirements for the degree of **MASTER OF ENGINEERING (MECHANICAL)** at Universiti Tunku Abdul Rahman.

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SUBMISSION OF FINAL YEAR PROJECT /DISSERTATION/THESIS

It is hereby certified that **LEE KONGTING** (ID No: **1606032**) has completed this final year project entitled " **Prediction of Bearing Remnant Life** " under the supervision of **Professor Andy Tan** from the Department of **Engineering Lee Kong Chian**, Faculty of **Engineering and Science**.

I understand that University will upload softcopy of my final year project in pdf format into UTAR Institutional Repository, which may be made accessible to UTAR community and public.

Yours truly,

____
(LEE KONGTING)

DECLARATION

I hereby declare that the dissertation is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

Name : LEE KONGTING

Date : 13 APRL 2018

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviations

L_d	Design life of the bearing [rpm]
L_{10}	Basic life predicted which may have 10% probability of lower life
C	Basic dynamic load rating/ force
P_d	Designed load applied on the bearing
k	Ball bearing constant
a_1	Life adjustment factor for reliability
a_{23}	Life adjustment factor for material and lubrication
K	Total number of HI values
$\frac{d}{dx}$	First order derivatives
$\frac{d^2}{d^2x}$	Second order derivatives
S	No. Of stages/ class
Sep_s	Separability of indicator of values
X_k	Indicator value at Tk
X_k^T	Mean trend value at Tk
C_k	HS at Tk
m_s	Mean class
σ_s^2	Variance
S_B	Matrix between class scatter
S_w	Matrix within class scatter
X_n	HI vectors
$X_{n,k}$	$X_n$at Tk
$\overline{X_n}$	Mean of X_n
P_{EoL}	Vector of HI values at end of life
P_o	Vector of HI at initial
$X_{i,}$	Feature vector
Y_i	Label assigned to vectors as a class

CHAPTER 1

INTRODUCTION

1.1 Overview

The bearing is used to support a radial or thrust load and support motion between two components. The bearing are formed with an inner race, an outer race and rolling elements such as balls, tapered roller, spherical roller or needle type. The housing of the machine will hold the outer race and the inner race are connected onto the rotating shaft to rotate the shaft.

The rotating element between the inner race and the shaft are used to reduce the friction of rotation between surfaces. The typical coefficient of friction for bearing is ranged from 0.001 to 0.005 which subjected to the availability of seals, lubrication and unusual loading (Mott and Tang, 2004).

There are many types of bearing available on market such as single row deep groove ball bearing, double row deep groove ball bearing, angular contact bearing, cylindrical roller bearing, needle bearing, spherical roller bearing and tapered roller bearing. The comparisons of the load capacity of the mentioned bearings are show in Table 1.1.

Besides bearings mentioned above, there are mounted type bearings that are attached directly on the machine frame itself. Mounted type bearings are usually found in heavy machines and special machines. Misalignment capability of the bearing is the key consideration on bearing selection.

Table 1.1 Comparison of bearing types (Mott and Tang, 2004)

Bearing Type	Rolling Element Type	Load Capacity		Misalignment Capability
		Radial	Thrust	
Single-row, deep groove ball	Ball	Good	Fair	Fair
Double-row, deep grove ball	Ball	Excellent	Good	Fair
Angular Contact	Ball	Good	Excellent	Poor
Cylindrical roller	Roller	Excellent	Poor	Fair
Needle	Needle	Excellent	Poor	Poor
Spherical roller	Roller	Excellent	Good	Excellent
Tapered roller	Roller	Excellent	Excellent	Poor

The loading exerted on a small area of the bearing produces high stress on the contact surface. The material for commercial bearings are made of very hard, high strength steel such as AISI52100 steel or ceramic such as silicon nitride Si_3N_4 to withstand the high stresses.

The manufacturer will provide the technical data of bearing basic static load rating. The static load rating is the loading that the bearing can withstand before permanent deformation happens. The bearing race will scratched by the rolling elements if the force exerted exceeds its basic static load. The wear and damaged part will increase the bearing failure to happen rapidly.

Maintenance is very important in industrial. Maintenance is the key to increase the reliability, functionality, and productivity. Early warning and detection of errors can prevent unnecessary or unplanned downtimes and safety or risk consequences. Typically, the industrial practices corrective maintenance which identifies and rectifies a failed system that has already caused loss of time and money. Unlike corrective maintenance, preventive maintenance performed servicing on functioning systems before the system failed.

There are many diagnostic and prognostic models developed and discussed in the literature. However, most of the models are still rely on human resources. Compare to programming and human brain, programming and computers can make more reliable decisions when it deals with the more complex situation. The ability to determine RUL automatically and accurately is crucial for operating and maintenance.

Condition-based maintenance (CBM) is one of the preventive maintenance that helps to reduce maintenance downtime, operating cost, avoid unproductive shutdowns on production lines and improve the productivity. The machine health is normally monitored either periodically or directly online by CBM through vibration sensors.

The computer monitoring system (CMS) merged with fault detection algorithms which alert the users to possible defects to avoid a complete breakdown. Online monitoring systems need large data storage to store and keep track on the historical data for system analyzation compared to the offline monitoring systems which in other words, the cost of an offline monitoring system is cheaper than online. However, the offline monitoring system has possibility fail to notice some important information.

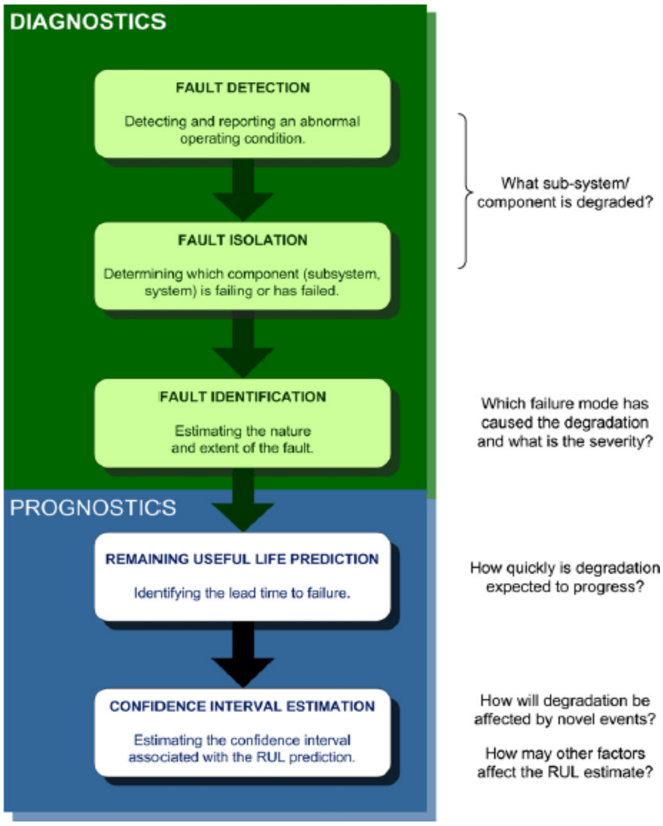

Figure 1.1 Steps involved in both the diagnostics and prognostics process (Sikorska, Hodkiewicz and Ma, 2011)

CBM as shown in Figure 1.1 (Sikorska, Hodkiewicz and Ma, 2011) usually has three phases, such as the detection, diagnosis, and prognosis. Diagnosis involves fault detection, isolation and identification to determine the defective components.

Prognosis studies the remaining useful life (RUL) of a component. Prediction of RUL is to forecast the period left before the failure happens based on the information fed from CMS.

An effective prognostic model allows maintenance team to schedule replacement in advance of machine failure. RUL predictions approaches can be categorized into three group such as statistical data-driven, physical model-based, and hybrid model.

1.2 Problem Statement

Failure of a machine due to faulty bearing always increased the downtime and reduces productivity. The prediction of bearing useful life is essential to improve the efficiency of the machine and for maintenance schedule planning.

There are two approaches for prognostic modelling which is data-driven and model based. Both techniques have different challenges and requirements for RUL prediction. The challenges such as:

1. <u>Type of data collection</u>

Most of the data driven prognostics collected run-to-failure historical data to analyse and input the degradation trend to form the predicted curve. But industry does not allow run to failure to happen as it is not cost and time effective. The type of sensor selected to collect data should be reflect on the parameter used in prediction scale.

2. <u>Quantity of data collection</u>

Eker, Camci and Jennions (2012) has concluded that data driven model requires sufficient datasets to ensure the accuracy and efficiency of prediction results. However, large datasets would requires extra time, cost and data storage to achieve.

3. Quality of data collection

The effectiveness of equipment and measurements used to collect test data is important as it will affect the accuracy of computed prognostic prediction. The background noise collected with the target signal should be removed to prevent reducing the prediction accuracy (Skaf, 2015).

1.3 Aim and Objectives

The aim of this project is to propose a predictive algorithm by experimental data collection to determine the remnant life of bearing.

The objectives of this project are:

i. To conduct bearing run-to-failure experiment
ii. To produce suitable curve to represent the trend from raw signals
iii. To analyse the feature extraction
iv. To propose a prognosis technique for bearing life prediction
v. To compare the actual RUL and predicted RUL

1.4 Scope of Report

This project has the following scopes:

i. This project is to determine the RUL of bearing.
ii. This project will run a few sets of bearing run-to-fail experiment to get the bearing life signal. The bearing break time is observed and bearing failure time too short or too long will be eliminated.
iii. This project studied few types of prognostics technique methods to select the suitable prognostic model for prediction based on the amount of dataset available from experiment.
iv. This project compares the actual and predicted RUL between two variables using the prognostic technique selected.

1.5 Limitation of Report

There are some limitation while conducting this project such as:

i. Manufacturer always design a durable and longer lifespan bearing. The bearing rated life is normally long but this project does not have long period of time to allow for normal operating and breakdown. Hence, this project has to apply a bigger force than the rated load to increase the bearing loading.
ii. The bearing installed into the test rig is smallest size compared to the other two supporting bearing to reduce the time required to perform run-to-failure test.
iii. The data collected for each bearing test are limited to every 5minutes due to the data storage limitation.

iv. Due to the working hour of laboratory, the bearing test can only run 10 hours a day. The cut in and cut out speed on the test rig will affect the signal collection of bearing health and this could bring inaccuracy when using the data on prognostics models.

1.6 Outline of Report

This paper will have 5 chapters. Chapter 1 will present the overview of the project background, problem statement, aim and objective, scope and limitation of this project. Next, this report will be supported with some theoretical bearing life prediction and some literature reviews discussing statistical data-driven prognostics techniques such as Support Vector Machine (SVM), Support Vector Regression (SVR), Artificial Neural Network (ANN) and Fuzzy Logic network which is available in today industry. Research methodology of this project will be presented in Chapter 3 which includes the experimental procedures and proposed prognosis technique method. The data analysis and results of work will be presented in Chapter 4 together with the discussion on the results generated. Last but not least, the conclusion and future works will be concluded in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Review of Theoretical Bearing Life Cycle

2.1.1 Introduction

Fatigue occurs over a large number of cycles of loading, for a bearing that would be a large number of revolutions. It is a statistical phenomenon with considerable spread of actual life of a group of bearings pf a given design. The rated life, L10 of 1 million of revolutions is the standard means of reporting the results of many tests of bearings of a given design. The manufacturer supplies you with one set of data relating load and life.

$$L_d = L_{10}\left(\frac{C}{P_d}\right)^k \times 60\mathrm{min/hr} \qquad (2.1)$$

The designed life (2.1) is specified by the designer considering the application usually in number of operations. If the actual speed or desired life is different from those rated values, a speed factor and life factor can be obtained from the supplier official website chart.

2.1.2 Theoretical bearing life estimation formula

The basic life, $\mathbf{L_{10}}$ is generally industrial practice and basis for data published by most manufacturers indicates 90% probability that selected would carry its rated dynamic load for specified number of design hours. The remaining 10% would have a lower life.

In 1989, the bearing life prediction equation is updated as new SKF life equation (2.2) for better reliability.

$$L_{10} = a_1 a_{23} \left(\frac{C}{P_d}\right)^k \qquad (2.2)$$

2.1.3 Bearing Degradation

The main factor causing the bearing to fail is due to the bearing vibration and friction between the contact point and surface of a rolling bearing. The terminology for the mechanism degradation is such as surface fatigue, scuffing, flaking and etc (Dolenc and Juri, 2014).

The degradation process weaken the bearing compound material properties by frictions which increased the surface temperature and lead surface fatigue to plastic deformation in the later stage if warning is not raised to the user. Scuffing or smearing as shown in Figure 1.2 (How to save bearing from Smearing and Scuffing, 2016) refers to the bearing surface is no longer smooth and has pores or scratches on the surface and surface roughness increased.

One of the causes for scuffing is due to the inadequate lubrication and leads additional contact among rolling element with the surface. Flaking is another defect which as shown in Figure 1.3 (How to avoid Bearing Failure form Flaking, 2016).

Figure 1.2: Smearing

Figure 1.3: Flaking

Figure 1.4: Fretting

Excessive load and improper handling will cause flaking. Fretting is caused by the vibration contacts between bearing inner surface and the shaft as shown in Figure 1.4 (Staff, 2011). The defects mentioned above are irreversible damages to the bearing surface; the only solution was to replace new bearings with the failed one. Each bearing defect will emit defective different frequencies. The defective frequencies recorded are related to the shaft rotational speed and bearing specification.

2.1.4 Summary

The above life equation is used as a guideline to predict the bearing RUL. The RUL will be more accurate with the prognosis techniques specification. Thus, this will improve the schedule maintenance planning and prevent the consequences of machine failure caused by a faulty bearing.

2.2 Review of Prognostic Program

2.2.1 Introduction

There are few technical processes for health prognostic program such as data acquisition, health indicator, health stage and RUL prediction (Lei et al., 2018). The signal collector and sensors are mounted on the desired location according to the specification of health checking. The raw data is collected and extracted for different features. The suitable features were then selected and extracted to construct a health indicator. The health indicator is used to present the life trend or the health stage of the component. The health stages are analysed for RUL prediction.

2.2.2 Data Acquisition

Data acquisition is the process to collect data from sensors that mounted on the desired machinery or component. The common sensors used are like the accelerometers (to obtain the vibration signals), the acoustic emission sensors (to produce the elastic wave form signals), the thermocouples (to observe the changes in temperature) and so on. The collected raw signals and data will be converted into software to analyse.

Acoustic emission (AE) is an elastic waves caused by the material undergone stress. An AE sensor is commonly used to detect the AE signal. AE signals are commonly used in health monitoring, evaluate the material mechanical performance and locate the source mechanisms such as friction and crack growth. Therefore AE is adapted in this project to detect the failure frequencies of the test bearing. The further detail explanation on data acquisition of this project will be discussed in Section 3. However, the challenge of acquire run-to-failure data are still existing. This is due to the degradation process are usually takes months to years to fail. Therefore the data storage is huge and cost inefficient.

Besides that, run-to-failure data are not suitable for machinery which works outside of lab where the weather and environment will be the factor to cause unrelated noise and signals to be recorded by the sensors and then reduced the accuracy of the prediction.

The rolling element bearing damage are usually unable to observed from the surface. The monitoring signals are introduced to monitor the degree of component damage. The health condition of components is presented in graph forms and unusual noise and peaks represents the potential risk of failure. There are papers studied the bearing defects by signal processing (SP) the parameter such as the root mean square (RMS), crest factor, kurtosis, fast Fourier transform (FFT), peak-to-peak and etc. with the help of monitoring techniques such as vibration sensor, AE, ultrasonic and etc.

For condition monitoring vibration analysis, collected data are commonly presented in the form of time domain or frequency domain. The frequency of different usage bearing has different characteristics. Therefore frequency domain approach depends on the periodic nature of each rotating machine but it is limited to steady-state waveforms. Fourier transformation (FT) is the popular method used in bearing diagnosed. However, most of the rotating machines are found in non-stationary waveforms, short time waveforms. Therefore advanced approaches such as short time Fourier transform (STFT) (Boashash, 2016) and wavelet transform (Pathak, 2009) are widely used for time-frequency analysis.

The time domain approach is used to segregate nominal and faulted bearing with raw signals by statistical measures such as mean, standard deviation, crest factor, peak-to-peak value, kurtosis, and skewness. Therefore, most of the mechanical fault detection is based on time domain waveforms. The parameters such as root mean square (RMS), skewness and kurtosis are normally extracted from the signals to study the component's degradation trend.

The RMS and peak values are commonly used for overall vibration level measurement. RMS value is the normalised second statistical moment of signals and widely used among the parameters to identify the relationship of vibration acceleration and rolling element failure throughout the lifetime. RMS error is used to measure the fault of the estimator fit of the signals.

The mean values are the mean between maximum and minimum vibration signals. The peak values are half the difference of maximum and minimum vibrations level. Crest factor is considering the ratio of the peak value to RMS.

Kurtosis is the normalised forth statistical moment of signal. Kurtosis, crest factor and Skewness are normally used to weight the vibration spikiness and non-linear signal.

The formula for common parameter such as RMS (2.3), mean (2.4), kurtosis (2.5), crest factor (2.6), skewness (2.7) and peak-to-peak (2.8) are as below:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x(i) - \bar{x})^2} \tag{2.3}$$

$$\mathrm{Mean} = \frac{\sum x(i)}{N} \tag{2.4}$$

$$\mathrm{Kurtosis} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x(i)-\bar{x})^4}{\mathrm{RMS}^4} \tag{2.5}$$

$$\mathrm{Crest\ Factor} = \frac{\mathrm{Peak}}{\mathrm{RMS}} \tag{2.6}$$

$$\mathrm{Skewness} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x(i)-\bar{x})^3}{\mathrm{RMS}^3} \tag{2.7}$$

$$\mathrm{Peak-to-peak} = \mathrm{RMS}\ \times 2\sqrt{2} \tag{2.8}$$

These common parameters were used for statistical analysis in time domain by many researchers such as Patel and Upadhyay, (2016) uses mean, peak difference, kurtosis, RMS, crest factor values trained and tested for both artificial neural network (ANN) and support vector machine (SVM) model.

There are also researchers who proposed other input besides the common parameters we mentioned above to use as the testing and training data for their model. Hemmati, Orfali and Gadala, (2016) has proposed to used ring down counts, burst duration as original features beside the common parameters mentioned earlier.

Yu, (2011)has used impulse factor, margin factor and the four common parameters for statistical features. Vakharia, Gupta and Kankar, (2016) proposed Shannon entropy from time, frequency and time frequency domain as selected features.

2.2.3 Health Indicator (HI)

For certain cases which the machinery are located outside of the lab, the challenges of recorded real machinery health signals are challenging. Besides that, effect of speed fluctuation which normally caused by machine start up and cut off operation will affect the real desired signals collection.

Hence, de-noising filters to filter the unnecessary and background noises are developed such as minimum entropy deconvolution (MED) , discrete/random separation (DRS), adaptive noise cancellation (ANC) and linear prediction methods (El-Thalji and Jantunen, 2015). There are some researchers uses other parameter based health indicator such as using the Mahalanobis distance to derived the HI. MD is a distance measured to dictate the comparability of the training sample to test sample.

Rai and Upadhyay, (2017) proposed a health indicator based on MD and cumulative sum chart by deriving the HI and bearing age as input while the life percentage as output to train time delay neural network model. Oh, Azarian and Pecht, (2011) uses MD based health index to merge the features input to estimate the remaining life of a fan bearing.

Lei et al. (2018) highlighted there are many types of prognostics evaluation metrics based on single or multiple HI, HI and time, HI and HS and etc. Then, the feature subset is selected based on essential feature such as monotonicity, robustness, identifiability, consistency and hybrid metrics.

Monotonicity is a property that represents the real degradation process which is irreversible. Therefore, the monotonic will always shows either increasing or decreasing trend. Monotonicity can be defined as the absolute difference of positive and negative of derivatives for each feature, formulas (Javed et al., 2015) proposed are shown in following Table 2.1.

The stochasticity of degradation process interrupts the stability of the curve and affected the accuracy of the results. Therefore, robustness which is also named as smoothing method helps to strengthen the real signals and reduces the uneven noise to provide an even trend (Zhang, Zhang and Xu, 2016).

Table 2.1 Prognostic metrics formula

Feature	Formula	
Monotonicity		
	$\mathrm{Mon1(x)} = \frac{1}{K-1}\left\lvert \mathrm{No.of}\ \frac{d}{dx} > 0 - \mathrm{No.of}\ \frac{d}{dx} < 0 \right\rvert$	(2.9)
	$\mathrm{Mon2+(X)} = \frac{\mathrm{No.of}\frac{d}{dx}>0}{K-1} + \frac{\mathrm{No.of}\frac{d^2}{d^2x}>0}{K-2}$	(2.10)
	$\mathrm{Mon2-(X)} = \frac{\mathrm{No.of}\frac{d}{dx}<0}{K-1} + \frac{\mathrm{No.of}\frac{d^2}{d^2x}<0}{K-2}$	(2.11)
	$\mathrm{Mon3(X)} = \frac{1}{S}\sum_{S=1}^{S} \mathrm{Sep}_s$	(2.12)
Consistency		
	$\mathrm{Con1}(X_1, X_2) = \frac{\sum_{k=1}^{K}(X_{1,k} - \overline{X_1})(X_{2,k} - \overline{X_2})}{\sqrt{\sum_{k=1}^{K}(X_{1,k} - \overline{X_1})^2 (X_{2,k} - \overline{X_2})^2}}$	(2.17)
	$\mathrm{Con2} = \exp\left(\frac{-\mathrm{std}(P_{EoL})}{\mathrm{mean}\lvert P_o - P_{EoL}\rvert}\right)$	(2.18)
Robustness		
	$\mathrm{Rob(X)} = \frac{1}{K}\sum_{k=1}^{K} \exp(-\frac{X_k - X_k^T}{X_k})$	(2.13)
Identifiability		
	$\mathrm{Ide1(X, C)} = \frac{\sum_{k=1}^{K}(X_k - \overline{X})\,(C_k - \overline{C})}{\sqrt{\sum_{k=1}^{K}(X_k - \overline{X})^2 (C_k - \overline{C})}}$	(2.14)
	$\mathrm{Ide2(X, C)} = \sum_{S=1}^{S}\sum_{d \neq S}^{S}\left(\frac{(m_s - m_d{}^2)}{\sigma_s^2 + \sigma_d^2}\right)$	(2.15)
	$\mathrm{Ide3(X, C)} = \frac{S_B(X,C)}{S_W(X,C)}$	(2.16)

2.2.4 Health Stage (HS)

There is a metrics which define the relation between HI and HS is identifiability. Bearing prognostics HS are commonly presented in multiple stages. The formula (2.14) shown in Table 2.1 are used to measure the identifiability towards linear correlation. Fisher's ratio is introduced to improve the sensitivity to non-linear correlations (Lei et al., 2018). For single and different units of HS, the variance of failure threshold shall be minimising. The consistency of different HI is calculated by (2.17).

As mentioned above, the degradation trends observed from the HI are normally divided into different stages before RUL prediction. A comprehensive review of HS division was presented by Lei et al. (2018) and Figure 2.1 shows the three degradation process with one, two and multiple stages.

Figure 2.1a shows the consistent rise trend throughout the whole cycle. For Figure 2.1b, there are two health stages noticed which is the healthy and unhealthy stage. During the healthy stage, the RMS values are consistent but it went up during the unhealthy stage after certain period and never fell. The RUL prediction point shall be noted at the starting point of unhealthy stage, which named as the first predicting time (FPT).

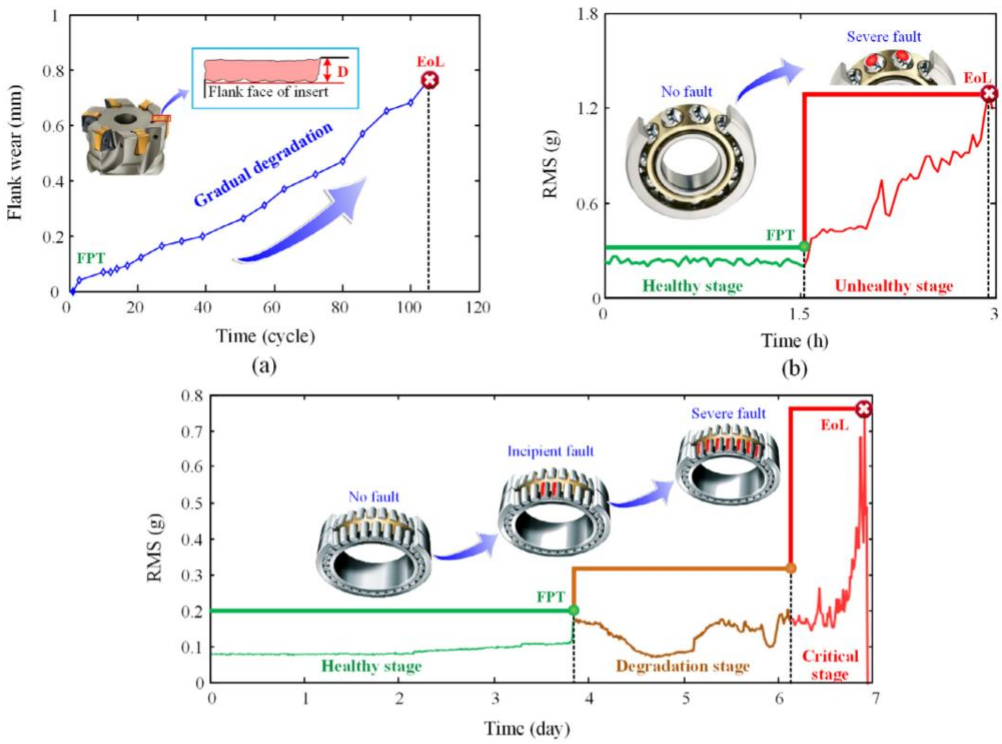

Figure 2.1 Three degradation process with one, two and multiple stages (Lei et al., 2018)

Figure 2.1c shows a multiple stage of degradation process, which is the healthy, degradation and critical stage. The RMS values were increasing slowly until the FPT. Then the degradation started due to the zig-zagged values and increased rapidly until it reaches the FT.

2.2.5 Remaining useful life (RUL) prediction

RUL prediction is to predict the time left for the component or machinery before it failed. Many papers reviewed on RUL prediction with different approaches and categories. There are two main procedures for RUL prediction which is select a suitable model of featured values and use the model with collected data to estimate the RUL. For RUL prediction, the review on RUL prediction basic techniques will be further discussed in the following subsection.

2.2.6 Summary

The health prognostic program includes processes such as data acquisition, health indicator, health stage and RUL prediction. The vibration or acoustic emission signals are acquired from the sensors mounted on the machine or component. The collected raw data are used to construct HI by extracting the suitable features and signal processing techniques. The lifespan of the component are usually presented in more than one type of degradation trend. Hence, the health stage can be divided into two or more stages. These health stages are analysed for RUL prediction based on the failure threshold (FT).

2.3 Review of Data Driven Method

2.3.1 Introduction

Data collections are the most important steps before employ any prognostics algorithm. Raw data based on different research topics were extracted for different features. In vibration analysis, collected data are commonly presented in the form of time domain or frequency domain. Time domain used to segregate nominal and faulted bearing with raw signals by statistical measures such as mean, standard deviation, crest factor, peak-to-peak value, kurtosis, and skewness. Bechhoefer and Kingsley, (2009) has reviewed another time domain approach- time synchronous average (TSA) to reduce the noise signal.

The frequency of different usage bearing has different characteristics. Therefore frequency domain approach depends on the periodic nature of each rotating machine but it is limited to steady-state waveforms. Fourier transformation (FT) is the popular method used in bearing diagnosed. However, most of the rotating machines are found in non-stationary waveforms, short time waveforms. Therefore advanced approaches such as short time Fourier transform (STFT) (Boashash, 2016) and wavelet transform (Pathak, 2009) are widely used for time-frequency analysis.

Modern techniques used to study the machine's failure mode have extended into the specific component than conventionally the assembled machine (Ben Ali et al., 2015). By monitoring the specific component it gave more precise historical data and trained more reliable RUL predictions.

Modern techniques for RUL prediction can be categorised into two groups which is data-driven based method and model based method. However many published journals and papers on bearing prognostics topic yet the taxonomy of prognosis method is still remaining unclear. Beginner and inexperienced researchers will get confused on the types of approaches and the method's pro and cons.

The pros and cons of each technique have encouraged researchers to combine different techniques and produced techniques that enhanced the pros and minimize the cons for certain objective (Dolenc and Juri, 2014). Hence, there are many hybrid model has been proposed by combining the pros of each method for the specific solution. The papers with mentioned methods will be discussed in later sub-section.

Data-driven method derived directly from the computer monitored historical data without the need to construct a physical model. The data-driven method relies on historical data to determine the signal characteristics for future trend and RUL prediction. Kim mentioned that data-driven method can convert high dimensional noise into low dimension but the effectiveness highly relies on the operating data (Kim et al., 2012). Data-driven methods can be classified into statistical approaches such as regression Gaussian process (GP) and support vector machine (SVM). Artificial intelligent approaches such as neural network (NN) and fuzzy logic.

Dolenc and Juri, (2014) expressed that the proposed model nowadays are too complex and costly. The simple model such as auto regression with exponential data smoothing can perform fast and cheaper than the proposed complex models. However, the exponential smoothing techniques assume the system is in steady state. Stochastic changes occur in most of the rotating machine; therefore, exponential smoothing technique may produce a reference guideline but not an accurate prediction. The most popular technique is the neural network.

2.3.2 Support Vector Machine (SVM)

Support vector machine (SVM) is one of the most popular, common and efficient classifier available in today's industry and researchers. SVM proposed by Vapnik to solve pattern recognition and classifications problems. SVM based on the statistical learning theory (SLT) applied to fault diagnosis of machinery. Current prognostic models based on SVM are univariate prognosis that not directs predication of the RUL because the RUL is time and are not ordinate the univariate time series (Chen et al., 2013). Today, there are many researcher studies the ways to combine SVM and other techniques to improve the generalization ability, learning efficiency and the size of predicted samples.

$$\left\{\left(X_{i,}Y_{i}\right) = i = 1, \dots, n, X_{i,} \in R_{d}, Y_{i} \in \{+1, -1\}\right\} \qquad (2.3)$$

Standard SVM samples have two classes which are the positive and negative class. The boundary curve is defined by subsets of the historical or training data. The SVM objective is to maximize the margin and distance between two classes with accurate high dimension data and efficient for real-time analysis.

Chen et al., (2013) highlighted that multivariable SVM examine various variables and explore potential information even in a small samples compared to univariate SVM which only employ the hidden dependence of univariate time. To determine the bearing degradation performance, advanced signal processing approaches are needed such as colony and genetic algorithm (Chen et al., 2013).

Granular support vector machine (GSVM) is one of the newly proposed techniques which combine the statistical learning theory and granular computing theory (Tang et al., 2004). Compare to the standard SVM, GSVM is a better generalization for linear non-separable problems. Guo and Wang, (2016) presented an improved granular SVM learning model to improve the learning efficiency and generalization performance of SVM based on hierarchical and dynamical granulation. The method used is by mapping the collected data to high dimensional space by using Mercer kernel and divided into several granules.

These granules were extracted and granulated on subtle level depends on the density and the radius degree. The hyperplane decision will be determined based on different hierarchical and dynamical granulation level. Tang et al., (2004) also uses the GSVM for complex medical binary classification applications.

Guo and Wang, (2016) proposed HD_GVSM that improves the generalization performance to solve larger scale classification with higher learning efficiency compared to traditional GVSM. Multivariable support vector machine (MSVM) which is proposed by Chen et al., (2013) are used to predict non-linear functions which have limited experimental and sample size. MSVM is the combination of multivariate regression and SVM. It combines the advantage of multivariate regression and prediction of a smaller sample with SVM.

2.3.3 SVM Regression

SVM Regression performs regression instead of just classification compared to the SVM. SVR maps the input data into higher dimensional space by using the loss function- epsilon insensitive and construct a linear or non-linear model into the space. The performance of SVR highly depends on the defined input parameters C, epsilon and kernel function. The difference between SVM and SVR is shown in Table 2.2.

Both the parameter C and epsilon affects the model complexity (Support Vector Machine Regression, 2016) The parameter C determines the complexity of the model. The bigger the C value, the lower empirical risk of the model. Besides that, parameter epsilon controls the width which used to fit in training data. The higher the epsilon, the lesser vectors are selected. SVR can be found in a few machine learning tools such as Python, LibSVM, LibLinear, Shogun toolbox and etc.

Zhao, Georgescu and Willett, (2011) has compared performance of SVM, SVR and PSVM model with turbofan engine degradation data and SVR has achieved the lowest error rate compared to the others. Yu and Kim, (2012) also studied the performance between linear SVR, RBF SVR and ranking SVM-named as RVM with benchmark datasets from LETOR. The result shows that the linear SVR has slightly higher accuracy than the rest but the RVM training time is shorter than SVR model (Yu and Kim, 2012).

Table 2.2 Comparison between SVM and SVR

SVM	SVR
• Performs classification	• Performs regression
• To increase margin between the classes	• To find the best fitting to minimizes the variation
• Separate data based on their labels	• Output based on the input model

2.3.4 Neural Network (NN)

Neural network (NN) is inspired by biological neural networks of the living organisms' brain based on mathematics and algorithms. It based on a collection of connected nodes that named as artificial neurons to transmit signal from one another. The output of the artificial neuron is commonly calculated by a non-linear function of the sum of its input. Artificial neurons are organized in layers to perform different kinds of transformations while transferring between layers.

There is a technique which combine nonlinear autoregressive neural network with wavelet filter to obtain higher accuracy of bearing RUL. Rai and

Upadhyay, (2017) derived HI and bearing age based on MD and cumulative sum (CUMSUM) chart to produce the life percentage for time delay neural network (TDNN) model's training time. This method is unlike the traditional ANNs which perform one-step ahead of bearing RUL.

2.3.5 Fuzzy Logic network

Among the data-driven methods, the fuzzy system is one of the common selections for machine health forecast. The fuzzy system can deal with more complex, incomplete system among the techniques. The linguistic variable is modified because the normal languages cannot express in fuzzy value scale directly.

Ladj et al., (2017) has proposed a variable neighbour search and fuzzy logic-Fuzzy VNS for predictive maintenance flow schedule. They had compared few procedures using VNS with fuzzy logic output to solve the permutation flow scheduling issue (Ladj et al., 2017).

Practically, the industry data has more noise compare to data collected through laboratory experiments. Besides, the linguistic used to define the fuzzy rules are varies among researchers. Chaochao Chen and Vachtsevanos, (2012) proposed an Interval Type-2 Fuzzy Neural Network (IT2FNN) which can perform better prediction even with corrupted additive noise of testing data with adaptive neuro-fuzzy interference system (ANFIS).

2.3.6 Hybrid approach

Ben Ali et al., (2015) proposed to combine simplified fuzzy adaptive resonance theory map (SFAM) neural network and Weibull distribution (WD) to evaluate health state and estimate the RUL. They modified Weibull failure rate function to Universal failure rate function (UFRF) to fit extracted vibration signals features in the time domain and train simplified fuzzy neural network (SFAM) (Ben Ali et al., 2015). The advantage of the proposed model by Ben Ali is that it needs only a single monitoring history data for training. The challenge and future work is to train this approach to able detect the type of fault.

Another proposed hybrid method is to combine non-linear autoregressive neural network (NARX-NN) with wavelet-filter technique (Rai and Upadhyay, 2017). The wavelet-filter to amplify the bearing signals impulsive for better fault feature extraction. The HI and bearing age are derived as the input while the bearing life percentage as output to train NARX-NN as time delay neural network (TDNN). Rai and Upadhyay, (2017) mentioned the results are compared with ordinary ANN and NARX-NN responds and provide earlier detection compared to ANN.

2.4 Review of Model Based Method

The model-based method requires a physical model to identify the model parameters and predicts the future trend of the RUL. The model-based method relies on the model accuracy. The model-based method needs lesser training data compared to the data-driven method. This is because of the real-time measured data will be counterchecked with the mathematical model's output to ensure the consistency of the outcome.

However, the model based method usually are designed on certain damage mechanism, therefore, the model may overlook other defects that were not pre-designed on the model. Besides the limitation of the model algorithm, some of the mechanical defects can hardly be detected but required physical inspection to recognize.

The common model-based approach used such as Paris’ Law, crack growth model. Since this paper focus on data driven model, therefore the detail descriptions about model based will not be further discussed in this paper.

2.5 Comparison between Data Driven Method

Table 2.3 Property comparison

PROPERTIES	SVM	NN	FL
Non-linear input data	H	H	H
Non-stationary time series input data	H	L	L
Small Dataset	H	L	H
Large Dataset	H	H	L
Learning/ Adaptability of system	L	H	L
High dimensional data handling	H	H	H
Incomplete system handling	L	L	H
Complex system handling	L	H	H
Noise immunity level	L	H	H
Real Time Analysis	H	L	L
Output accuracy	H	L	L

Note: H- High, L- Low

2.6 Summary

For most of the techniques, the biggest challenge is the uncertainties of the stochastic and physical degradation pattern of machine and bearing. All the models are based on the historical data whether from industrial historical tracking data or laboratory test data. However, the material quality and degradation are inconsistent due to the different manufacturer.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The test rig setting, data collection, data analysis and life prediction will be shown in the following sub-sections. This experiment uses AE sensor collector, therefore the AE signals collected requires a method to filter the background noise but remain the desired signals.

The analysis of each parameter and prediction of life are the main focus in this project. The data is collected from an experiment of run-to-failure bearing testing. Each testing will compound one bearing run-to-failure results. The test bearing used is a single-row, deep groove ball bearing, model MISUMI-B6002. The specification of the bearing is shown in Table 3.1.

Table 3.1 Test bearing specification (Deep-Groove Ball Bearing B6002)

Item	Specific	Item	Specific
Raceway Ring Shape	Ball	Basic Dynamic Load Rate (N)	5600
Outer Diameter (mm)	32	Basic Static Load Rate (N)	2830
Inner Diameter (mm)	15	Allowable Rotational Speed (rpm)	24000
Width (mm)	9	Load Direction	Radial

3.2 Study Design

3.2.1 Test Rig Setting

The test rig used in this project is as shown in Figure, this was designed by UTAR. This test rig is designed in vertical axis and to produce high torque. However the misalignment of this test rig shaft happens when there is need to replace the test bearing.

Figure 3.1 Test Rig

There are three support bearings placed in between the coupling and test bearing to reduce the reaction force from coupling. The thermocouple is mounted at opposite of AE sensor to record the temperature of bearing. The test bearing size is smaller than support bearing due to the time limitation for run-to-failure test. The data is recorded every 5minutes.

3.2.2 Experiment Procedures

Figure 3.2 Experiment Setup

1. The test bearing and test rig shaft are connected to the drilling machine as shown in Figure 3.2.
2. The AE sensor, thermocouple and accelerometer are mounted on the test bearing housing horizontally.
3. The support housing is installed loosely to prevent additional force applied on the support bearing and caused difficulty for shaft rotation.
4. The support and test bearings are lubricated before testing.
5. The experiment is conducted under three different speed such as 1400rpm, 1200rpm and 900rpm respectively.
6. The static load of 3kN is applied on the test bearing.
7. The static load is removed after the bearing fail.
8. The experiment is repeated by replacing another test bearing.

3.2.3 Experiment Instrumentation/ Equipment

3.2.3.1 Hardware

Table 3.2 List of Hardware Equipment

No	Item	Model	Description
1	Test Rig	-	Provided by UTAR research
2	Test bearing	MISUMI-B6002	Single-row, deep groove open ball bearing
3	Drilling Machine		Variable speed can be controlled while drive the shaft
4	Acoustic Emission (AE) Sensor	MISTRAS	Elastic wave released from mechanism is converted into electrical signal by AE sensor. The sensitivity is higher compared to accelerometer due to the piezoelectric transducer.
5	Accelerometer	KSTLER type 8704B50T	The acceleration of the test bearing is measured for bearing defective test.
6	Thermocouple		The temperature of test bearing is monitored by the thermocouple.

3.2.3.2 Software

Table 3.3 List of Hardware Equipment

No	Item	Model	Description
1	AE acquisition system	AE Win	AE Win is employed to show the continuous AE waveform
2	Signal Processing	Matlab	Matlab is employed for signal processing. Matlab equipped with various signal processing aids and tools that reduce the time for arranging coding.

3.3 Feature Extraction

In this project, the common feature extraction techniques such as mean, RMS, Kurtosis, crest factor, skewness and peak-to-peak is applied. These techniques are used to compare the bearing life trend and analyse the warning line signal waveform in time series. The formula for each feature extractions are shown in Section 2.2

3.4 Summary

The project consists of two parts, which the first part is test rig experiments to obtain the bearing life signals. There were 6 sets of test conducted. Next, the raw signals recorded are then programmed by Matlab to get feature extracted. Because of the data sets obtained is small capacity, therefore SVM model is employed for the prognosis of bearing RUL as compared to the other common prognosis models.

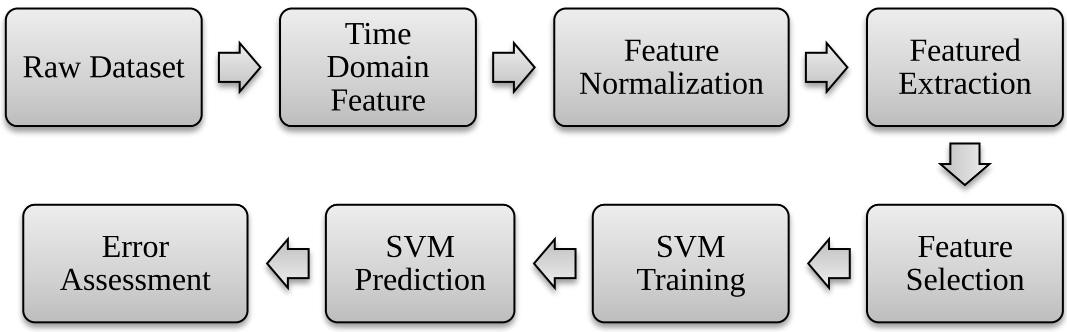

Figure 3.3 The overall process of SVM method

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Tested bearing information

A few number of new healthy bearings were undergone the run-to-failure test under the UTAR designed test-rig as mentioned in Section 3. The AE signals are captured at every 5minutes for 2seconds duration throughout the test. The test is run continuously until it breaks down. However, due to the existing laboratory working hour restriction, the bearing test will stop and resume by the next day. Hence there are some sudden jump-start of signals are noticed from the collected signals.

There are more than 6 numbers of bearing were tested however, only the six bearings data was recorded and present here as the others failed too early due to inaccurate installation of the bearing and took too much time to fail compare to the others. The tested bearings details are shown in Table 4.1.

Table 4.1 Tested bearing information

Test	Bearing Type	Load (kN)	Break time (mins)	Number of sample data
1	MISUMI-B6002	3	1705	340
2	MISUMI-B6002	3	645	128
3	MISUMI-B6002	3	1630	325
4	MISUMI-B6002	3	2200	439
5	MISUMI-B6002	3	3865	772
6	MISUMI-B6002	3	2810	561

Table 4.1 shows that the tested bearing life is highly nonlinear. All the bearings were the same type and used under the same conditions of load, however the

failure time for each bearing is not the same and the sample data collected is different too. Next, the experimental results will be extracted into few time domain variables to compare which feature is best descript the entire lifespan of the tested bearing.

4.2 Feature extracted over bearing complete lifetime

The raw signals were collected and filtered with the Matlab machine learning toolbox 1.1. The defect feature are extracted from them such as the mean value, RMS, skewness, kurtosis, peak to peak and peak to RMS. Figure 4.1(a)-(f) shows the trend of six-time domain features over the six tested bearing complete lifetime respectively.

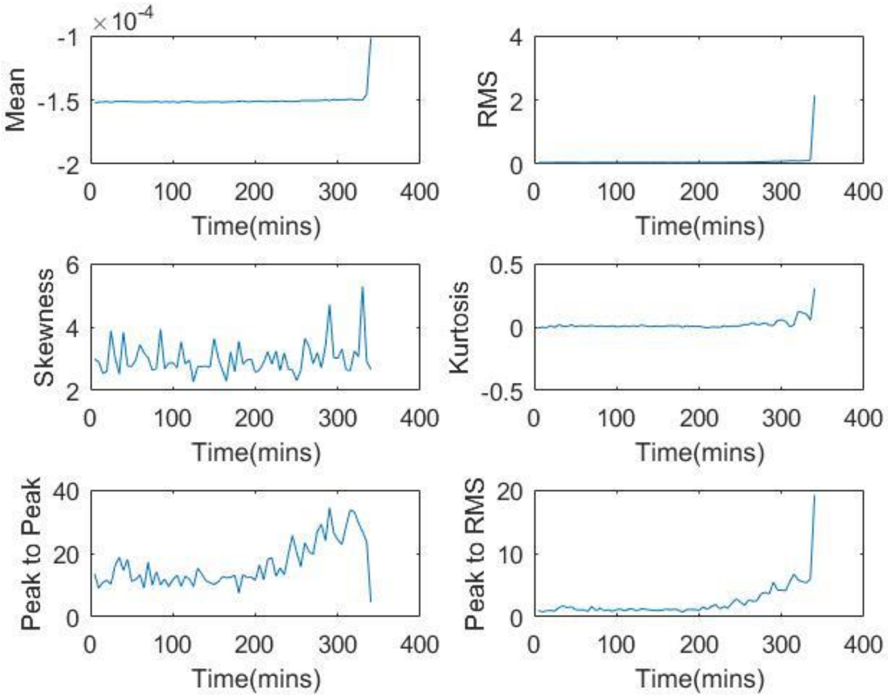

Figure 4.1a Feature extracted over the complete lifetime of Test 1 bearing

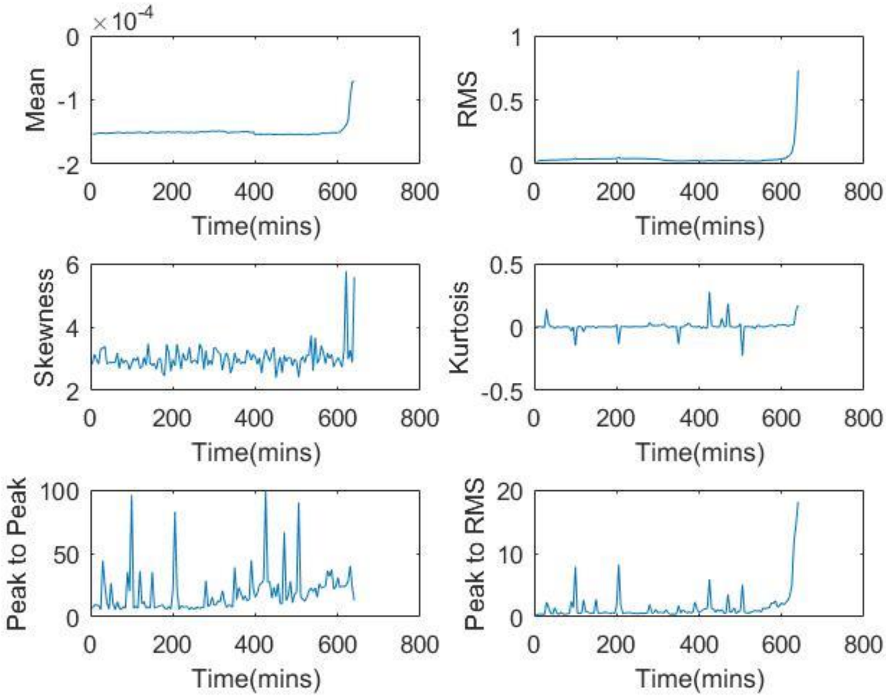

Figure 4.1b Feature extracted over the complete lifetime of Test 2 bearing

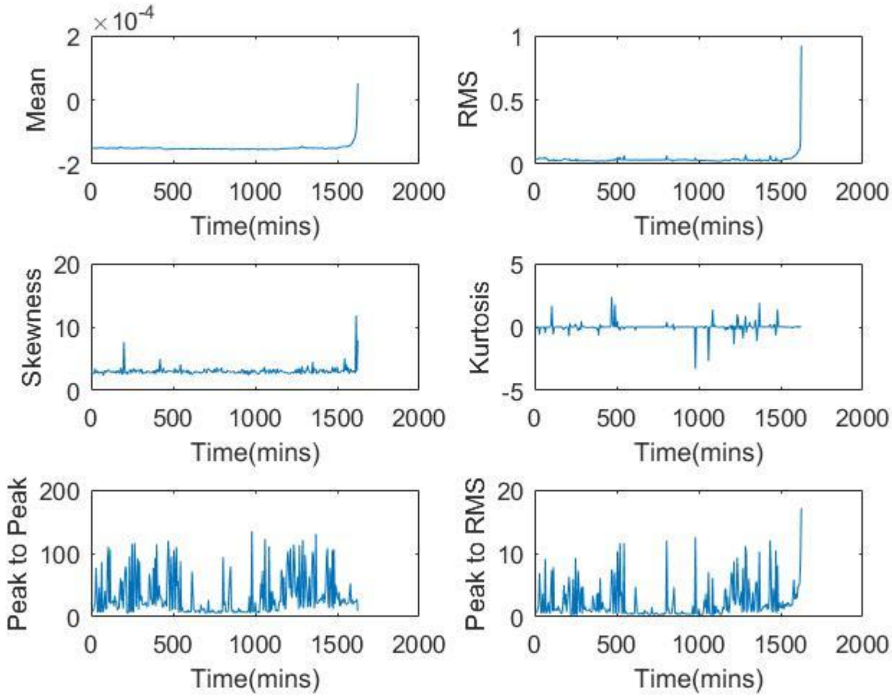

Figure 4.1c Feature extracted over the complete lifetime of Test 3 bearing

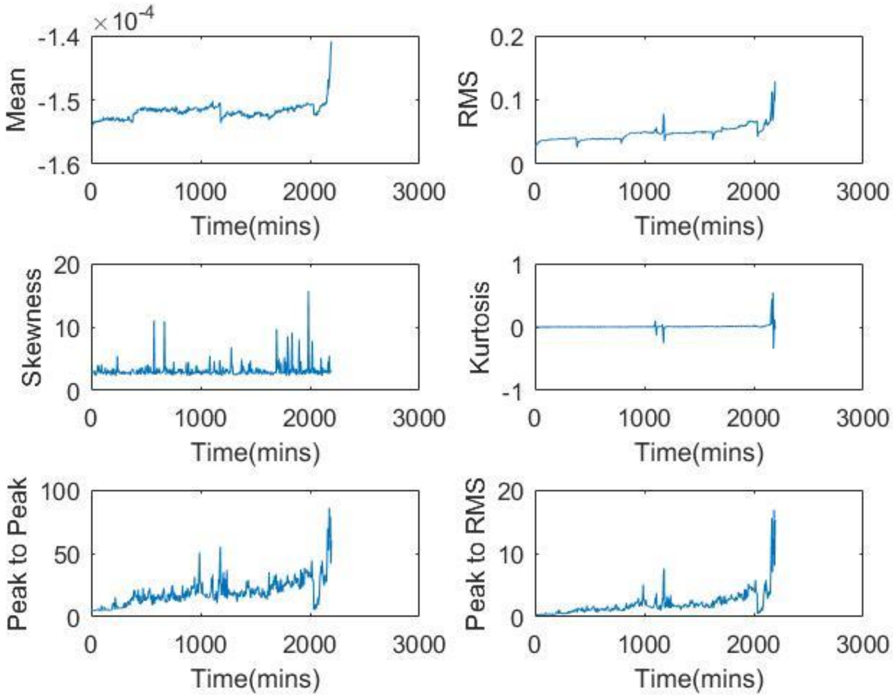

Figure 4.1d Feature extracted over the complete lifetime of Test 4 bearing

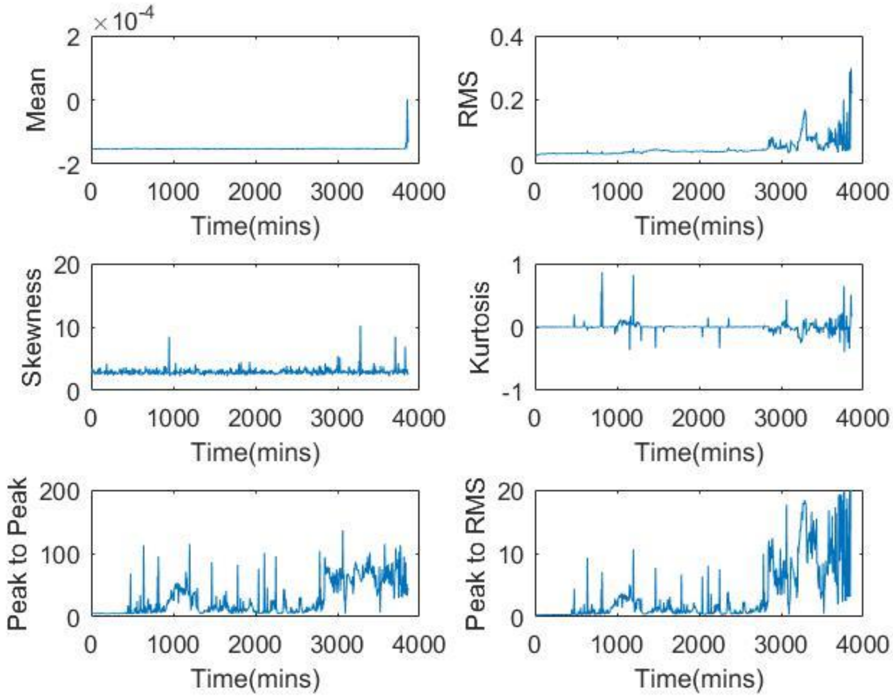

Figure 4.1e Feature extracted over the complete lifetime of Test 5 bearing

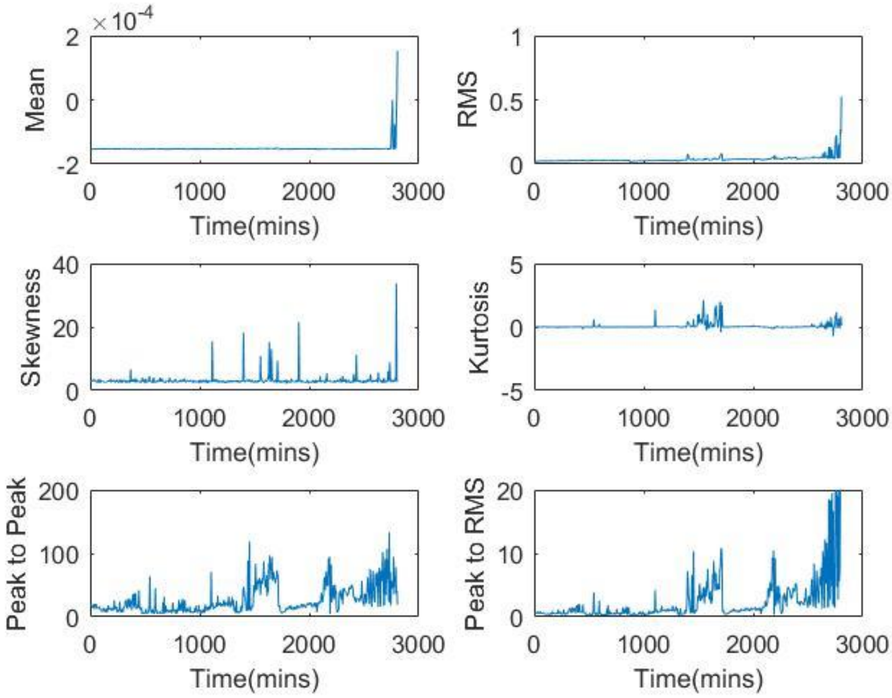

Figure 4.1f Feature extracted over the complete lifetime of Test 6 bearing

From Figure 4, the mean values are consistent at the early stage which is known as the healthy stage except for Test4 bearing. However, the bearings trend shows sudden increase at 390minutes (Test1), 610minutes (Test2), 1500minutes (Test3), 2200minutes (Test4), 3800minutes (Test5) and 2700minutes (Test6).

The sudden change and fluctuation of gradient is considered as unhealthy stage which it has higher probability of failing compare to the healthy stage. The inconsistent vibration level shown in Test 4 is observed and is caused due to the inaccurate shaft positioning.

The RMS graphs has a similar trend like the mean values. However the sudden changes of RMS value is not obvious compare to mean values as it is the effective value of the total waveform. Peak to peak is the difference between the maximum positive and negative amplitudes of waveform. Hence, a peak-magnitude-to-RMS ratio/ crest factor feature is plotted to indicate the failure evaluation in the tested bearings.

From the skewness graph, the fluctuated line did provide a clear trend for degradation and health stage study. On the other hand, the Kurtosis line shows few sudden peak throughout the whole lifespan. For instance, in test 2, there are sudden up and down shown at the 20th minutes, 110th minutes, 210th minutes, 380th minutes, 430th minutes, 480th minutes and 500th minutes before the bearing breaks at 645th minutes.

4.3 Feature Selection

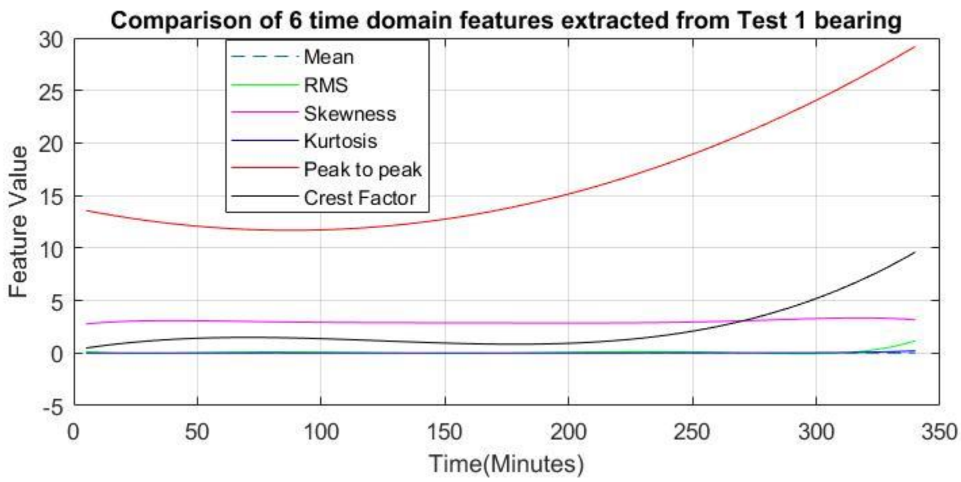

Figure 4.2a Feature comparison for test 1 bearing

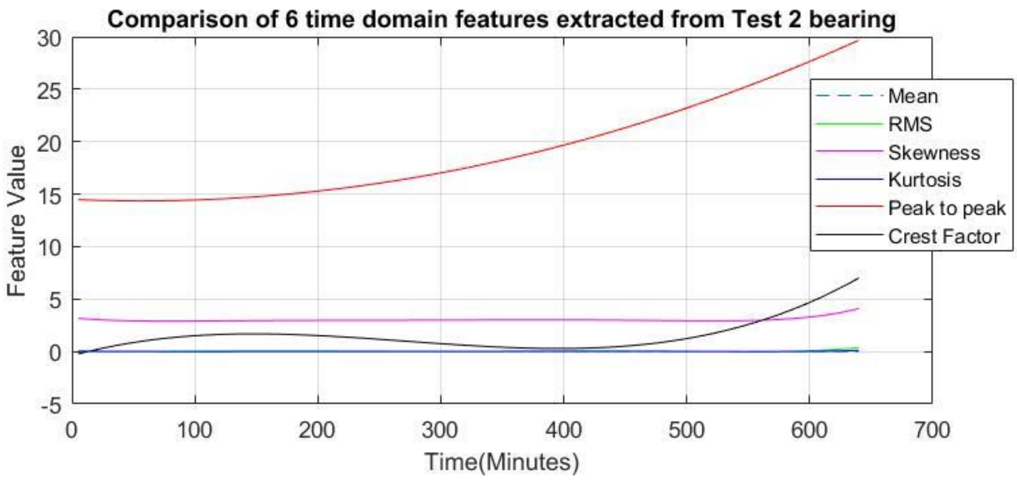

Figure 4.2b Feature comparison for test 2 bearing

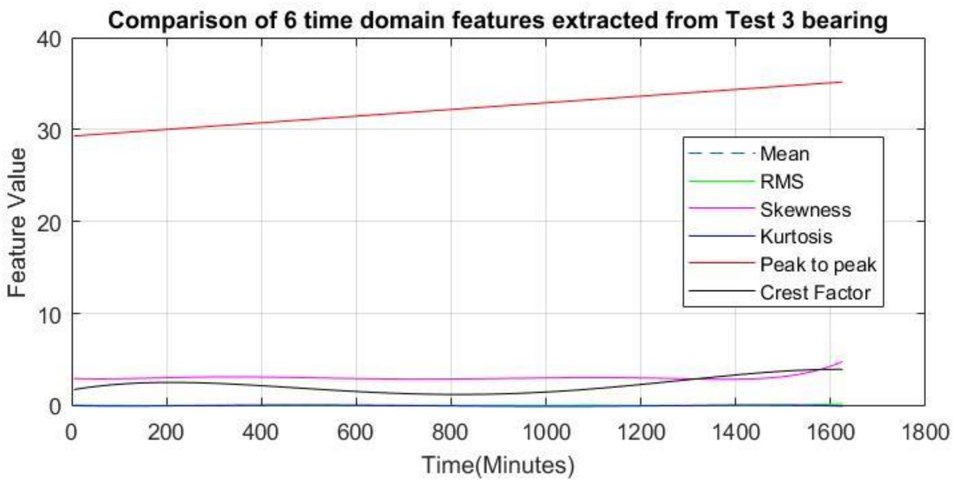

Figure 4.2c Feature comparison for test 3 bearing

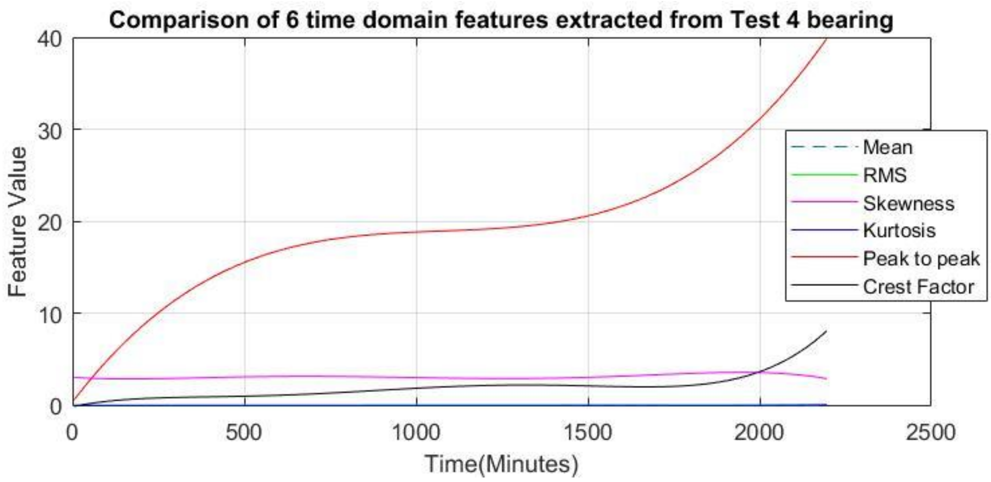

Figure 4.2d Feature comparison for test 4 bearing

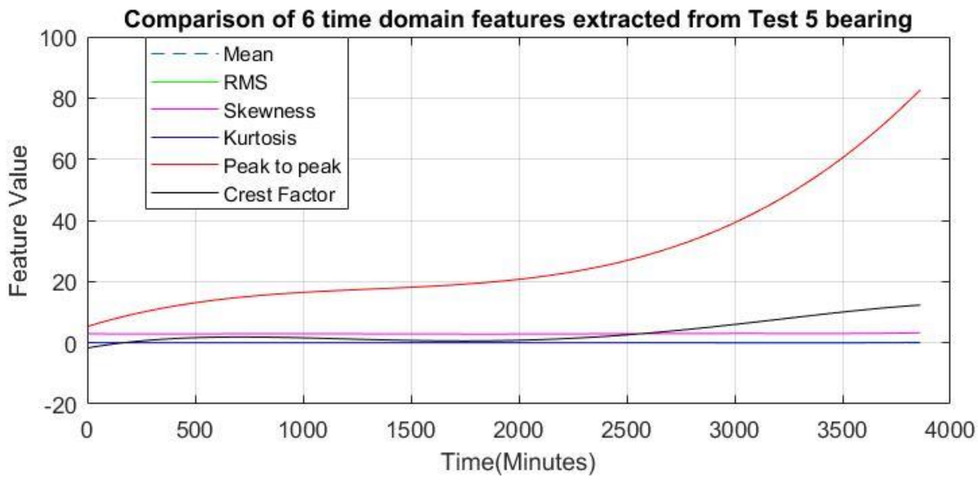

Figure 4.2e Feature comparison for test 5 bearing

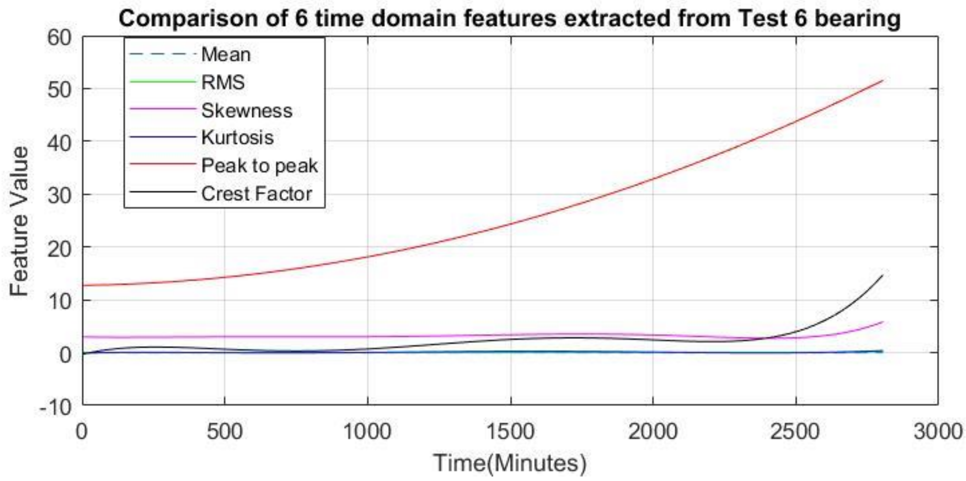

Figure 4.2f Feature comparison for test 6 bearing

Figure 4.2(a)-(f) shows the 6time domain feature extracted fitting among the 6 experiment bearings. To obtain a better characterize degradation trend, the selection of fitting features are important. But Ben Ali *et al.*, (2015) highlighted this assumption is only restricted to mechanical irreversible process, for instance, battery which have potential self-repair periods are not suitable with this assumptions. For this case, the bearing will not self-repair once it has crack growth and the damage will continuously increase until it breaks.

In this report, we are using a manual feature selection by comparing the graphs generated for each bearing. Based on the graphs, it is noted that both peak-to-peak and crest factor variables shown good life curves compared to the others. Hence, both variables are chosen as the characteristic variables. The first 5 sets of historical operation hour collected from the experiment is used as training data input and the last sets of data as the testing data to validate the prediction.

There are a few types of Kernel selection, such as polynomial and Gaussian type and the parameters such as penalty parameter (eg. C), Kernel parameter (eg. α, β, r) and RBF kernel parameter (eg. C, γ). The three types of kernel function used here, they are the Gaussian Kernel, the linear Kernel and the polynomial Kernel function.

$$K_{\mathrm{linear}}(x, y) = \sum xiyi \tag{4.1}$$

$$K_{\mathrm{poly}}(x, y) = (\sum xiyi + 1)^3 \tag{4.2}$$

$$K_{\mathrm{gass}}(x, y) = e^{-\frac{\|x-xi\|^2}{2\sigma^2}} \tag{4.3}$$

In the proposed SVM model (code refer to Appendix A), the parameters are set as the maximum number of iterations= 50, the eps= 0.1 used as iteration stopping threshold, tolerance value 0.2. In this section, author used loess function, one of the smoothing fitting method to allow more accurately real bearing degradation trend. Besides, there are three approximation function is used to meets the data points. The function used are first degree, third degree and ninth degree polynomial.

4.4 Prediction results of test failure history

Figure 4.3 and 4.4 shows the results of estimated bearing remnant life and its comparison with the actual RUL for both peak to peak and crest factor variable. The X-axis and Y-axis is the current prediction time and life percentage. The solid line in red shows the predicted value of proposed SVM and the blue dotted curve shows the actual value.

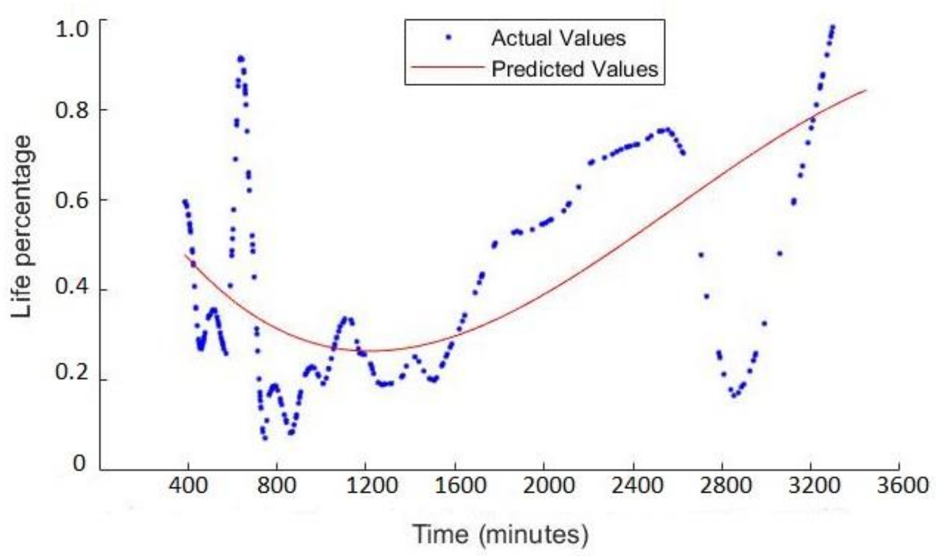

Figure 4.3 Prediction results with variable -peak-to-peak

The intersection points for both actual and predicted curves are the potential failure points. From Figure 4.3, there are few intersection points during the early state, it might be due to the dust or small objects trapped in the test rig and increased the friction for bearing to work harden. However by observing the graph up to intersection at time 2680minutes, the value drops rapidly and raised again after time 2840minute. This fluctuation are caused by the sudden turn off and start up of test rig. However the bearing are predicted failed at

3260minutes and the actual bearing failed at the time 3380mintues. The predicted time difference is 120minutes. The RUL prediction error is calculated with Equation 4.4. The prediction of bearing RUL error is 96.5%.

$$\text{RUL Prediction Error} = 1 - \left(\frac{\sum \text{actual} - \text{predicted}}{actual}\right) \qquad (4.4)$$

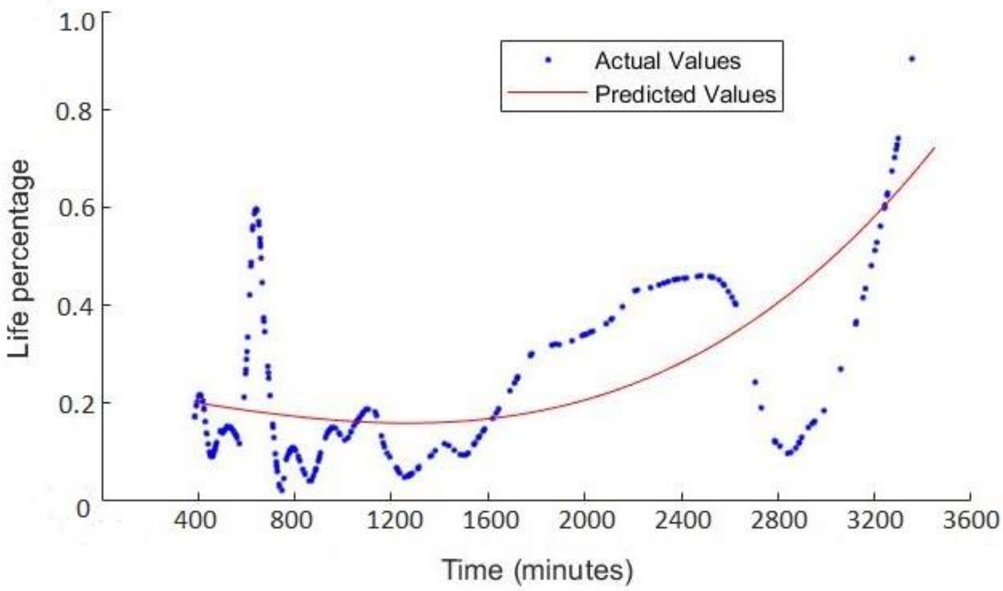

Figure 4.4 Prediction results with variable -crest factor

From the prediction graph of crest factor, the life percentage are not end at the 100%.This should be further investigate with more datasets as the crest factor value are actually affected by the ratio of peak and RMS, hence, the inconsistent of these values caused some impact on crest factor value. The graph are similar with the peak-to-peak variables that have few intersections point in the earlier state. The predicted failure of bearing shown is at time 3210minutes while the actual time to fail is at the 3340minutes. The predicted time is 130minutes advanced from the actual break down. The predicted bearing RUL error is 96.11%.

Table 4.2 is computed with the comparison prediction accuracy and errors of prediction bearing life between both peak-to-peak and crest factor variable. The root mean square error (RMSE), coefficient of determination (R-Squared), sum squared error (SSE) and accuracy of overall predicted values are calculated with Matlab in-built formula to evaluate the prediction results. R-squared shows the proportion of the total sum of squares. The larger the R-squared, the variability of the model.

Table 4.2 Prediction errors and accuracy

Variable	R-Squared	RMSE	SSE	Accuracy (%)
Peak-to Peak	0.6413	0.1566	7.1123	49.50
Crest Factor	0.7344	0.0513	0.7634	77.23

Despite the discrepancies shown in the Figure 4.3 and 4.4, the overall trend are similar with the actual bearing life percentage. Noticed that the life trend increased rapidly after reaching the unhealthy state compared to the beginning healthy state. This shows the necessity to predict the ending life to prevent sudden breakdown of the bearing.

The average prediction accuracy for peak-to-peak and crest factor are 49.50% and 77.23% over the entire range of data. It is observed that the proposed approach to predict the RUL using peak-to-peak variable are not satisfying compared to the crest factor. However, the crest factor variable prediction accuracy is not satisfy too.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

This project has completed the aims and objectives stated in Chapter 1. The experiment is conducted and the signal from a few number of bearings run-to-failure is collected. The signals collected has been programmed and trend curve and features are extracted and presented. The bearing life curve is classified by SVM and performed regression to show the bearing life. Lastly, the proposed predictive algorithm to determine the bearing remnant life is used to compare results of actual and predicted RUL between two variables.

The process from data collections, feature extract and selection, data analysis and RUL prediction has been presented step-by-step in this report. This project also included some fundamental information on prognostic programme and discussion on data-driven techniques available used in bearing degradation performance evaluation.

5.2 Future Works

The future works to improve this project would be increasing the number of historical datasets to allow selection of optimal failure time bearing. Besides, due to the limited number of historical data, the prognostic model are limited and restricted to a few types.

In order to improve the accuracy of the prediction, neural network model is suggested to be used for prediction. This is because of the accuracy and performance for this technique are higher for large number of datasets.

On the other hand, the raw signals collected should be filtered using other filter method available besides of Matlab inbuilt signal smoothing or de-noising function to ensure only the real signal created from the bearing is picked than the background noises.

The failure pattern and actual degradation trends of bearings still require further investigation to improve the overall accuracy of prediction and prevent giving false warning to user which defeated the origin of the condition monitoring system.

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Appendix A

```
% SVM code

close all;
clear all;
clc;

% Normalization of Data
data=zscore(csvread('result_test_01.csv'));
temp=zscore(csvread('result_test_02.csv'));
data = [data; temp];
temp=zscore(csvread('result_test_03.csv'));
data = [data; temp];
temp=zscore(csvread('result_test_04.csv'));
data = [data; temp];
temp=zscore(csvread('result_test_05.csv'));
data = [data; temp];

test_data=zscore(csvread('result_test_06.csv'));
% data = [data; temp];

% x is the input matrix. Each row represents the feature for a single input
% y contains corresponding target values
x=data(:,2:end);

% y is the variable to be predicted.
y=data(:,6); %col 6: peak-to-peak, col 7: crest factor

% Number of inputs
N=length(data);
alpha=zeros(N,1);

% Tolerence value
norm1=10e2; tol=0.2;

% Maximum number of iterations
itr=0; maxItr=50;
eps=0.1;

% Algorithm
while (norm1>tol && itr<maxItr)
    alpha_old=alpha;
    alpha_=alpha;
    for i=1:N
        alpha(i)=alpha(i) + y(i) -eps*sign(alpha(i))...
            -alpha'*kernel(x,x(i,:),'g')';

        if alpha_(i)*alpha(i)<0
            alpha(i)=0;
```

```
        end

    end
norm1=norm(alpha_old-alpha);
itr=itr+1
end
fprintf('Total number of iteration %d',itr)

% Weights
w=sum(alpha.*x)

% Bias
b=mean(y-(w*x')' -eps*ones(N,1))

% Testing Phase
test_X = test_data(:,2:end);
test_Y = test_data(:,6);
N = size(test_X,1);

% Predicted values
for i=1:N
    pred1(i,:)=alpha(i)*kernel(test_X,x(i,:),'g')';
end
pred=sum(pred1)';
disp('[Actual Values  Predicted Values]');
disp([test_Y(1:10) ,pred(1:10)]);

%%
ttX=test_X(:,4);
[sorted_ttX, I] = sort(ttX);
sorted_Y = test_Y(I);
sorted_pred = pred(I);


% Plotting
figure
hold on
% plot(x(:,1),y,'r-');
% plot(x(:,1),pred,'b-');
%scatter3(test_X(1:50,5),test_X(1:50,6),test_Y(1:50));
%scatter3(test_X(1:50,5),test_X(1:50,6),pred(1:50),'*');

nx=300;

%pick one for smoothing
test_Y(1:nx) = smooth(sorted_ttX(1:nx),test_Y(1:nx),0.1,'rloess');
%test_Y(1:nx) = smooth(sorted_ttX(1:nx),test_Y(1:nx),'sgolay')

%pick one for approximation
%f = fittype('poly1');
```

```
%f = fittype('poly3');
f = fittype('poly9');
%f = fittype('cubicspline');

[fit1,gof,fitinfo] = fit(sorted_ttX(1:nx),test_Y(1:nx),f);
plot(fit1,sorted_ttX(1:nx),test_Y(1:nx));

disp(fit1);
disp(gof);
disp(fitinfo);


%nx=300;
%T=polyfit(sorted_ttX(1:nx),sorted_pred(1:nx), 4);
%K=polyfit(sorted_ttX(1:nx),test_Y(1:nx), 1);
%xfit = 0:325;
%yfit=polyval(K,xfit);
%yfit2= polyval(T,xfit);
%hold on
%plot(xfit,yfit2,'b-');
%plot(sorted_ttX(1:nx),test_Y(1:nx),'r-');

hold off
xlabel({'Time (minutes)'});
ylabel({'Life percentage'});
legend1 = legend('Actual Values','Predicted Values');

%%
 AC= sum(test_Y-pred) / numel(test_Y); %Accuracy
ACP = 100*AC; %Accuray percentage
```