공학석사학위논문

베어링 고장 선감지, 진단 및 고장기준 정의를 통한 비감독 수명예측

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2018 년 2 월

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지도교수 윤 병 동

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전병주의 공학석사 학위논문을 인준함

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Abstract

Bearing Incipient Fault Detection, Diagnosis, and Unsupervised Prognosis with Failure Thresholding

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Bearings are core components in rotating machines. Thus, early detection of faults and accurate prediction of a machine' s health state is highly desirable throughout the total lifecycle of a bearing. Rolling element bearing failure is one of the critical causes of breakdowns in rotating machinery; these types of failures are common in mechanical systems as well. Such failures can be catastrophic and can result in costly downtime.

Particularly in industrial fields, minimization of downtime is critical. Thus, health monitoring of rotating machinery during operation is the focus of significant research interest. Accurate bearing health prediction is needed for these settings. There remains a need for health state prediction that can be accomplished in real-time, without future data.

Therefore, a data-driven and real-time algorithm for bearing health monitoring is suggested in this thesis. The research objectives pursued to improve the bearing PHM framework include 1) full−time health monitoring, 2) definition of a failure threshold for rolling elements in general bearings, and 3) life prediction in real−time and in unsupervised situations.

To classify the health state of bearings for detection of incipient faults and fault points, the Mahalanobis Distance is applied. For life prediction, previous researchers have experienced severe problems, particularly when the life prediction required analytic assumptions as a prerequisite, for example, those emerged at Particle Filters. To solve this problem, the research outlined in this paper suggests a new model and a threshold decision method that enables prediction of the Remaining Useful Life in real time (i.e., in unsupervised situations).

This thesis is organized as follows. Section 1 provides an introduction, including the research motivation and an overview of the research objectives. Next, in Section 2, methodologies for detection of incipient anomalies, fault diagnosis, and failure prognosis are explained, along with a suggested definition and a trend projection model. Then, Sections 3 and 4 validate the suggested threshold and model using data acquired from Schaeffler Korea and Seoul National University, respectively. Finally, Chapter 5 concludes this thesis with a summary of the research contributions and suggestions for future work.

Keywords: Incipient Anomaly Detection, Diagnosis and Prognosis, Failure Threshold, Asymptotic Model

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Chapter 1. Introduction

1.1. Background and Motivation

Rolling element bearing failure is one of the critical causes of breakdowns in rotating machinery and common mechanical systems. Researchers in PHM (Prognostics and Health Management) have studied ball bearings for a long time [(1), (2), (3)]. However, little research to date has focused on the real−time monitoring. Additionally, full−time health monitoring – from normal state to failure – is greatly needed in industrial fields. This type of health monitoring will allow users to be continuously aware of the health status of their rotating machines and enable them to make plans to repair and retain machinery in working condition.

Varying failure criteria presents another problem for researchers, since different thresholds can be applied for each bearing depending on its purpose. For example, bearings that are built for use in precision operating machines would require a conservative threshold of failure, while others may not.

According to previous research[(4)], the evolution of wear in rolling bearings progresses sequentially through five stages: the running−in stage, the steady−state stage, the defect initiation stage, the defect propagation stage, and the damage growth stage. In many cases, the very first initiation of spall should be detected and the health state should be subsequently monitored continuously to ensure productivity of the machine.

In prognostics, many researchers have attempted to make more effective and generally applicable algorithms to predict Remaining Useful Life[9]. However, all popular algorithms, such as the Particle Filtering method and Artificial Neural Networks, have pros and cons. In this thesis, objectives are established, and the most relevant algorithm is suggested for the defined objectives.

1.2. Research Objectives

The first motivation for this research is the growing need for full-time health monitoring. In many settings, it is desirable to know the status of the mechanical system over its total life. Previous research has concentrated on the comparison of normal and abnormal signals.[10] However, in real-world settings, simultaneous health monitoring is desirable during operation of machinery, as it can provide information necessary to enable early planning for repairs needed to maintain the system in a usable state.

Prognostics is another significant motivation for this research. The primary goal of prognostics is to provide useful insight into a system's health by combining three aspects: complexities of real-time systems, accurate and full utilization of data, and variable operating patterns. However, there are many limitations to prognostics due to its required assumptions, including the threshold decision problem. Therefore, an algorithm is needed that provides data−driven, real−time, and short−calculations for threshold definition.

Inspired by these motivations, the research objectives of this project are defined as follows: 1) full−time health monitoring for bearings, 2) suggestion of a failure threshold decision algorithm, and 3) real−time, unsupervised life prediction.

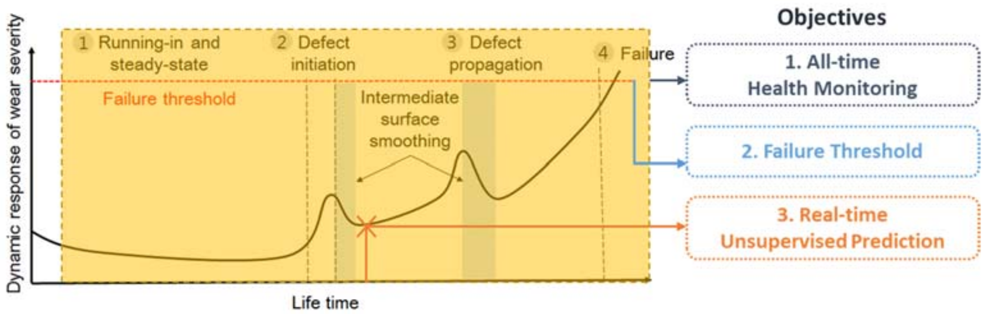


Figure 1-1 Research objectives throughout the life of a bearing

1.3. Thesis Layout

In order to solve problems and accomplish the research objectives, overall PHM procedures for bearings are conducted throughout normal, incipient fault, and failure states. This thesis is organized as follows. Section 2, explains the methodologies of bearing fault detection throughout incipient anomaly, fault, and failure, which is followed by suggestions of life prediction algorithm. Next, Section 3 provides a case study of prognostics with bearing dataset from Schaeffler Korea. In Sections 4, another case study of bearing dataset with SNU Bearing Testbed is explained. Finally, section 5 concludes thesis with contributions and future works.

Chapter 2. Methodology

2.1. Overall PHM Flowchart for a Bearing

Previous PHM research has mainly focused on diagnosis and prognosis for a specific application. In the research described here, the application is a bearing. This research outlined here covers the entire range of life: from normal state to failure. In order to classify the life stages, the bearing state is defined in four states: normal, incipient anomaly, fault, and failure. These states represent increasing levels of severity of health defects.

The PHM process should define how far the bearing has come and how long it will take for eventual failure. To do so, vibration signals are used for analysis. After a vibration signal is acquired, preprocessing and feature extraction stages follow. Next, based on a health index, which is also called Mahalanobis Distance, the health monitoring system will detect incipient fault features. The diagnosis stage and prognosis stage follow. These procedures form the real-time health monitoring system.

To be more specific, features are selected for each step of incipient anomaly detection, fault diagnosis, and failure prognosis. Blue-lined boxes in the PHM flowchart on figure 2-1 indicate the selected features. Yellow boxes show the results of each section. In this research, a health index (HI) with Mahalanobis Distance, a threshold decision method, and a degradation model are all suggested.

As shown in the figure, the results from each step are used for each subsequent step. During the incipient anomaly detection step, the health index is calculated continuously. Here, if HI increases over 5 (i.e., moves into the fault range) the bearing monitoring system process moves on to fault diagnosis. Next, after a faulty part of a bearing - among the outer race, the inner race, or the ball - is diagnosed, failure prognosis for predicting RUL is conducted. The following sections explain each of the procedures.

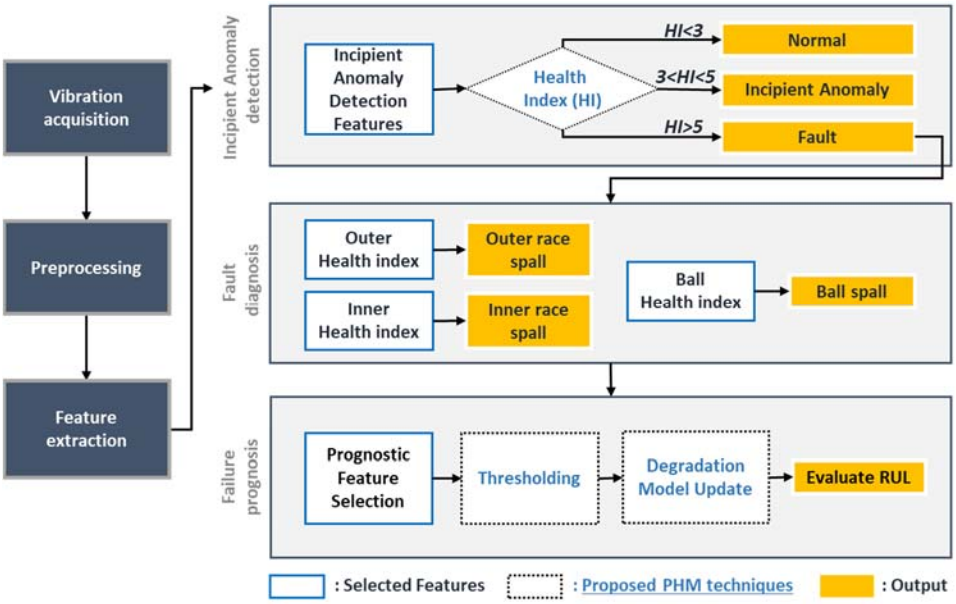


Figure 2-1 PHM flowchart for health monitoring of bearings

2.2. Preprocessing and Feature Extraction

Features are extracted using the rearrangement method defined by the Bearing PHM team of Seoul National University. The bandpass filtering method, Hilbert transform, and envelope processing are applied to obtain fault–related frequency domain features. Ball Pass Frequency of Outer race(BPFO), Ball Pass Frequency of Inner race(BPFI), and Fundamental Train Frequency(FTF) frequencies are calculated in a certain range of frequency band (1000~4000 Hz) to get high frequency range features. Then, as shown in the bearing health monitoring flowchart, features are selected for diagnosis and prognosis.

Each frequency domain feature expresses the health state of one part of the bearing: inner race, outer race, and ball. BPFO, BPFI, and FTF frequency features represent the outer race, inner race, and ball, respectively. For each part of the bearing, energy features are calculated using the power series of the characteristic's frequencies. Due to deviations from the exact calculated values of the characteristic frequencies and real data Fast Fourier Transform (FFT) results, a certain range of error term is considered.

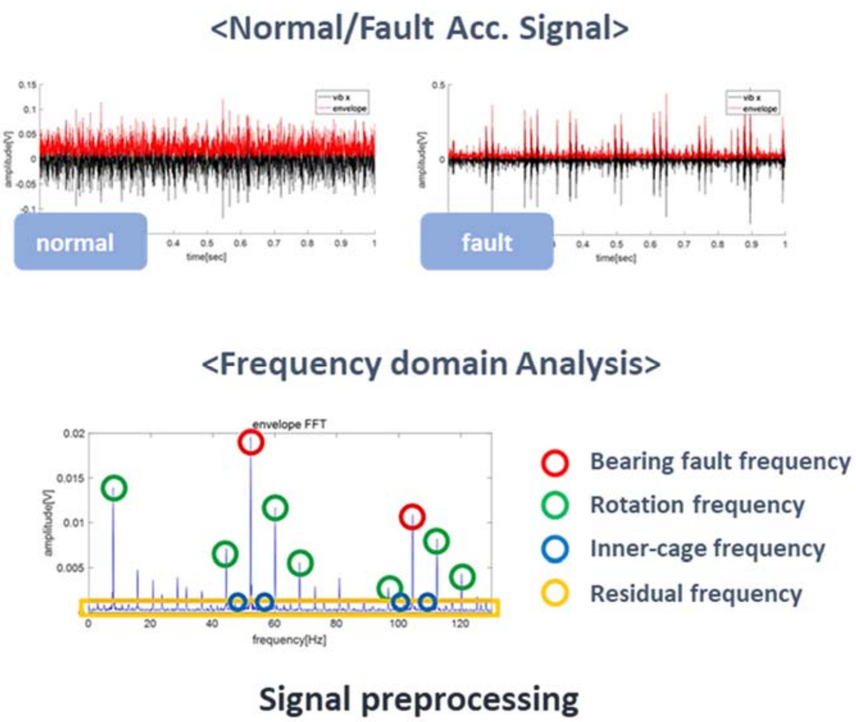


Figure 2-2 Feature extraction from a raw acceleration signal to the frequency domain

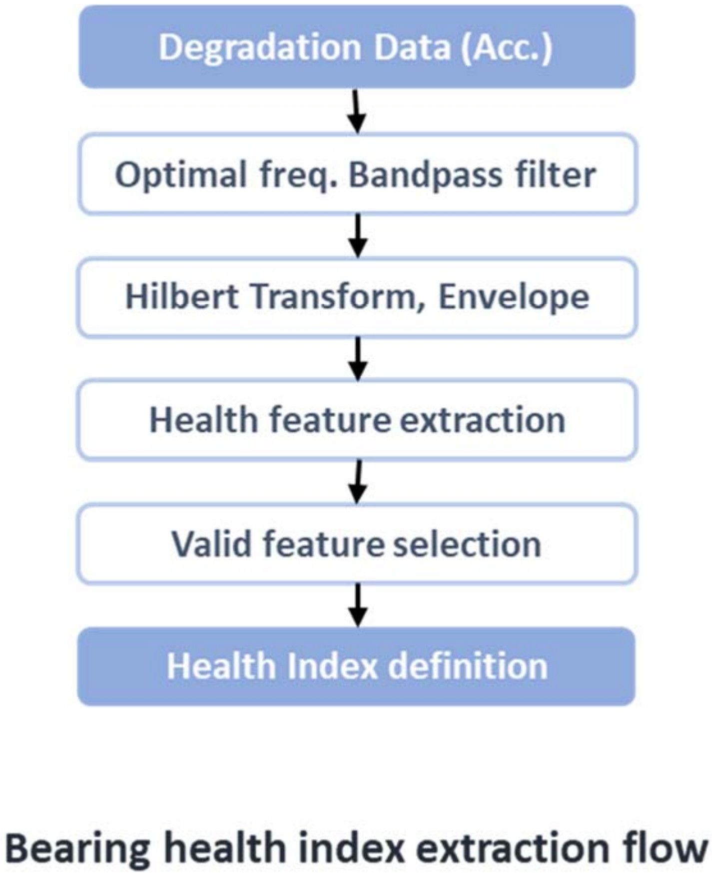


Figure 2-3 Flowchart of the process from preprocessing to defining the health index

2.3. Bound Decision for Incipient Anomaly and Fault

Diagnostic and prognostic results for PHM in bearings depends on the range of the dataset; this range has varied in previous research. Thus, in this research, we used data from the normal state to the time of the emergence of actual spall initiation. Spall initiation can be determined by analyzing the root mean square (RMS) value.

In the research described in this thesis, incipient anomaly detection, diagnosis, and prognosis procedures are conducted sequentially. First, incipient anomaly, fault, and failure are defined. Incipient anomaly means finding the signal of a fault. Fault diagnosis means classifying the fault source. Failure prognosis is the procedure of predicting Remaining Useful Life (RUL). Definition of an incipient anomaly, fault, and failure are based on the Mahalanobis Distance (MD), which calculates the distance of datapoints from the normal state. Datapoints that are far in MD scale from normal-state datapoints can reasonably be determined to be abnormal. MD is calculated by $\mathrm{D_M}(\vec{x}) = \sqrt{(\vec{x}-\vec{\mu})^T S^{-1}(\vec{x}-\vec{\mu})}$, which indicates the distance between the current datapoint and the distribution of normal data collected from the earlier stage of the experiment. MD calculates the dissimilarity between random variables x and y. For an incipient anomaly, a fault is defined as a Mahalanobis Distance value of between 3 and 5 sigma. These values represent a possibility of deviation of 99.73% and 99.9999%, respectively. These values are also verified on the pre-test results.

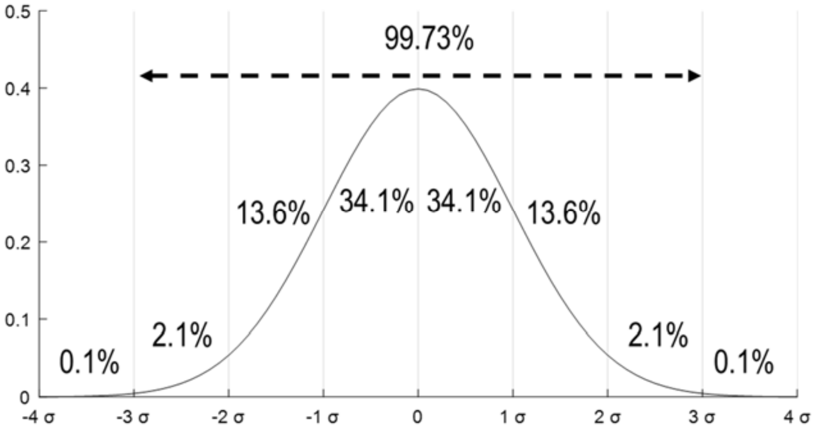


Figure 2-4 3-sigma rule

When an incipient anomaly is detected, fault diagnosis is initiated to determine which part of the bearing is causing the faulty signals. This procedure is defined as fault diagnosis. Consequently, when MD increases and reaches above the value of 5, the algorithm starts to predict RUL using the selected prognostic feature. The issue of the failure threshold will be covered in a subsequent section, section 2.6.3.

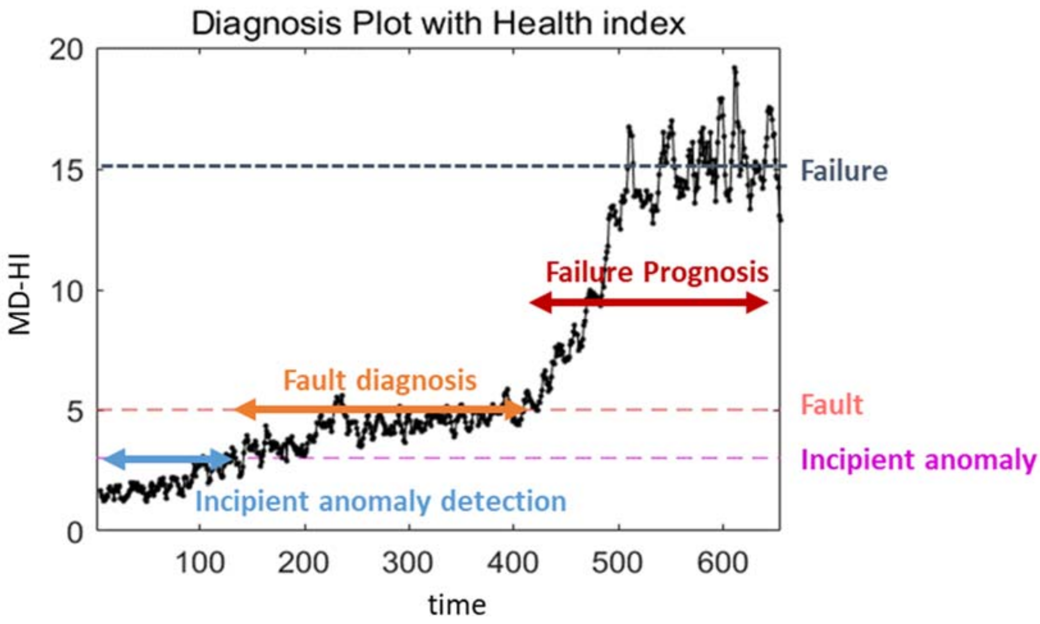


Figure 2-5 Bound definition of incipient anomaly and fault based on MD

2.4. Incipient Anomaly Detection

An incipient anomaly is mainly caused by a sub−surface crack or spall initiation.[4] It is the state before any spall propagation is generated and before extension of spall and failure emerge. Although an incipient anomaly is a less severe state than fault or failure, it is obviously an ‘abnormal’ state. As such, this indicates that signals from the application during an incipient anomaly should be clearly different from normal state signals.

As defined above, an incipient fault can be detected when MD is equal to 3. An accelerometer measures acceleration data; this includes noise from external sources that raises outliers up. To alleviate the effect of outliers that emerge through this noise, a moving average of 11 points can be calculated. The moving average includes the previous 5 points, the current point, and the posterior 5 points. The moving average is calculated after the posterior 5 points are acquired.

When a bearing fault is detected early, it means that the current state has deviated significantly from the normal state that was gathered in the earlier part of the experiment. At this stage, detailed information about which fault has emerged and why is undetermined. Instead, by detecting the fault earlier, it is possible to prepare a repair plan for the device.

Using a bearing dataset from Schaeffler Changwon Research Center, incipient anomaly detection was conducted, as shown in

Figure 2–6. Specific data descriptions will be introduced in Section 3.1 because the description of how the dataset is primarily processed is outlined in that section. Here, the HI plot shows that the incipient anomaly is detected far before failure (30 days). One time unit means 100 minutes on the x axis. As suggested above, MD with a moving average is applied; this evidently points out the instant of energy fluctuation.

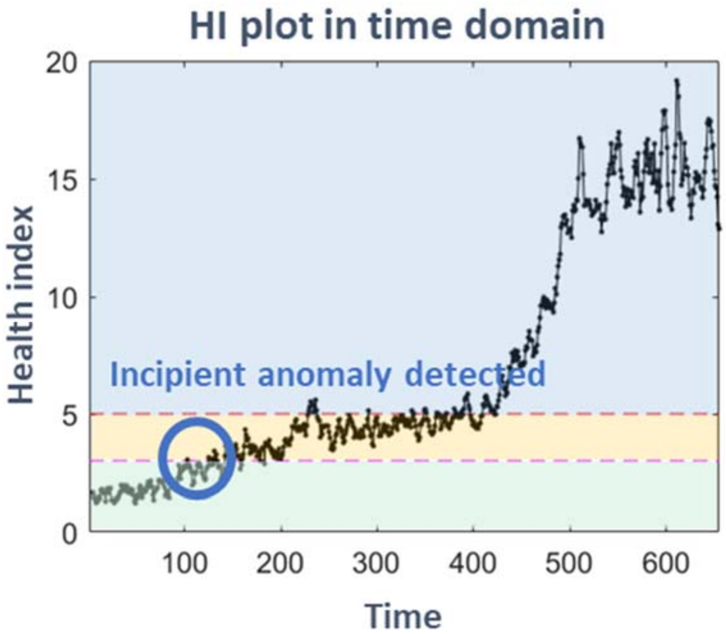


Figure 2-6 Results of incipient anomaly detection

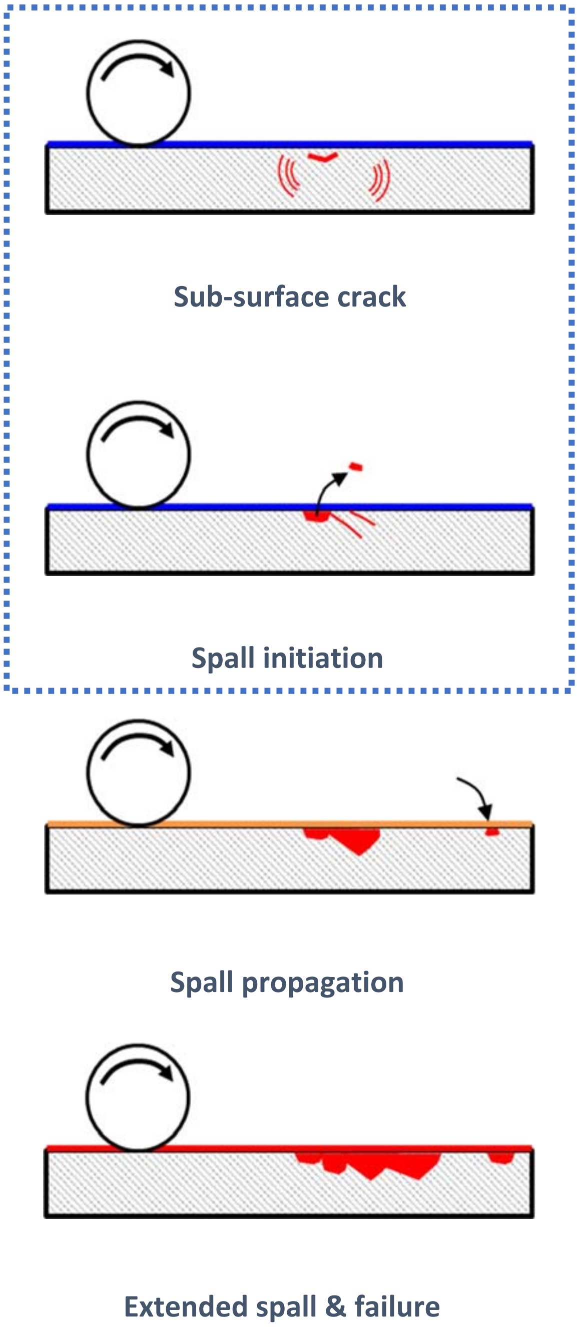


Figure 2-7 Stages of rolling contact fatigue and degradation

2.5. Fault Diagnosis

This section describes the process of bearing fault diagnosis. Diagnosis is used to determine which component is in an abnormal state, among the inner race, outer race, and ball components. Fault diagnosis also enables determination of any sudden failure that occurs due to a slip between the axis and the bearing. However, this is not meaningful, because sudden failure is not predictable. Slip failure is an accident. It is impossible to plan for repair or exchange that is needed based on an accident in an industrial field.

The research described in this thesis focuses on three main parts of a bearing: the outer race, the inner race, and the ball of the bearing. They are the primary parts of a bearing, parts that are found in almost every bearing. The cage is excluded for two reasons. First, the health of the cage is usually dependent on the ball. When a cage is faulty, it mostly occurs with and is caused by a faulty ball. Health features of a cage are extracted from a characteristic frequency that is shared with the ball features. Second, cage faults are an unusual situation. A cage is typically only in a faulty state when slip or axis distortion occurs.

Using the same dataset as in Section 2.4, the data is processed in an algorithmic flow. The diagnostic HI plot shows the health indices for inner race, outer race, and ball. The diagnostic result of each part shows bar-shaped results that indicate how healthy (or faulty) each index indicates. The inner race index shows the most dramatic increase in both of the plots; this is the same result as was observed with the disassembly of the bearing after the acceleration test.

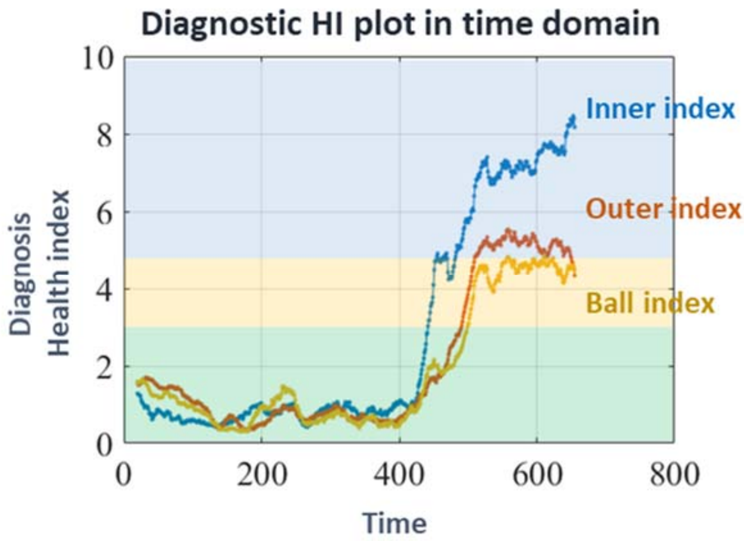


Figure 2-8 Fault diagnosis plot for inner race, outer race, and ball

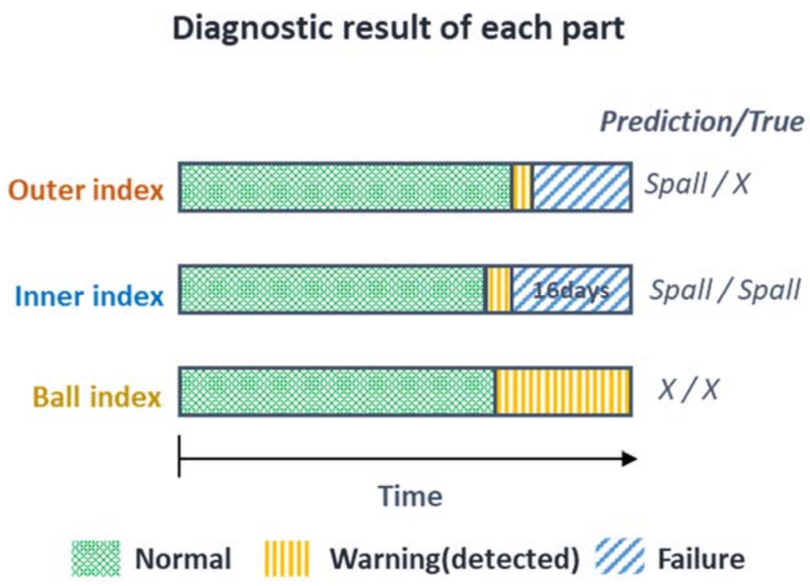


Figure 2-9 Results of Fault diagnosis

2.6. Failure Prognosis

Bearing prognosis has been researched using various methods. In the research described in this thesis, bearing prognosis study mainly focused on the trend projection model with selected prognostic features. This section focuses on two suggestions: trend projection using an asymptotic model as the Sigmoid model, and a threshold decision methodology based on the ratio of the diagnosed point and the failure point.

2.6.1 Background

Many previous researchers[(5), (6)] have studied conventional methods to predict Remaining Useful Life(RUL). There exist pros and cons of each data-driven prognostic model.

First, the Particle Filtering (PF) method does not require large amounts of historical failure data and is able to generate probabilistic results. However, it requires significant resources for higher dimensions and needs to define an analytic model. Another conventional method, exponential projection using an Artificial Neural Network (ANN), enables estimation of the actual failure time, instead of providing a condition index at future time steps. ANN has a longer prediction horizon; however, it assumes that all bearing degradation follows an exponential pattern and requires training on ANN for each historical dataset. Regression analysis and fuzzy logic do not provide time to failure (TTF) or probability of failure, although they emphasize the most recent condition information.

Based on the disadvantages described above, in this research, the trend projection model was selected to predict the RUL of bearings. Trend projection has the advantage of easy calculation, which is highly desirable for real−time RUL calculation. Additionally, trend projection is a better approach for unsupervised RUL prediction, since it does not require a large amount of training data.

2.6.2 Trend Projection

Conventional research has primarily focused on the use of exponential or linear models to predict life, primarily based on the Root Mean Square (RMS) value. However, some previous researchers have shown that certain features, such as entropy features or spectral flatness, do not follow an exponential trend[(6), (8)]. In this research, an asymptotic model is suggested. Unlike an exponential model, the asymptotic model has a static range that converges to a certain asymptotic value. The model suggested in this paper is a sigmoid model, as defined below.

$$(Feature) = \boldsymbol{a}\left(\frac{\mathbf{1}}{\left(\boldsymbol{b}+\boldsymbol{c}*\boldsymbol{exp}(-\boldsymbol{dt})\right)}-\frac{\mathbf{1}}{\boldsymbol{b}+\boldsymbol{c}}\right)$$

This model converges to an asymptotic line, which means it has an obvious static range. Consequently, when a feature’s tendency decreases, that component can be regarded as faulty. This conclusion is reasonable because the projection does not fit the tendency before the actual failure. There are other asymptotic or semi-asymptotic models, such as the inverse exponential model and the bi-exponential model. The following section outlines the advantage of the sigmoid model over these other models. In trend projection, the nonlinear least square is calculated to find the curve using the bisquare weights method.

2.6.3 Threshold Decision

This research suggests a ratio-based thresholding methodology. First, a dataset from a bearing of interest is needed to derive the relevant ratio. The ratio of a to b is calculated, where a is an average of the last 100 points immediately before failure and b is a diagnosed point health feature value from the fault diagnosis section. Afterwards, b' can be found; b' is a diagnostic result of the test dataset. Next, the value $a' = b' \times \frac{a}{b}$ is found, which is decided as the failure threshold. If there is no intersection point between the fitted curve and the threshold, the RUL value remains as the NaN at the point. The procedure is depicted in Figure 2-10.

The curve fit is compared between the suggested sigmoid model, the inverse exponential model, and the bi-exponential model. The Root Mean Squared Error (RMSE) is calculated to indicate the performance of each model. As indicated in the table and graphs, the suggested sigmoid model shows the least error among the three models. The linear model was ignored because it does not make sense with the suggestions in this research. In other words, linear model is unable to reflect feature trend of prognostic features, as well as the fact that a bearing does not degrade infinitely. In the graphs, the outer feature and the inner feature trends are compared with the true RUL line. If the feature RUL prediction curve shows a tendency of −1 gradient, it indicates that the RUL is predicted with great accuracy. In the graphs, the outer feature RUL curve seems to show better performance of the −1 gradient. This is because the training data used for the decision of the ratio threshold (TBS#2−1) has an outer race fault. Thus, the calculated threshold is highly dependent on the bearing's outer race characteristic frequency. Although outer race features are dominating, the inner race also follows the trend of failure, which makes it reasonable to predict the RUL by applying outer race fault data (TBS #2−1) to inner race fault data (TBS#2−2).

Table 2-1 Errors for each trend projection model

Model	Curve Equation	RMSE
Sigmoid	$a\left(\frac{1}{\left(b+c\cdot exp(-dt)\right)}-\frac{1}{b+c}\right)$	56.06
Inv-exp	$a-b\cdot\exp(-ct)$	57.98
Bi-exp	$aexp(bt)+cexp(dt)$	118.07

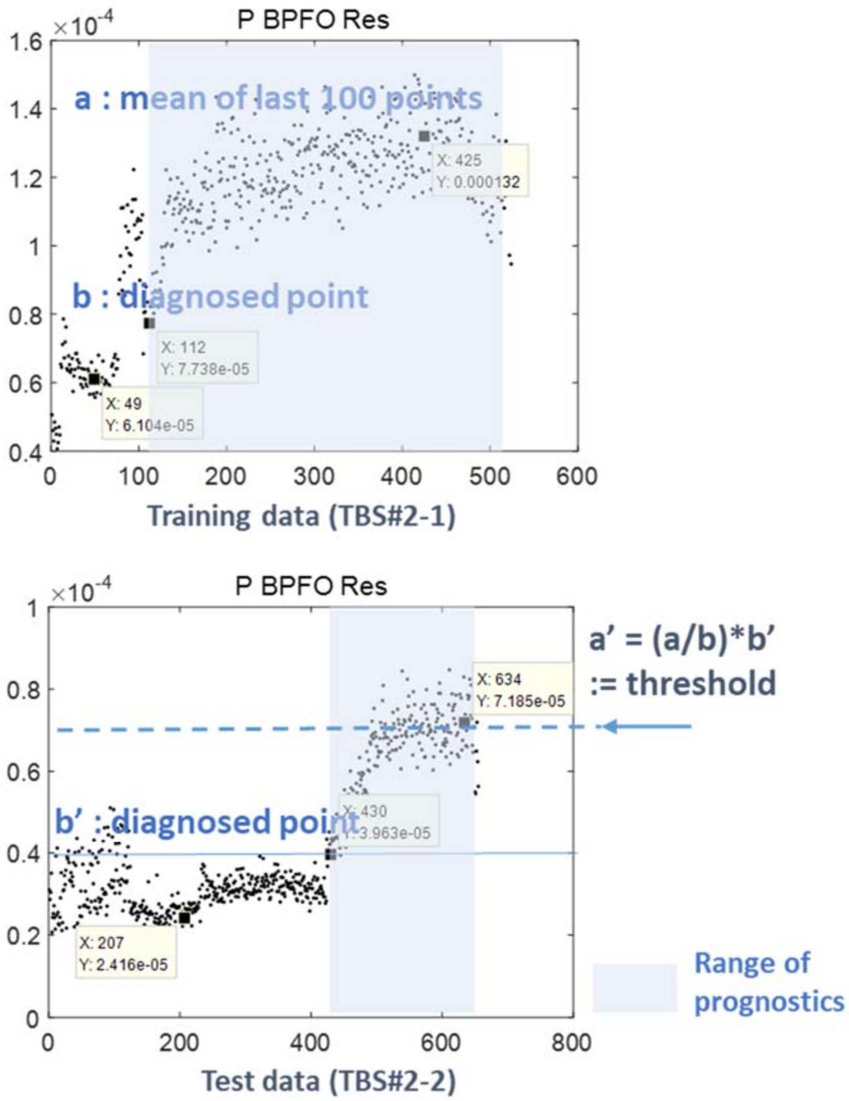


Figure 2-10 Ratio-based threshold decision method

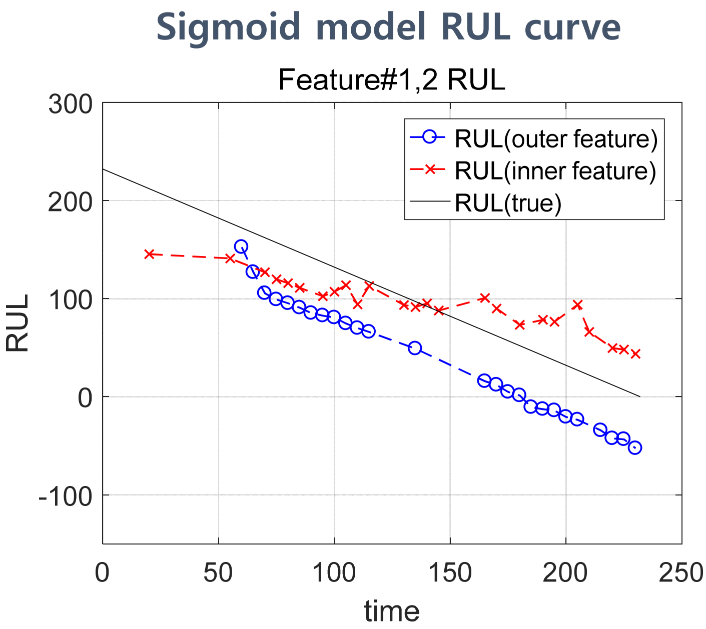


Figure 2-11 Sigmoid model RUL prediction result

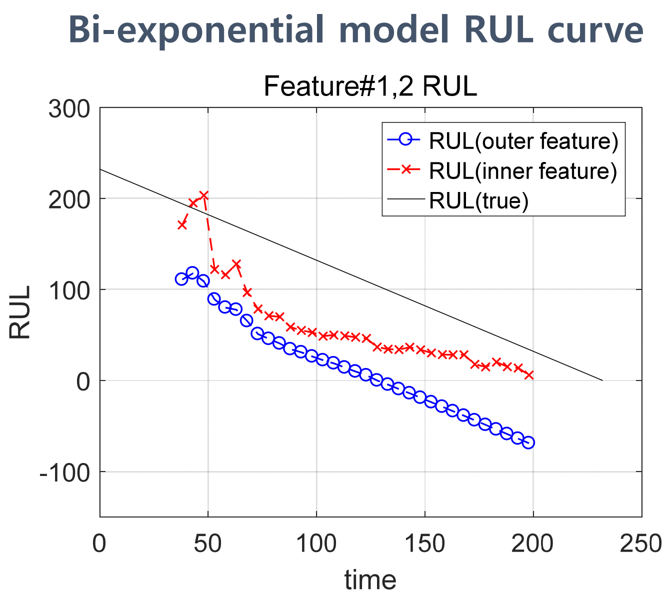


Figure 2-12 Bi-exponential model RUL prediction result

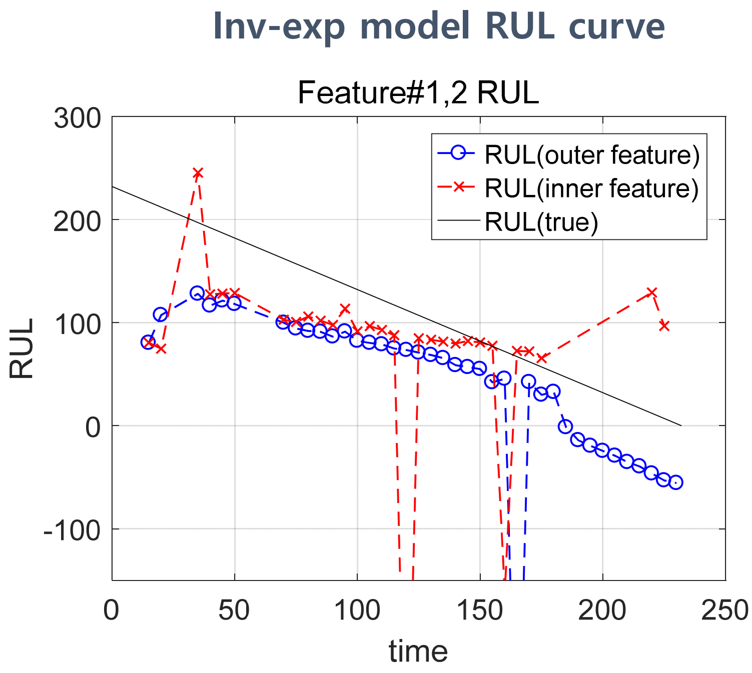


Figure 2-13 Inverse exponential model RUL prediction result

Chapter 3. Case Study 1: Schaeffler Bearing Data

3.1. Data Description

Life endurance test data from Schaeffler Korea was collected from a deep-groove ball bearing. The specifications of the ball bearing are listed in the table. Additionally, four datasets were collected from the testbed; three pre-tests and one validation test. Among pre-tests, one stopped due to a sudden problem that was caused by slip between the axis and the inner race. Another one had a power failure (blackout) problem. Therefore, in this research one pre-test and one validation test were applied to test the suggested diagnostic and prognostic techniques.

The sampling number was 10240 Hz and the interval between samplings was 60 seconds. For faster calculation, data points for every 100 points were selected, which indicates that the interval between data points is 100 minutes. In other words, 1 time unit means 100 minutes.

Table 3-1 Schaeffler bearing test specification

Item	Specification
Bearing designation	Deep groove 6204
Equivalent load (%)	45% of dynamic load rating
Rotating speed	3,982 RPM
Lubrication	Oil

Table 3-2 Schaeffler bearing experiment description

Category	Pre-test	Validation test
	TBS #2-1	TBS #2-2
Fault mode	Outer spall	Inner spall
Total lifetime	66 days	46 days
Early detection	-30 days	-16 days
Etc.	Sudden fault	Gradual fault

Figure 3-1 Life endurance tester and bearing spalls

3.2. Prognostic Result

A full−time RUL curve is generated in the time domain, which means it only uses data collected before the moment. It shows the RUL during the whole life of the bearing. Before the diagnostic result is achieved, the RUL is calculated with fating fatigue life L_{10}, based on the International Standard Organization's, ISO 281. According to ISO 281, $L_{10} = \frac{10^6}{60n}\left(\frac{C}{P}\right)^3$, showing the fating fatigue of life to be 1240.3 hours, which means the 744.1639 time unit.

The feature trend was projected using the sigmoid model. Since the sigmoid model is a revised version of the exponential model, sufficient data is needed to fit the curve equation. Thus, a curve fitting preparation range is required. The algorithm predicts the RUL based on the fating fatigue life in this range. To specify the region, the RUL curve is divided into two regions: the RUL prediction curve without PHM and the RUL prediction curve calculated based on PHM techniques.

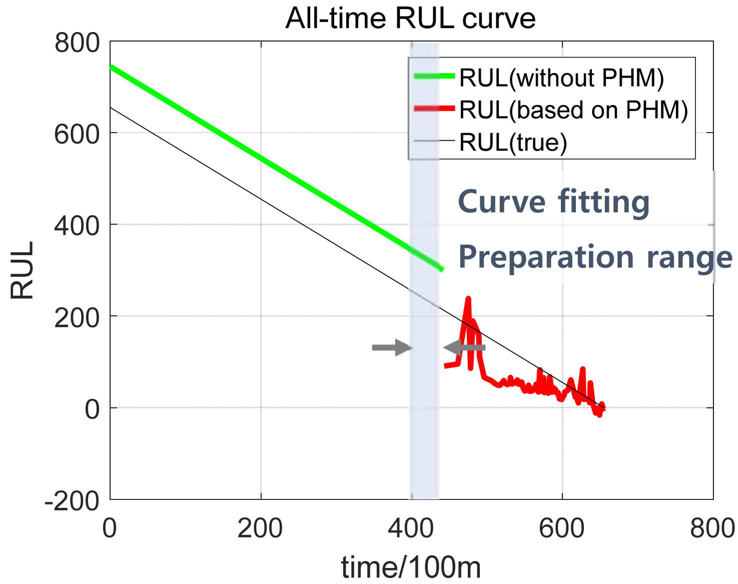


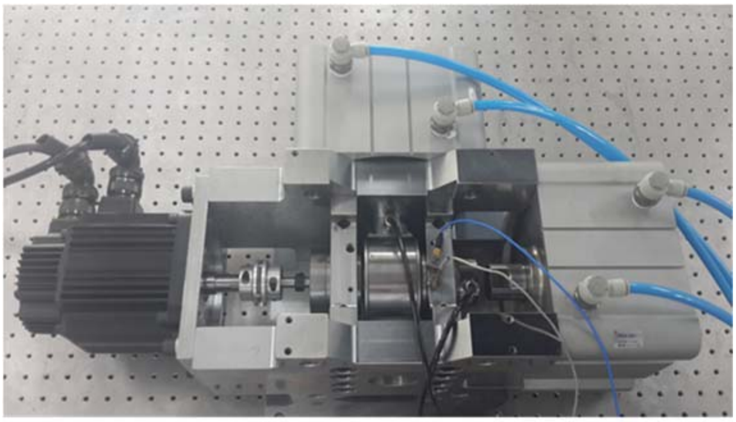
Figure 3-2 Full-time RUL curve with fating fatigue life L_{10}

Chapter 4. Case Study 2: SNU Bearing Testbed Data

4.1. Data Description

To verify the RUL prediction method proposed in this research, the suggested method was applied to bearing data gathered from the testbed of Seoul National University's System Reliability and Health Monitoring laboratory. This Seoul National University Bearing Data (SNU data) is based on experiments with NSK angular contact ball bearing 7202A with a rotating speed of 1457 RPM. The experiment proceeded through three stages, with input axial loads of 0.1, 0.35, 0.1 MPa, respectively. Meanwhile, an input radial load of 0.1 MPa is applied.

The number of samples for the experiment was 100,000, and the sampling rate was 10,000 Hz; this indicates a sampling time of 10 seconds. The interval between samplings is 15 seconds. For faster calculation, data from every 20th point is selected; this indicates an interval between data points of 300 seconds.



SNU testbed
(SHRM Lab.)

Figure 4-1 SNU testbed for small bearings

Table 4-1 Schaeffler bearing test specification

Item	Specification
Data name	Normal #12, 13, 14, 17
Bearing designation	Angular Contact 7202A
3-stage axial load	0.1, 0.35, 0.1 MPa
Radial load	0.1 MPa
Rotating speed	1457 RPM
Lubrication	Rolling bearing grease
Sampling rate/number	10,000Hz / 100,000
Interval	15 sec(sampling) × 20 (points)

4.2. Prognostic Result

The dataset is comprised of three stages; however, only the third stage dataset was utilized because previous two stages represent the normal stage and the stage of degrading from normal to abnormal, respectively. In this case, a RUL curve with a bandpass-filtered RMS feature was derived to check the overall prognostic ability. This approach is meaningful, under the assumption of an undiagnosed situation. Two predictions were set: one is learning Normal #12 data and test Normal #17 data(Figure 4-3, 4-4, 4-5, 4-6); the other is learning Normal #13 data and test Normal #14 data(Figure 4-7, 4-8, 4-9, 4-10).

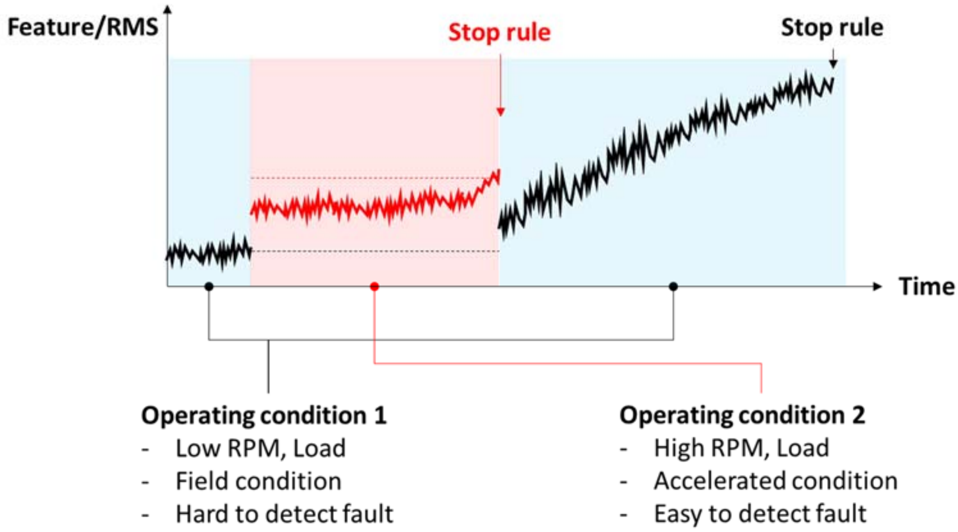


Figure 4-2 SNU bearing test sequence

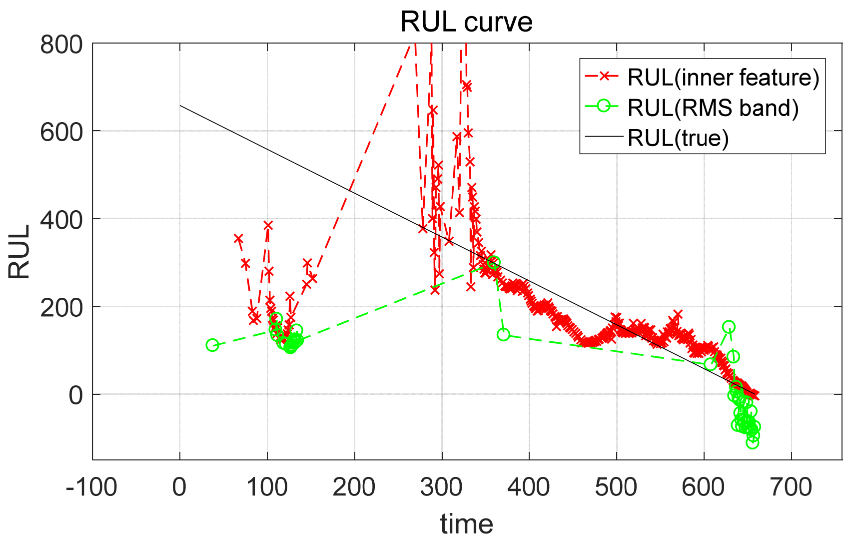


Figure 4-3 RUL prediction result with inner race feature and bandpassed RMS feature

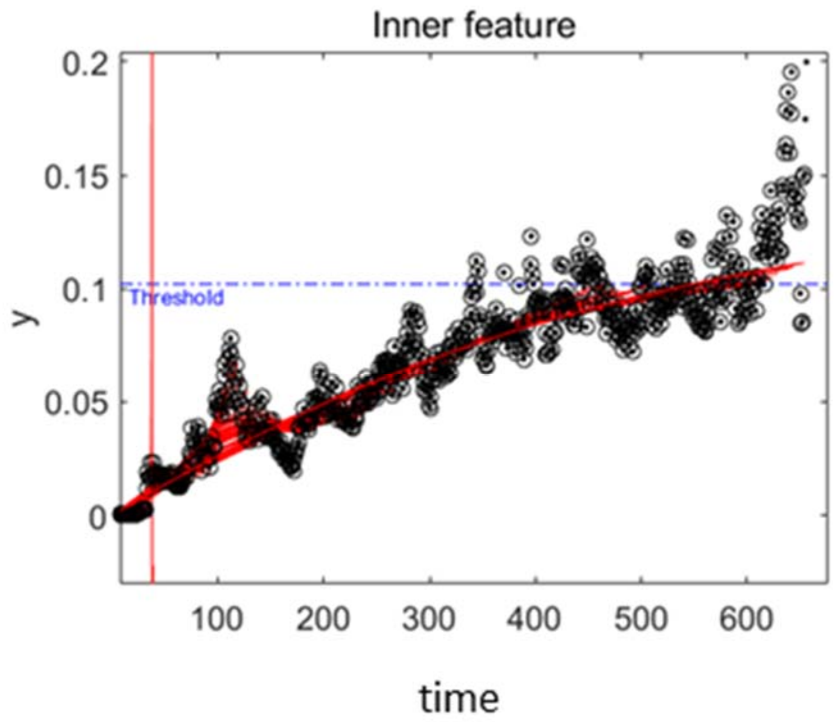


Figure 4-4 Inner race feature trend and projected curves of Normal #17 with threshold from Normal #12 data

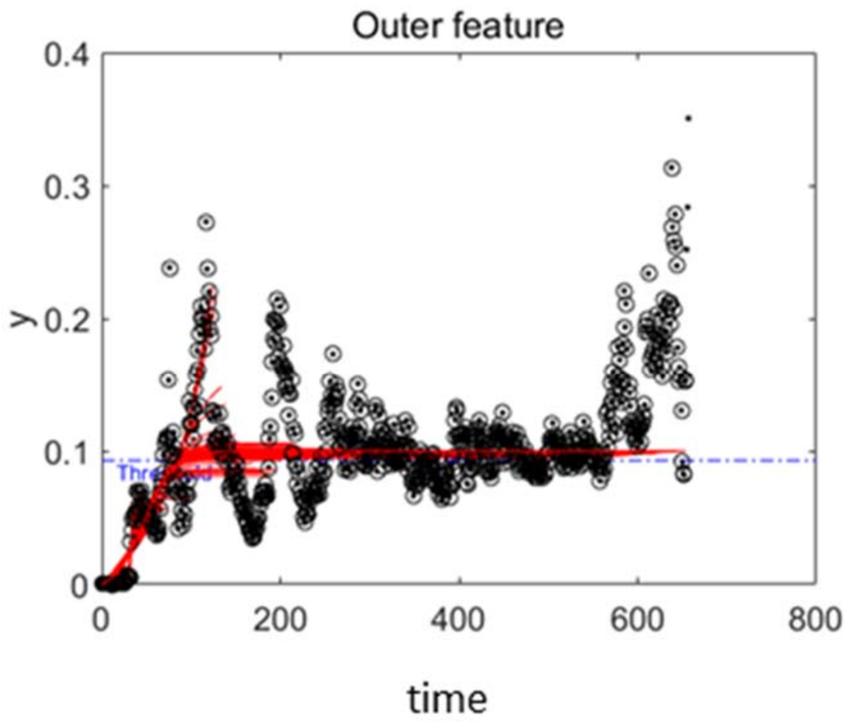


Figure 4-5 Outer race feature trend and projected curves of Normal #17 with threshold from Normal #12 data

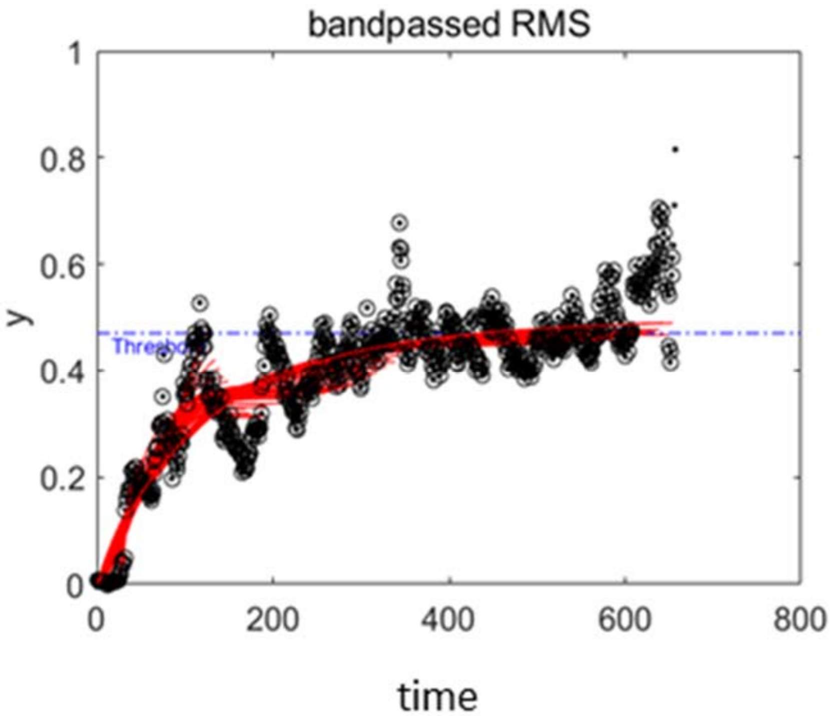


Figure 4-6 Bandpass-filtered RMS feature trend and projected curves of Normal #17 with threshold from Normal #12 data

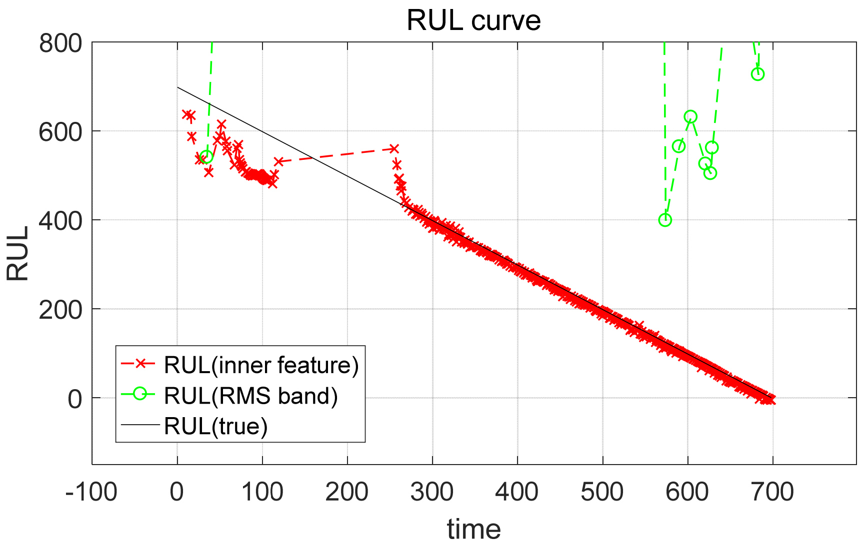


Figure 4-7 RUL prediction result with inner race feature and bandpassed RMS feature (Normal #13, 14)

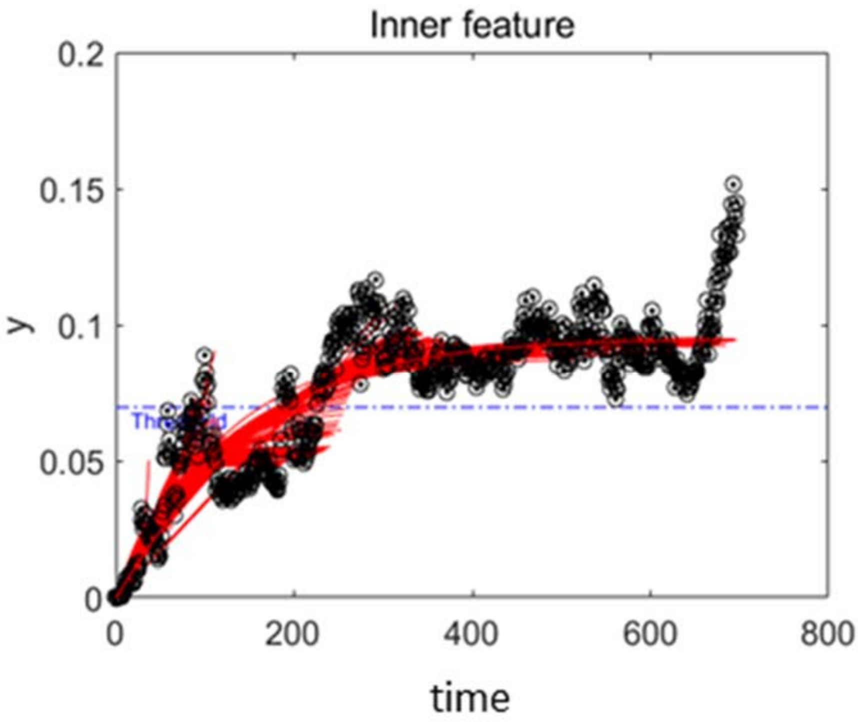


Figure 4-8 Inner race feature trend and projected curves of Normal #14 with threshold from Normal #13 data

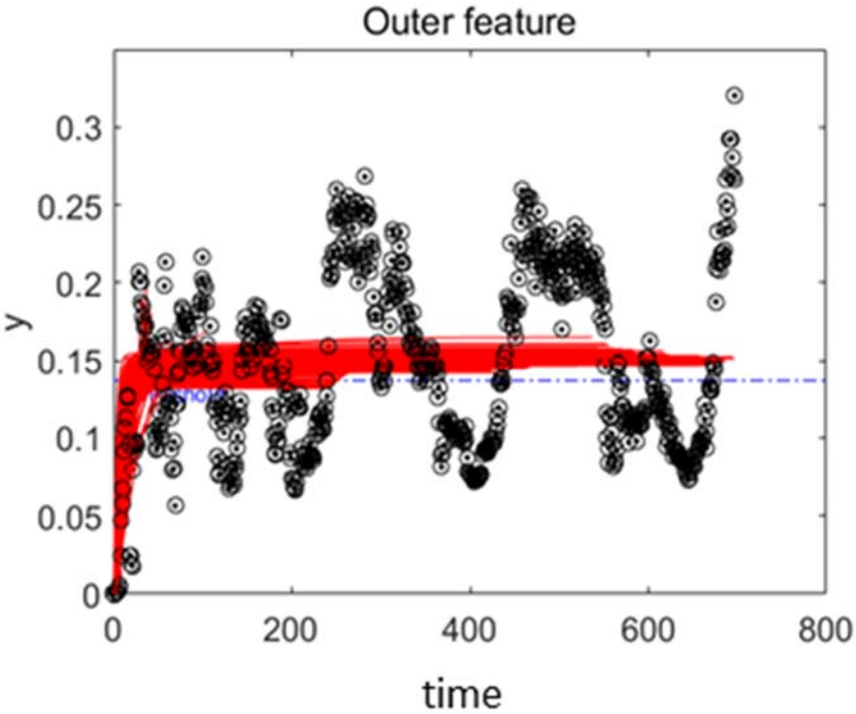


Figure 4-9 Outer race feature trend and projected curves of Normal #14 with threshold from Normal #13 data

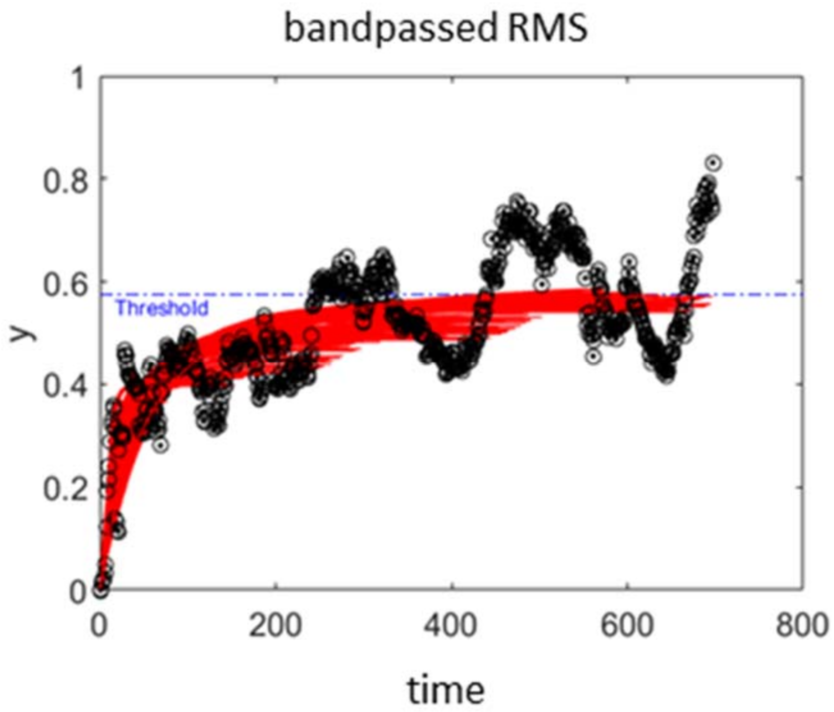


Figure 4-10 Bandpass-filtered RMS feature trend and projected curves of Normal #14 with threshold from Normal #13 data

Chapter 5. Conclusion

5.1. Conclusions and Contributions

Incipient anomaly detection, fault detection, and failure prognosis are studied in this research for the overall life of a bearing. To enable real−time monitoring and obtain relevant results, decisions about incipient fault, fault, and failure were decided using Mahalanobis Distance (MD). Moreover, a threshold decision methodology was suggested using the ratio of normal and abnormal signals. As a result, the prediction of overall bearing life was calculated for every data point.

As described in research objectives, industrial fields require full−time and real−time diagnosis and prognosis. However, prior research has focused on the comparison between normal and failure data using whole−life data; these prior approaches are not suitable for real−time diagnosis and prognosis. This paper solves the problem of separation between academic researchers and industrial fields and finally generates a full−time RUL prediction curve using PHM techniques and the fating fatigue life $\mathbf{L_{10}}$ value from the International Standard Organization.

In addition, the research outlined in this thesis suggests an asymptotic model for trend projection of the feature trend as a substitute for the currently popular exponential model. The disadvantage of the exponential model is that features extracted from the frequency domain do not follow an exponential tendency. Although the trend reasonably ascends, the exponential model does not appropriately reflect the static tendency of a bearing's characteristic frequency features.

The contributions of this paper are mainly concentrated in two areas. One contribution is the suggested threshold decision methodology. The other is the asymptotic line, which is suggested for trend projection of features for prognosis to generate an RUL prediction curve. This approach is suggested to replace the conventional exponential or linear model.

5.2. Future Work

Future work should explore the Extended Kalman Filter or Particle Filter method with fitted trend projection curve as an analytic model for prognosis features. In future research, a broad variation of prognostic features near failure will also be considered by relating the aspect with Cook's distance. Likewise, future work should be pursued to further develop a fitted curve convergence value threshold method to suggest a more general threshold decision methodology.

Finally, in future work, additional experiments will be conducted with the SNU bearing testbed in a full-time, one stage condition. Here, another threshold decision method will be developed based on the convergence value of the asymptotic model.

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국문 초록

베어링은 회전체 기계 시스템에서 핵심적인 부품이다. 따라서 베어링 결함의 선 감지와 더불어 건전성 상태의 예측은 베어링 전체 수명을 통틀어 중요한 요소이다. 회전체 요소 베어링의 고장은 회전 기계 시스템 뿐만 아니라 많은 기계 시스템 전체의 고장을 일으키는 매우 주요한 요인이다. 이러한 고장은 경제적 및 안전의 측면에서 위험하다.

특히 산업 현장에서는 업무 효율을 극대화하기 위하여 기계의 미작동 시간(downtime)을 최소화 하는 것이 매우 중요하다. 이는 PHM 기술(Prognostics and Health Management) 따라서 현장에서는 회전체가 작동하는 동안에 실시간으로 기계의 상태를 모니터링하고 앞으로의 수명을 예측하는 것이 더 큰 중요성을 갖게 된다. 게다가 건전성 상태는 반드시 미래의 데이터 없이 현 상태까지 축적된 데이터만 가지고 산출되어야 한다.

따라서, 베어링을 포함하는 기계 시스템의 모니터링 시스템은 데이터 기반의 실시간 알고리즘을 지향해야 한다. 이를 반영한 본 연구의 목적은 다음과 같다. 첫째, 전주기적 건전성 모니터링, 둘째, 일반적 볼 베어링에서의 고장 기준 정의 방식, 셋째, 비감독 상태에서의 실시간 수명 예측이다.

베어링의 건전성 상태를 분류하여 고장 선감지, 결함 및 고장을 정의하기 위하여 본 연구에서는 Mahalanobis Distance를 적용하였다. 또한 수명 예측의 경우, 많은 이전의 연구들이 가지고 있는 문제점들을 파악하고 연구 목표에 맞는 알고리즘과 모델을 제시하였다. 예를 들어, Particle Filter의 경우 미리 정의된 analytic model이 존재해야 한다는

치명적 단점을 가지고 있다. 이는 실제 현장과의 연결성에서 부족한 방식이다. 이러한 문제를 해결하기 위하여, 점근성(asymptotic)의 모델을 제시하였으며 더불어 고장 기준 정의 방식을 제시하였다. 이를 실데이터에 적용하여 전주기 실시간 수명 예측을 수행하였다.

본 연구를 설명하기 위하여, 논문은 다음과 같이 작성되었다. 연구의 동기 및 목표가 먼저 설명된 뒤 전체 PHM 순서도를 포함하는 제시된 방법론을 설명한다. 다음으로 이 방법론을 토대로 베어링의 수명예측 방식을 실데이터에 적용한 결과를 설명하였다. 마지막으로 본 연구에 이어질 연구에 대해 설명되어 있다.

논문의 연구 내용은 크게 두 가지의 의미를 갖는다. 첫번째로 논문에서 제안하고 있는 베어링 고장 기준 정의와 분류 방식은 비감독 상태에서의 고장 기준을 제시하고 있으며 이를 서울대학교 테스트베드에서 수집된 데이터를 가지고 검증하였다. 둘째로 일반적인 지수 모델(exponential model)과 달리 점근성 모델을 제시함으로써 고장의 기준 및 회귀 모델에 대한 패러다임을 제시하였다.

주요어: 고장 선감지, 진단 및 예측, 고장 기준 정의, 수렴성 모델

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