DEVELOPMENT OF EFFECTIVE APPROACHES FOR PROGNOSTICS OF INDUSTRIAL SYSTEMS

M.Tech. Thesis

By

PRADEEP KUNDU

DISCIPLINE OF MECHANICAL ENGINEERING

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "**DEVELOPMENT OF EFFECTIVE APPROACHES FOR PROGNOSTICS OF INDUSTRIAL SYSTEMS"** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** in **MECHANICAL ENGINEERING** with specialization in **PRODUCTION and INDUSTRIAL ENGINEERING** and submitted in the **DISCIPLINE OF MECHANICAL ENGINEERING** at **INDIAN INSTITUTE OF TECHNOOGY INDORE,** is an authentic record of my own work carried out during the time period from May 2014 to June 2015 under the supervision of **Dr. Bhupesh Kumar Lad**, Assistant Professor of Mechanical Engineering, IIT Indore and **Dr. I. A. Palani**, Assistant Professor of Mechanical Engineering, IIT Indore

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Signature of the student
(PRADEEP KUNDU)

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

Signature of the Supervisor
(Dr. Bhupesh Kumar Lad)

Signature of the Supervisor
(Dr. I. A. Palani)

PRADEEP KUNDU has successfully given his M.Tech. Oral Examination held on **24^{h} June 2015**.

Signature of Supervisor of M.Tech. Thesis
Date:

Convener, DPGC
Date:

Signature of PSPC Member
Date:

Signature of PSPC Member
Date:

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Pradeep Kundu

M.Tech. (Production & Industrial Engineering)

Discipline of Mechanical Engineering

IIT Indore

Dedicated to My Mother Santra Devi, My Brother Sandeep Kundu, My Nephew Parikshit Malik, My Niece Vibhooti Malik and My Late Brother-In-Law Jagat Singh Malik

Abstract

Machine availability and reliability are two of the most essential concerns for an industry. Increased availability is required by industries to stay competitive in today's global market competition. To achieve increased availability, a good maintenance strategy is required that reduces the losses due to unplanned shutdowns and keep the preventive maintenance at minimum. Among all available maintenance strategies; Condition Based Maintenance (CBM) is the most effective strategy to achieve these goals. Effectiveness of Condition Based Maintenance (CBM) strategy depends on accuracy in prediction of Remaining Useful Life (RUL). Prognostic is the technology used to predict the RUL based on monitored parameters. Prognostic approaches can be broadly classified into two categories: physics based prognostic approaches and data driven prognostic approaches. Current research focus is only on data driven prognostic approaches.

Presence of noise in the data reduces the accuracy of RUL prediction with data driven prognostic approaches. Presence of unknown initial wear and presence of multiple failure behaviour in data may act as sources of data noise. If these sources of data noise are not handled appropriately, then it may give poor prediction of the RUL. Another major issue found with the data driven prognostics approaches is the larger variation present in the historically observed Condition Monitored (CM) data obtained from the fleet. This leads to poor model performance. Updating the model parameters based on new information for a unit can help in reducing the variation and improve accuracy of prediction. Third issue is handling of multidimensional features (i.e. RMS, kurtosis, skewness, mean, median etc.). Features are generally extracted from the raw data to represent the degradation of the component. Number of features can be extracted from the raw data to represent the degradation of the component. If all these features have been taken as input to the model, then it will over fit the model. Over fitting is the situation where model performs well during training, but shows significantly poor performance during testing.

The objective of this thesis is to increase the prediction accuracy of prognostic model while considering the presence of the noise, effect of multidimensional condition monitoring features and continuously updating the model parameters. Different industrial systems have been considered for this study such as aircraft engine, gas turbine, and roller ball bearings. Also, life prediction for a smart material components (SMA springs) is also demonstrated.

Remaining Useful Life Prediction of an Aircraft Engine under Unknown Initial Wear is presented. Two Artificial Neural Network (ANN) models were developed. First model is developed by neglecting the effect of the presence of noise in the data (i.e. sample with abnormal initial wear); while the second model is developed after removing the noise associated with the data.

Another model is developed by considering another type of noise in the data. Inner race failure, outer race failure and cage failure are the major failure modes associated with ball bearing. Presence of multiple failure modes and their interaction may cause noise in the data set. Clustering and Change Point Detection Algorithm (CPDA) is used for identification of presence of multiple failure behaviour due to multiple failure modes in the data. Combined output of Clustering and CPDA is used for developing RUL prediction model. Separate models for single failure behaviour and multiple failure behaviour are constructed. General Log- Linear Weibull (GLL- Weibull) model is used for the same. Effects of multidimensional features are also considered here.

A PCA-ANN based algorithm is used to predict the RUL of ball bearings while considering the effect of the multidimensional features. Instead of giving all features directly to the model, the best three principal component values obtained from PCA are used as input parameters to the model.

A risk based maintenance strategy to optimize forecast of a gas turbine failures is also presented. The algorithm does not completely rely on historically observed condition monitored data but also updates the model parameters as and when new information is available. Bayesian approach is used to update the model parameters.

Second part of thesis focuses on reliability estimation of Shape Memory Alloy (SMA) springs. The reliability of the SMA springs was estimated by using life test data of the springs. The spring has undergone thermo mechanical fatigue and it was observed that recovering to original shape is disappearing with number of cycles due to inelastic deformation. The life prediction model was developed here using GLL- Weibull. Bayesian approach is used to update the parameters of the model. As experiments were performed on accelerated condition; an accelerated life testing model was also developed to extrapolate the Probability Density Function (PDF) at normal use condition.

In essence, present thesis contributes towards the development of accurate approaches for prognostic of various components. Thus, the outcome is of high importance in effective planning of Condition Based Maintenance of asset intensive systems and reducing unplanned down time losses to the industries. Also, the novel attempt is made to first time study the life prediction approaches for shape memory allow springs. The results are encouraging and open up further scope prognostics for systems with such components.

LIST OF PUBLICATIONS

PATENT

1. Lad, B.K., Palani, I.A., Kundu, P., Nath, T., (2015) Shape memory alloy directional control valve and test rig to characterize its life by fusion of Bayesian algorithm and GLL-Weibull distribution. (**Submitted for internal approval**)

INTERNATIONAL JOURNALS

1. Kundu, P., Chopra, S., Lad, B.K., (2015) Development of a risk based maintenance strategy to optimize forecast of a gas turbine failures, International Journal of Performability Engineering, 11(5), 403-412
2. Kundu, P., Chopra, S., Lad, B.K., (2015) Multiple failure behaviour identification and remaining useful life prediction of ball bearings, Mechanical Systems and Signal Processing. (**Under review**)

INTERNATIONAL CONFERENCES

1. Jain, A.K., Kundu, P., Lad, B.K., (2014) Remaining useful life prediction of an aircraft engine under unknown initial wear. In: proceedings of 5th International and 26th All India Manufacturing Technology, Design and Research Conference (AIMTDR 2014), IIT Guwahati, Guwahati, India, December 12-14.
2. Kundu, P., Lad, B.K. (2015) PCA- ANN based approach for roller ball bearings remaining useful life prediction, In Annual Conference of the Prognostics and Health Management Society, California, USA, October 19-24. (**Under review**)

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ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
CBM	Condition Based Maintenance
CM	Condition Monitoring
CPDA	Change Point Detection Algorithm
GLL	General Log Linear
MSE	Mean Square Error
NASA	National Aeronautics and Space Administration
PHM	Prognostics and Health Management
PVE	Proportion of Variance Explained
RBM	Risk Based Maintenance
RUL	Remaining Useful Life
SEM	Scanning Electron Microscopy
SMA	Shape Memory Alloy
TGA	Thermogravimetric Analysis

Chapter 1

Introduction to Thesis
- Literature Review
- Objectives
- PHM in Industry

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Prognostics and Heath Management Overview
- Steps Involved in PHM
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SMA Reliability Estimation and Life Prediction
- Reliability Estimation and Life Prediction Models for Shape Memory Alloy Springs undergoing Thermo Mechanical Fatigue

Chapter 1

Introduction

1.1 Background and Motivation

Maintenance and repair costs cover a significant portion of Life Cycle Cost (LCC) of any asset intensive system. For examples, airlines in India spend 13-15% of revenue towards the maintenance which is second highest cost after the cost of the fuel [1]. Similarly, about one third of total defense budget of USA in 2002 was used for maintenance and repair activities [2]. Therefore, a cost effective maintenance strategy is required for industries. Maintenance strategy can be broadly classified in two categories: proactive maintenance and reactive maintenance. Reactive maintenance is generally a corrective or break down type of maintenance which is performed on failure of the unit. It generally leads to excessive unplanned downtime losses. Proactive maintenance is again divided in two parts viz., preventive and predictive maintenance. Preventive maintenance is performed after a fixed interval of time. The time is either the calendar time or age of the unit. The objective of preventive maintenance is prevention of failures. It is very conservative, typically costly, labor intensive, and often makes unneeded inspection and repairs in an effort to ensure failures do not occur. Predictive maintenance is an on-demand maintenance strategy. It is performed based on the condition of the unit. Therefore, it is often referred to as Condition Based Maintenance (CBM). CBM is also a costly technique because prediction of condition requires costly sensors and lots of historical data. The effect of the cost on different maintenance approaches is shown in figure 1.1.

From figure 1.1 it can be seen that corrective maintenance approach has a relatively low maintenance cost but high operating costs associated with the high cost of unplanned shutdowns. In contrast, preventative maintenance generally has a low operating cost, but often results in high maintenance cost associated with the removal of components before they have reached the end of their useful lives [3]. Most efficient approach is to plan proactive maintenance just before the failure of the machine. CBM can be used for the same. From above it can be concluded that CBM is a cost effective maintenance strategy.

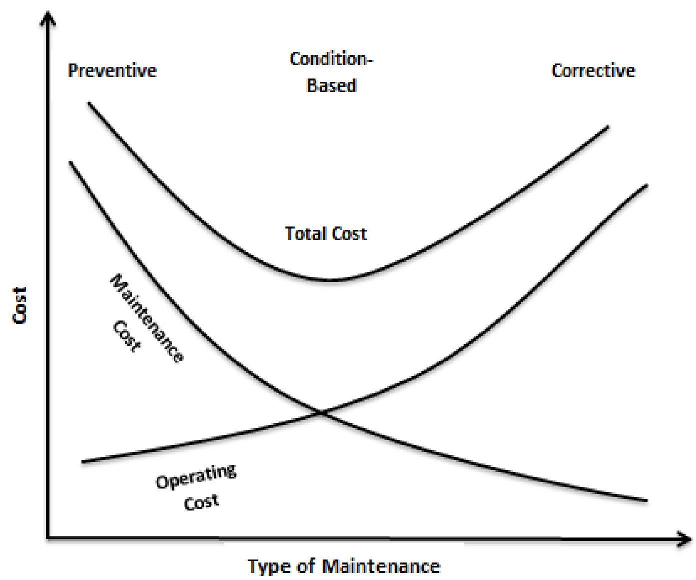

Figure 1.1 Cost associated with different maintenance approaches [3]

But, effectiveness of CBM strategy depends on accuracy in prediction of RUL. Prognostics is the technology used to predict the RUL based on monitored parameters. Advancement in sensor and computing technologies have already made prognostics a promising solution for reducing unplanned outages, increasing operational safety, increased asset availability by effective spare management and extracting maximum life of the machine by performing maintenance only when needed. However, effective implementation of prognostics requires an accurate model for predicting the RUL of components and system risk assessment. In this thesis, following five such approaches are developed.

a) Remaining Useful Life Prediction of Aircraft Engine Based under the presence of initial wear in the data.
b) Multiple Failure Mode Identification and Remaining Useful Life Prediction of Ball Bearings.

c) PCA- ANN Based Approach for Roller Ball Bearings Remaining Useful Life Prediction.
d) Development of a Risk Based Maintenance Strategy to Optimize Forecast of a Gas Turbine Failures.
e) Shape memory alloy springs reliability estimation and life prediction using Bayesian approach.

1.2 Literature Review

Advancement in sensor and computing technology make more condition monitored data available, and in last few years there have been an increase in number of publications in the field of prognostics. But still there are areas which require more attention from researchers to increase accuracy in RUL prediction. Based on the above motivation; literature review is done to identify some of the key issues that need to be consider during prognostics model formation. Following sub section highlights the information gained from the literature survey that helped in formulating the problem statement.

1.2.1 Data Noise

The current technology of prognostics is facing difficulties associated with data noise. Presence of unknown initial wear and presence of multiple failure modes in a components failure data are two of the important sources of data noise. If these sources of data noise are not handled appropriately, then it may give poor prediction of the RUL.

1.2.1.1 Presence of Initial Wear

In real life system initial wear is commonly observed because of manufacturing inefficiencies. Presence of initial wear makes a difference in useful operational life of the component and effect the RUL prediction accuracy [4]. This initial wear should be considered during model formulation.

1.2.1.2 Presence of Multiple Failure Modes

A single mechanical component may fail due to different types of failure mode such as a roller bearing can fail due to inner race failure, outer race failure, and cage failure. The condition monitored data indirectly observe these failure modes. The existence and interaction among these different failure modes may cause uncertainty in the model and results in poor prediction accuracy. It is difficult to predict the RUL if these failure modes are not identified and treated appropriately. Literatures on prognostics models to handle such kind of noise (i.e. multiple failure modes) are completely absent. Some work has been reported for reliability estimation of a system with multiple failure modes.

Wang (2013) developed a reliability model for mechanical components with dependent failure modes. The joint probability density function is derived to correlate all the failure modes. Drawback with this model is linear correlation was assumed between different failure modes, which never possible [5]. The reliability model for electronic devices with multiple competing failure modes was developed by Haung and Askin (2003). The failure mode assumes in this study is solder/Cu pad interface fracture (e.g. catastrophic failure) and light intensity degradation (e.g. degradation failure) [6]. Moghaddass and Zuo (2014) developed a prognostics model for a system with multistate degradation and with two independent failure modes. The independent condition monitor indicator was assumed for each failure modes [7]. This study also elaborates the importance of considering different failure modes of a device. Mixed Weibull proportional hazard model was present by Zhang et al. (2014) to combine the multiple failure modes of an overall system. The model parameter estimates by combining the historical lifetime and condition monitor data of all failure modes. The system reliability and failure time was estimated by proportionally mixing the failure probability density function of multiple failure modes [8]. Son (2011) represents a mathematical model for estimating the mechatronic servo system reliability. The system performance is measured by considering the competing failure modes of the system with degraded phenomena [9].

So, a prognostics model is required that can handle all these kind of noise in the data set.

1.2.2 Multidimensional Features Handling during Model Development

The raw data obtained from the sensors is not suitable to represent the degradation of the component because it is associated with the noise and bias in sensor measurement. Features are generally extracted from the raw data to get the relevant information about component degradation. Obtaining the most effective feature and inputting to prognostics system is a challenge, because the effectiveness of any prediction models based on the quality and sensitivity of features utilized to evaluate the condition and spread of the faults [10]. Some attempts have been made to identify the sensitive features which correlate with the fault propagation in the component.

In order to avoid the problem of dimensionality related to features and improve the accuracy of prediction, Chen et al. (2011) used correlation analysis to identify the best features set. It selects salient features of tool wear state and discards the irrelevant or redundant features [11]. Root Mean Square (RMS) and kurtosis of vibration signals are generally used as features for prognostics of bearing failures. However, Mahamad et al. (2010) used the fitted measurement value as input parameters to the model instead of real measurement value. It helped in reducing the external noise from the measurement data [12]. Autoregressive and extreme learning machine algorithm is presented by [13] to select the best features from non-trending condition monitoring data. The shortcoming with this algorithm is that it will not help in removing the noise associated with the signal. Therefore, denoising filter technique is separately required to remove the noise associated with the signal.

The all above mentioned approach are focused on selecting the best feature that can best fit to the model. But it is always not possible to identify the features which are more sensitive to the fault propagation. Even though possible, significant amount of time and expert judgment is required to identify the features. On the other hand, number of features may come out which are sensitive to fault propagation in the component. However, all these features should not be used as input parameters to the RUL prediction model. If the entire set of features has been taken as input parameters to the model, then it may over fit the model i.e. during training the performance may be good but during testing performance is significantly worse.

Therefore, an algorithm is required which can fuse all these features in such a way that it reduce the dimensionality of the features and at the same time retain the sensitivity or variability of all the features.

1.2.3 Model Parameter Updating

Model for RUL prediction generally requires historically observed condition monitored data from the fleet of machinery. It means the developed model will give the distribution of the fleet. But, the damage parameters such as crack length and wear may differ for similar components operating under the same condition. In addition, in future two type of scenario can be happen: damage parameters can come better then fleet or damage parameters can come worse than fleet. So, completely relies on the historically observed condition monitored data can make under prediction or over prediction in RUL estimation.

For example, from first scenario; when a unit will inspect, the damage parameters may be find smaller than the fleet (shown by yellow dots in figure 1.2). The blue distribution represents the expected distribution of the damage based on any prediction model. If damage is calculated using the normal model for the next inspection, then it will state that machine is not safe till next interval and it will reach critical damage level before the next inspection interval. But practically, the unit is safe at the next interval and will reach to critical damage level after the next inspection. So, for the current problem a model is required which can shift the distribution down by a certain amount.

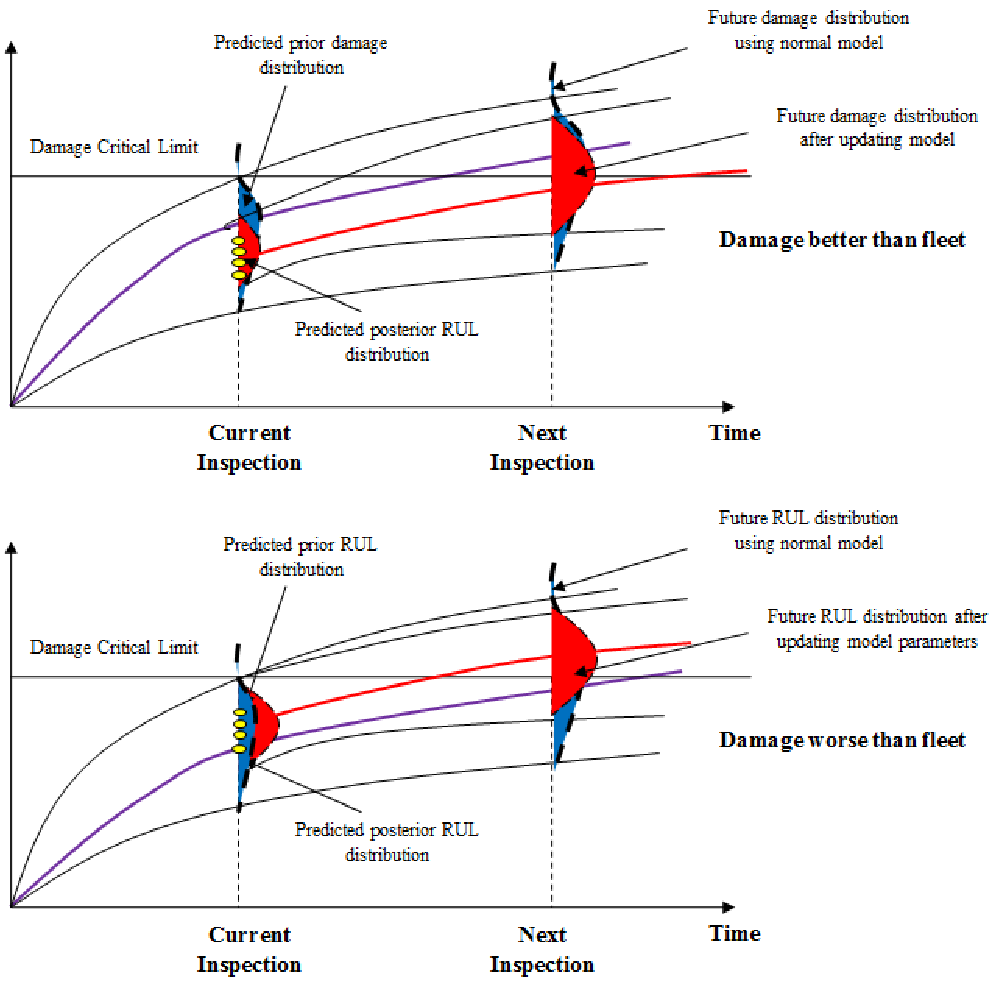

Figure 1.2 Approach for model parameter updating

From second scenario; when a unit will inspect, the damage parameters may be find larger than the fleet. If damage is calculated using the normal model for the next inspection, then it will state that machine is safe till next interval and the critical damage level will reach after the next inspection. But practically, the unit already reaches to the critical damage before the next inspection. So, for this problem a model is required which can shift the distribution up by a certain amount.

In addition, the damage parameters value may come which is not historically observed. For example, when model was developed then bearing crack length values ranges from 1mm to 5mm. But in future for some component of the fleet , the damage parameters value may observed greater than 5mm or less than 1mm. In that case, if conventional method of prognostics has been used; then again new model has to be developed for considering the new damage parameters value. But, it will be time consuming.

To overcome these uncertainty, an approach is required that can automatically update the model parameters based on new available information. This parameter update methodology is divided in two main phase: offline and online. In offline phase, RUL prediction model is developed that can best fit to the available data set. In online phase, model parameter will get updated based on new online available information. The work reported in literature for model parameter updating is presented here under:

[14] Used the Bayesian approach for estimating the failure rate of a transformer based on new available condition monitored information. It was found that Bayesian approach is very flexible to estimate the failure rate of each individual transformer with different conditions. The uncertainty in clinical decision making is reduced by using Bayesian approach. Methodology reported help in integrating the clinical and medical background knowledge; which helps in representing the uncertainty and discovering the patterns in biomedical data [15]. Mosallam et al. (2013) used the Bayesian methodology for accurately predicting the RUL of Lithium- ion battery. The methodology includes the sources of uncertainty such as system, model and sensory noise while predicting the RUL [16].

1.3 PHM in Industry

In last few years, a significant amount of research has been undertaken to develop prognostics models. But fewer industries have applied this tool for their component life prediction. But this tool is very important for industries, because today’s complex and advanced machine demand highly sophisticated and cost effective maintenance strategy [17]. The industries which has been successfully implemented this tool are gas turbine industry, wind turbine industry, aviation industry. Approaches applied by these industries for their component life prediction are given hereunder.

1.3.1 PHM in Gas Turbine Industry

A classification model has been presented to diagnosis any malfunction of the combustion system. Exhaust temperature spread has been collected to detect the combustion chamber problem. Two multiclass classification algorithms, one based on logistic regression, the other on artificial neural networks, have been trained on labeled patterns extracted from real cases of normal behavior, sensor anomaly, cold spot and hot spot [18]. Anomaly detection rules and models are presented to monitor the gas turbine health [19]. A neural network based algorithm is presented for fault detection and isolation in gas turbine [20]. Neuro-fuzzy algorithm has been presented for fault diagnosis of gas turbine working on different operating points [21].

The hybrid approaches which can combine the bearing health monitoring data and model based technique are presented for aircraft gas turbine [22].

1.3.2 PHM in Aviation Industry

A physics based approach is used for the health monitoring of a pumping unit in an aircraft engine fuel system [23].

1.3.3 PHM in Wind Turbine Industry

Model is developed for fault prediction of the bearing of a large utility scale wind turbine. Using the developed models, it is possible for wind farm operators to identify wind turbines in which a potential fault within the main bearing is developing. The particle filter approach was also used manage the uncertainty associated with predicting the future behavior of degrading component [3]. Wind turbine gearbox lubricating oil RUL is predicted using physics based model. It helped in establishment of mathematical relationship between the lubrication oil degradation and particle contamination level [24]. A fault detection methodology is proposed for wind turbine bearing. The methodology uses adaptive filter technique to improve the fault signal to noise ratio [25]. Adaptive Neuro-Fuzzy

Inference System (ANFIS) and Nonlinear Autoregressive Model with exogenous inputs (NARX) were used to measure the wind turbine gearbox health [26].

In addition, following are the major issue with data during implementation of PHM in industry:

1. Failure of component with very low exposure.
2. As the component age is increasing, the component operational hour or start is decreasing.
3. Data contain zero values (indicate missing value in the data).
4. Data associated with sensor noise and bias.
5. For a system, the component level aging parameters are different than the system level aging parameters due to replacement of some component.
6. Damage parameters values can come beyond the model critical limit.
7. Lack of data availability for newly installed fleet.
8. Data can come beyond the expected values (i.e. outliers)

1.4 Objectives

From the above literature survey, research objectives are identified. The major objective of this thesis is *"to develop efficient RUL prediction algorithms for various components of industrial systems while considering the effect of the data noise, multidimensional features and model parameter updating".* Following are the sub objectives which direct relate with the overall objective.

Sub Objective 1: *Development of methodologies to handle the effect of the initial wear in the data source.*

Sub objective 2: *Development of methodologies to handle the effect of the multiple failure behaviour in the data source*

Sub Objective 3: *Managing Multidimensional features during model development.*

Sub Objective 4: *Model to update the parameters when new information is available.*

Sub objective 5: *Development of life prediction models for Shape Memory Alloy springs undergoing thermo mechanical fatigue.*

1.5 Summary

This chapter presented an overview of the research problem, i.e., *"Development of effective approaches for Prognostics of Industrial System".* Background and motivation for the research is also presented. Based on literature review; objectives of current research were identified. Application of PHM in different industries and issues with implementation of PHM in industry is also given.

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- Literature Review
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Chapter 2

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- PHM approaches

Handling Initial Wear

- Aircraft Engine RUL prediction Using ANN

Handling Multiple Failure Modes

- Roller Ball Bearing RUL prediction using GLL- Weibull and multiple failure behaviour identification using CPDA and Clustering

Handling Multidimensional Features

- PCA- ANN Based Approach for Roller Ball Bearings Remaining Useful Life Prediction

Model Parameter Updating

- Risk Based Maintenance Strategy to Optimize Forecast of a Gas Turbine Failures using Bayesian Approach

SMA Reliability Estimation and Life Prediction

- Reliability Estimation and Life Prediction Models for Shape Memory Alloy Springs undergoing Thermo Mechanical Fatigue

Chapter 2

Prognostics and Health Management

2.1 Background

The objective of PHM technologies is to enhance the effective reliability and availability of a product during its life-cycle by detection of current condition and approaching failures. It aims at predicting and protecting the integrity of equipment and complex systems, and avoiding unanticipated operational problems leading to mission performance deficiencies and adverse effects to mission safety [27].

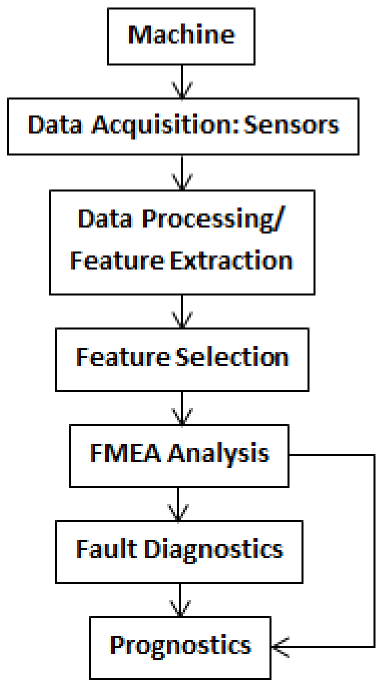


Figure 2.1 Stages of PHM architecture

Figure 2.1 provides an overview of the PHM architecture. PHM system is an integration of six stages. Description of each stage is given hereafter.

Stage 1: Data Acquisition

It is used to provide the collection of data from the sensors. It usually measures the real world physical conditions and converts the resulting samples into digital numerical values that can be manipulated by a computer. To predict health of any component, lots of information about the condition of that component is required. So, numbers of sensors are put on the various location of machine to monitor various parameters. The sensors mainly used for monitoring the health of the component are: accelerometer used for measuring vibration in rotating components; thermocouple used for measuring gas turbine exhaust temperature spread; dynamometer used for measuring force signal in milling machine etc. Collection of all sensor readings is done by data acquisition system.

Stage 2: Data Processing/ Feature Extraction

The second stage of any PHM systems typically involves appropriate processing of equipment sensor data. This stage is often referred as feature extraction. The feature extraction stage within a PHM system is designed to generate a vector of data features, which can be used to infer the current fault status of a monitored system. The generation of an appropriate feature vector is typically application dependent and is one of the most important stage in a PHM system. One of the methodologies for feature extraction from the raw vibration signal is shown in figure 2.2

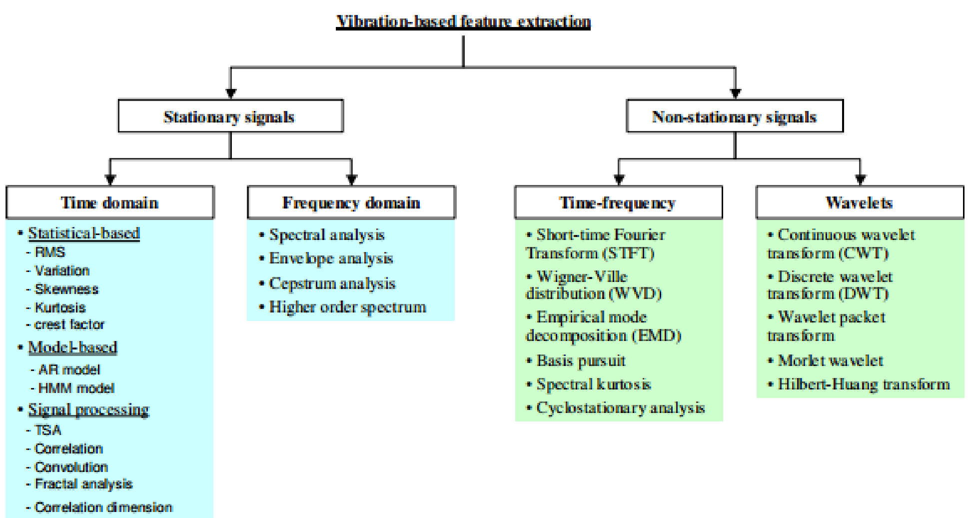


Figure 2.2 Vibration based feature extraction methods [28]

Stage 3: Feature Selection:

Features selection is the most critical step for implementation of prognostics models; because the effectiveness of such models depends on the quality and sensitivity of features utilized to evaluate the condition and spread of the faults. Many features may be extracted which are sensitive to fault propagation in the component or system. However, all these features should not be used as input parameters to the RUL prediction model. If many features are used in the model development, it may tend to describe the random error or noise instead of underlying relationship [29]. This is called over fitting of the model i.e. during training the performance may be good but during testing performance is significantly worse. Figure 2.3 shows the over fitting associated with the prognostic model.

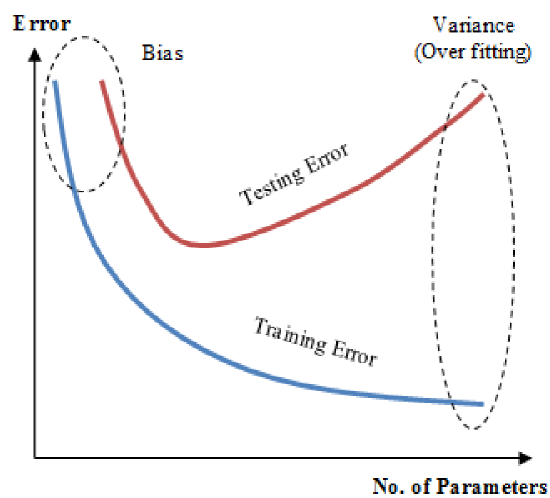


Figure 2.3 Over fitting in prognostics model

Many algorithms are available for selection of optimum set of features in a prognostics model: PCA, p value approach, fuzzy based feature selection, trendability etc. P value approach and PCA based algorithm for feature selection are discussed in chapter 4 and 5 respectively.

Stage 4: FMEA Analysis

The objective of FMEA studies is to relate the failure events to root causes. It generally investigates all relevant issues regarding potential failure modes of monitored systems including: the severity of different failure modes, their frequency of occurrence, their testability, and the fault symptoms which are suggestive of systems behaviour under different fault conditions.

Stage 5: Fault Diagnosis

Fault diagnosis is concerned with detecting, isolating, and identifying an impending, or incipient, failure condition in a system. The term fault here implies that the system under observation is still operational, but cannot continue operating indefinitely without maintenance intervention.

Step 6: Prognostics

Prognostics involve predicting the time progression of a specific failure mode from its incipience to the time of component failure. This module generally takes the data from all previous modules and predicts the RUL of the component or system.

From the entire above step; key step is how to do prognostics. Next section will focus on prognostics.

2.2 Fault Prognosis

Fault prognosis is the ultimate goal for machine health monitoring. Prognostics means remaining useful life prediction of any mechanical system based on their current health state and its past operation profile. From figure 2.4 RUL can be written as below:

$$RUL = Predicted\ time\ \left(t_p\right) - Current\ time\ (t) \qquad (2.1)$$

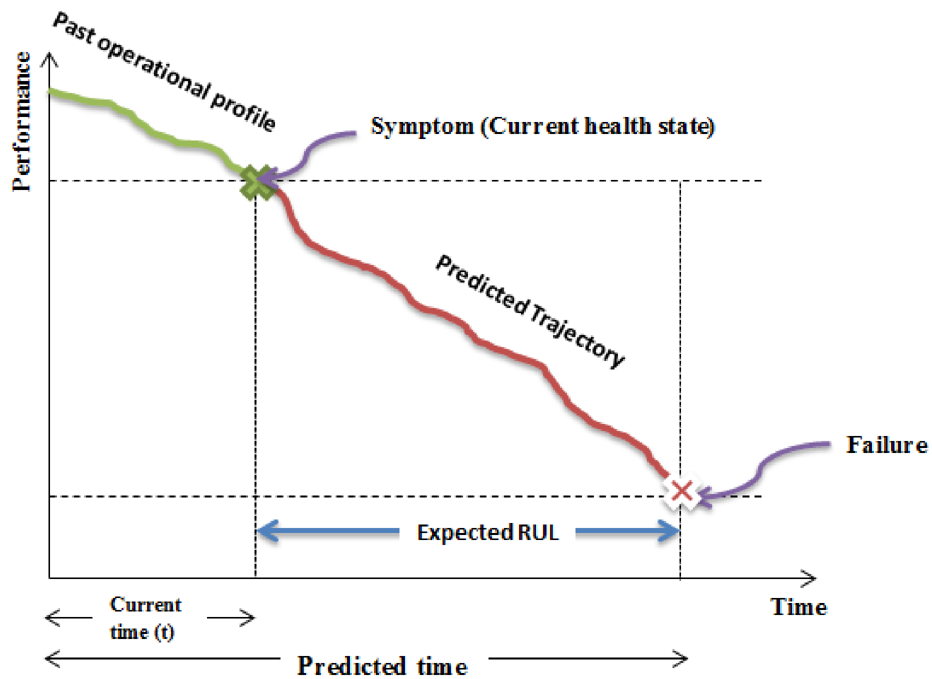


Figure 2.4 Illustration of RUL

Any model is used for prognostics should be able to understand past operational profile of that component. Because based on that profile only RUL will be calculated. RUL predicted from model always have some uncertainty; because actual system performance and model performance are very difficult to coincident. Well understanding of the data and use of prognostics algorithm that best fit to the data generally helps in reducing this uncertainty. The number of approaches available in literature for prognostics; all of them are discussed in next section.

2.3 Prognostics Approaches

Various prognostics approaches have been developed for system RUL calculation. These approaches can be broadly classified in two categories: physics based prognostics approach, and data driven prognostics approach. Figure 2.3 illustrates how, as we move from data based to physics based prognostics approach, with increased capabilities and performance, there is a likewise decrease in the applicability of the different approaches. The reduction in applicability is a reflection of the increasing complexity/ cost of the different approaches [3]. Table 2.1 shows the advantages and disadvantages associated with different prognostics approaches.

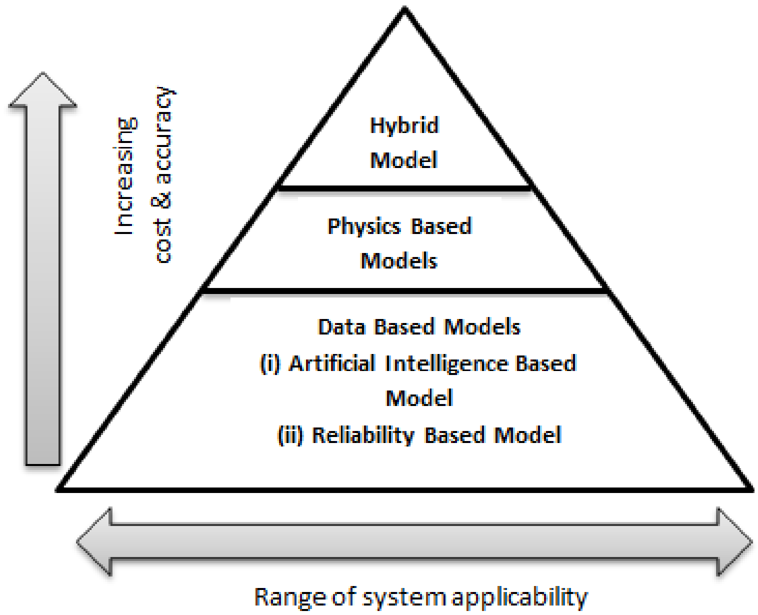


Figure 2.5 Technical approaches to prognostics [3]

2.3.1 Physics Based Prognostics Approach

Physics based prognostics are generally required the stress at each failure site as a function of loading conditions, the product geometry and material properties. Damage models are then used to determine fault generation and propagation [31]. Paris law for crack propagation [32], Foreman law crack growth modeling [33] and stiffness based damage rule [34] model are generally used for modeling the physics of failure. These physics models are used to make prediction of how long it will take for the failure to progress to a predefined state such as a crack to grow to a certain size.

2.3.2 Data based Prognostics Approach

Data driven prognostics approach use historical and current data statistically and probabilistically derive prediction of RUL of a system [35]. It can again categorize into two different areas: Artificial Intelligence (AI) based prognostics approach and reliability based prognostics approach.

Table 2.1 Advantages and Disadvantages with prognostics approaches [17]

Approach Name	Advantage	Disadvantage
Physics Based	• Can be highly accurate if physics of models remain consistent across systems • Require less data than data driven technique	• Real life system physics is often too stochastic and complex to model • Defect – Specific **Ex: Paris Crack Growth Model etc.**
Artificial Intelligence Based	• Do not require assumption or empirical estimation of physics parameters. • Ease of Calculation	• Generally required a large amount of data to be accurate • Rely on past degradation pattern and can be lead to inaccurate forecasts in time of change. **Ex: ANN, SVM, Random Forest etc.**
Reliability Based	• Do not require Condition monitor data • Population characteristics information enable longer-range forecast.	• Only provide general, overall estimates for the entire population of identical units. • Not necessarily accurate for individual operating units. **Ex: Weibull, Lognormal Model etc.**
Covariate Based Reliability Model	• For prediction it will not consider time only, but also consider the covariates under which it is operating.	• Require both event and condition data to be accurate. **Ex: Weibull-PHM, Lognormal -PHM**

2.3.2.1 Artificial Intelligence based Prognostics Approach

This is the most widely used approach for RUL calculation. The prognostics knowledge in this approach is developed using failure data to learn the time-to-failure characteristics of a specific failure. This a19pproach is generally used to solve non-linear problems and don’t require any empirical estimation of physics parameters. Generally these methods require a large amount of data to be accurate, which sometimes can be limitation.

The prediction requirement using AI approach can be qualitative or quantitative. Predicting a qualitative response (healthy or faulty prediction) for an observation can be referred to as classifying that observation, since it involves assigning the observation to a category, or class. Accuracy can't be used as reliable metric for a classifier, because for unbalanced data set it will yield misleading results i.e. when the number of samples in different classes varies greatly. For example, if there were 90 faulty units and only 10 healthy units in the data set, the classifier could easily be biased into classifying all the samples as faulty.

So, the performance of every classification approach is described by confusion matrix which is also called error matrix. It is a specific table layout with two rows and two columns and visualizes the performance of an algorithm.

Table 2.2 Confusion Matrix

Model Results			
Healthy	**Faulty**		
True Positive	False Positive (Type 1 Error)	**Healthy**	**Actual Results**
False Negative (Type 2 Error)	True Negative	**Faulty**	

Sometime output requirement is quantitative instead of qualitative i.e. crack length, wear etc. Quantitative model accuracy is defined by error (%) or score value, which is more, illustrated in chapter 3 and 4. Artificial Intelligent (AI) methods such as neural networks [36, 37, 38, and 39], logistic regression model [40], support vector machine [41], hidden markov model [41] and clustering methods [42] have been applied for prognostics. The present study uses Artificial Neural Network (ANN) and clustering algorithm, both of them are discussed here under:

2.3.2.1.1 Artificial Neural Network

Artificial Neural Networks (ANNs) are nonlinear data driven self-adaptive approach, which is inspired from the biological nervous systems. Like biological neural network it contains large number of highly interconnected processing elements (neurons) work as a single language to solve a specific problem. Like human brain system; ANN is also learns by example. It has many applications such as pattern recognition, data classification and prediction through a learning process. The pictorial view of the biological and artificial neural network is shown in figure 2.6 and 2.7 respectively. From figures it can be seen that ANN is a mathematical model of biological neural network.

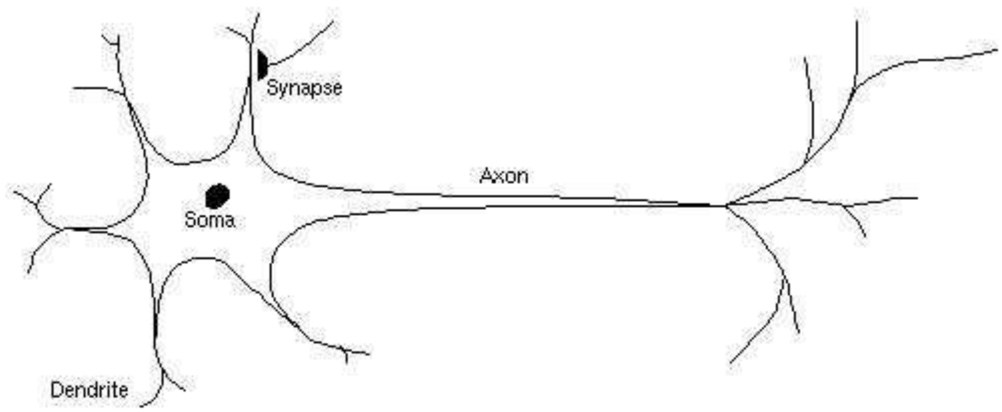


Figure 2.6 Biological Neural Network [43]

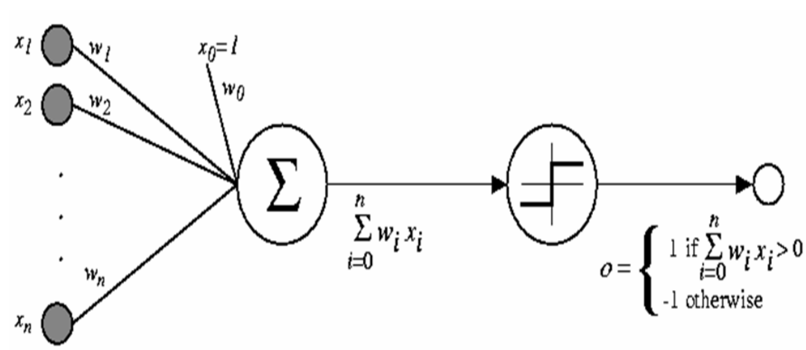


Figure 2.7 Artificial Neural Network [43]

In actual neurons the electric signals received by the dendrite from the axons of other neurons, in ANN these electrical signals are represented as numerical values. At the synapses between the dendrite and axons, electrical signals are modulated in various amounts. This is also modeled in the ANN by multiplying each input value by a value called the weight. An actual neuron fires an output signal only when the total strength of the input signals exceeds a certain threshold. In ANN this phenomena is modeled by calculating the weighted sum of the inputs to represent the total strength of the input signals, and applying a step function on the sum to determine its output.

During training of the ANN, the weights of the each unit are adjusted in such a way that the error between the desired output and the actual output is reduced, i.e., it calculates how the error changes as each weight is increased or decreased slightly.

2.3.2.1.2 Clustering Algorithm

Clustering is an unsupervised learning algorithm and it can be directly applied to measured vibration data. Thus, it simply eliminates the need of the training data from the defective bearing. Clustering in general groups the similar data in to same cluster and divides dissimilar data in to different clusters by using some predefined criteria. There are number of clustering methods are available, two best known are hierarchical and K-means clustering.

K- Means Clustering:

This algorithm divides the data set into K distinct, non-overlapping clusters. It is the oldest and most popular approach for finding groups in multivariate data set, which has five steps [44]:

1. Choose K, number of clusters.
2. Calculate the means of the K clusters and collect the mean values. Collection of these means is called as centroids.
3. For each observation, calculate the distance from that observation to each of the k centroids and assign that observation to closet cluster, i.e. centroid
4. After all the observation have been assigned to one and only one cluster, calculate the new centroid for each cluster using the observations that have been assigned to that cluster. The cluster centroids “drift” toward areas of high density, where there are many observations.

5. If the new centroids are very different from old centroids, the centroids have drifted. So return to step 3. If new centroids and the old centroids are the same so that additional iterations will not change the centroids, then the algorithm terminates.

The advantage of this algorithm that its execution time is proportional to the number of observations, so it can be applied to large data set. The disadvantage is that it requires us to pre-specify the number of clusters K.

Hierarchical Clustering:

Hierarchical clustering is an alternative approach which does not require that we commit to a particular choice of K. Hierarchical clustering has an added advantage over K-means clustering in that it results in an attractive tree-based representation of the observations, called a dendrogram. In this approach at the start of the algorithm, each observation is considered as its own cluster. The distance between each cluster and all other clusters is computed and the nearest clusters are merged. Following are the steps generally performed for hierarchical clustering:

1. At starting assume each observation as its own cluster and calculate the initial cluster distance by using squared Euclidean distance between cluster points:

$$d_{ij} = d(\{y_i\},\{y_j\}) = ||y_i - y_j||^2 \quad (2.2)$$

2. Nearest clusters are merged after calculating the distance between each cluster and all other clusters
3. At each step after merging, find the pair of clusters which leads to minimum increment in total with in clusters variance.
4. If there are n observations, this process is repeated n-1 times until there is only one large cluster.

2.3.2.2 Reliability based Prognostics Approach

This is the simplest approach among all the prognostics approach. In this approach, only historic time to failure data is required for RUL calculation. This approach doesn't have predictive capability and cannot be described as truly predictive prognostics techniques. This approach is mainly used where sensor data is not available and has wide applicability in system with low criticality or cost.

Weibull, poisson, exponential and log-normal probability distributions have been used for calculation of probability of failure.

The major challenge with reliability based prognostics approach is that it generally doesn't consider factors such as environmental and operational conditions while estimating the RUL. Typically, systems operating in harsher operating and environmental condition will fail at earlier times than those in milder environments. To fix this disadvantage covariate based reliability model has been used. Benefit of using this over conventional reliability model that it consider the other factors like, environmental and operational conditions which influence probability of failure instead of time to failure only i.e. reliability as a function of time as well as covariates under which it is operating. Most widely used models in this category are the GLL- Weibull model and GLL- Lognormal Model. Both of these methods are explained in chapter 4 and 5 respectively.

2.5 Summary

This chapter presented about the overview of Prognostics and Health Management (PHM). The various step involved while doing prognostics is also discuss. Various approaches used for prognostics with advantages and disadvantages are also given here.

Introduction to Thesis

- Literature Review
- Objectives
- PHM in Industry

↓

Prognostics and Heath Management Overview

- Steps Involved in PHM
- PHM approaches

↓

Chapter 3

Handling Initial Wear

- Aircraft Engine RUL prediction Using ANN

↓

Handling Multiple Failure Modes

- Roller Ball Bearing RUL prediction using GLL- Weibull and multiple failure behaviour identification using CPDA and Clustering

↓

Handling Multidimensional Features

- PCA- ANN Based Approach for Roller Ball Bearings Remaining Useful Life Prediction

↓

Model Parameter Updating

- Risk Based Maintenance Strategy to Optimize Forecast of a Gas Turbine Failures using Bayesian Approach

↓

SMA Reliability Estimation and Life Prediction

- Reliability Estimation and Life Prediction Models for Shape Memory Alloy Springs undergoing Thermo Mechanical Fatigue

Chapter 3

RUL Prediction of an Aircraft Engine under Unknown Initial Wear

3.1 Problem Description

Predicting the progression of damage in aircraft engine turbo machinery under unknown initial wear is very important task for CBM planning. Initial wear can occur due to manufacturing inefficiencies and are commonly observed in real systems.

In the present work we have taken the problem which was reported in PHM 2008 prognostics data challenge [45]. System monitored data of an aircraft engine is taken from National Aeronautics and Space Administration (NASA) Prognostics Center of Excellence Data Repository [46], which consist of multiple multivariate time series. Each time series is from a different engine; i.e., the data can be considered to be from a fleet of engines of the same type. The engine is operating normally at the start of each time series, and starts to degrade at some point during the series. The initial wear is modeled by variations in flow and efficiencies of the various modules. There are three operational settings and 21 sensor measurements that have a substantial effect on engine performance. Table 3.1 gives the details of operational settings and sensor measurements [45].

The main challenge with this data is the presence of initial wear in the system monitored data, as it may make a difference in useful operational life of a component. The objective is to predict the number of remaining operational cycles in the test set, i.e., the number of operational cycles after the last cycle that the engine will continue to operate properly.

3.2 The Proposed ANN RUL Prediction Models

ANN has been considered to be one of the most promising approaches for prediction of RUL due to their adaptability, nonlinearity, and ability of arbitrary function approximation [37]. Three layers Feed Forward Neural Network is used for RUL prediction in this work. Figure 3.1 shows the configuration of the network. The network is divided into three layers; input, hidden and output layers. For ANN training, there are 25 inputs fed into the network, out of which one is current age (t_i), three are operational conditions and 21 are sensor measurements.

Table 3.1 Operational settings and sensor measurements description

Operational Settings		
S.No.	**Description**	**Range**
1	Altitude	0-42K ft.
2	Mach number	0-0.84
3	Throttle resolver angle	20-100
Sensor Measurements		
S.No.	**Description**	
1	Total temperature at fan inlet (°R)	
2	Total temperature at LPC outlet (°R)	
3	Total temperature at HPC outlet (°R)	
4	Total temperature at LPT outlet (°R)	
5	Pressure at fan inlet (psia)	
6	Total pressure in bypass-duct (psia)	
7	Total pressure at HPC outlet(psia)	
8	Physical fan speed (rpm)	
9	Physical core speed (rpm)	
10	Engine pressure ratio (P50/P2)	
11	Static pressure at HPC outlet (psia)	
12	Ratio of fuel flow to Ps30 (pps/psi)	
13	Corrected fan speed (rpm)	
14	Corrected core speed (rpm)	
15	Bypass Ratio	
16	Burner fuel-air ratio	
17	Bleed Enthalpy	
18	Demanded fan speed (rpm)	
19	Demanded corrected fan speed (rpm)	
20	HPT coolant bleed (lbm/s)	
21	LPT coolant bleed (lbm/s)	

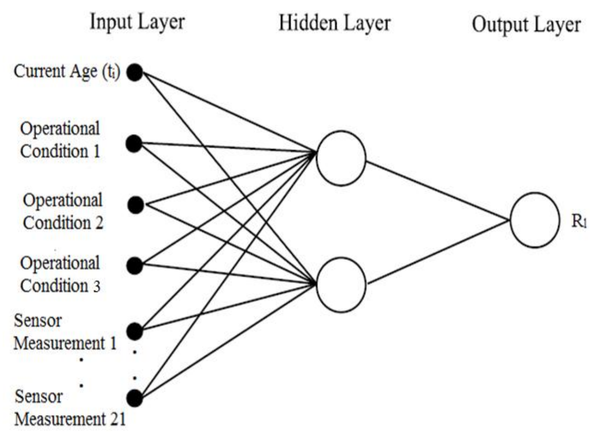


Figure 3.1 Feed Forward Neural Network model for aircraft engine RUL estimation

The3 percentage residual life of engine $R_l$is used as the output of the network. R_l is calculated as follows:

$$R_l = \frac{(Time\ to\ failure - Current\ age)}{Time\ t\ failure} \tag{3.1}$$

The output is normalized between 0 and 1, which gives same order of magnitude variables to avoid numerical instability [39]. 1 indicates that 100% life is remaining (i.e. component is new) and the unit is failed when the residual life percentage reaches 0.

Levenberg Marquardt (LM) learning algorithm [37] is used to train the network. MATLAB neural network tool box is used for the training of ANN model. The configuration of ANN model uses tansig (Hyperbolic tangent sigmoid) transfer function in its hidden and output layer.

In order to avoid over fitting of data, two different sets of data are required for training and validating the network. In the training set, the degradation grows in magnitude until a predefined threshold is reached beyond which it is not preferable to operate the engine. In the validation set, the time series ends some time prior to complete degradation. During over fit situation, Mean Squared Error (MSE) for the validation set decreases first and comes to a minimum value and later increases, though the MSE of the training set continues to decrease. When the MSE of the validation set increases, it is assumed that the regression algorithm is over fitting the training data [36]. Thus, the training is stopped as soon as MSE in the validation set begins to increase. For the selection of Feed Forward Neural Network topology, there is no specific method. Trial and error search method is the best option to select the optimum topology for the prediction.

In this work, the training set uses the original data from input feed to the network but the validation set is perturbed with +10% of the fed. The ANN model is train and validated in order to find the minimum validation error. The training and validation for ANN are setup from two to thirty nodes or neurons. The network which gives minimum validation error is selected as the optimum model.

The trained ANN model is tested with test data set and performance of the model is evaluated. For performance assessment Mean Squared Error (MSE) in RUL cycles and average score indices are calculated. These are defined as follows:

Mean Squared Error: MSE is the average of the squares of the difference between the actual observations and predicted values.

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{t_i} - \mathrm{a_i})^2 \tag{3.2}$$

Where, $\mathrm{t_i}$ = Predicted value, a_i= Actual value, N= Number of data points.

Score: The score for one prediction is defined as the exponential penalty to the prediction error; and the score of an algorithm is defined as the total score S from all the predictions for the units in the testing data set [47].

$$\mathrm{S} = \begin{cases} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{e}^{-(\mathrm{d}/13)} - 1\,, & \mathrm{d} < 0 \\ \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{e}^{(\mathrm{d}/10)} - 1\,, & \mathrm{d} \geq 0 \end{cases} \tag{3.3}$$

Where, S is the computed score, d is the difference between estimated RUL and actual RUL, and n is the number of units under test.

The penalty function is asymmetric as if give more penalty to late predictions. Lower scores are better; a perfect algorithm would score zero. Average of the calculated score for the given units in test data set is used for performance assessment in this chapter. The overall procedure of the proposed method can be illustrated in a flow chart as shown in figure 3.2.

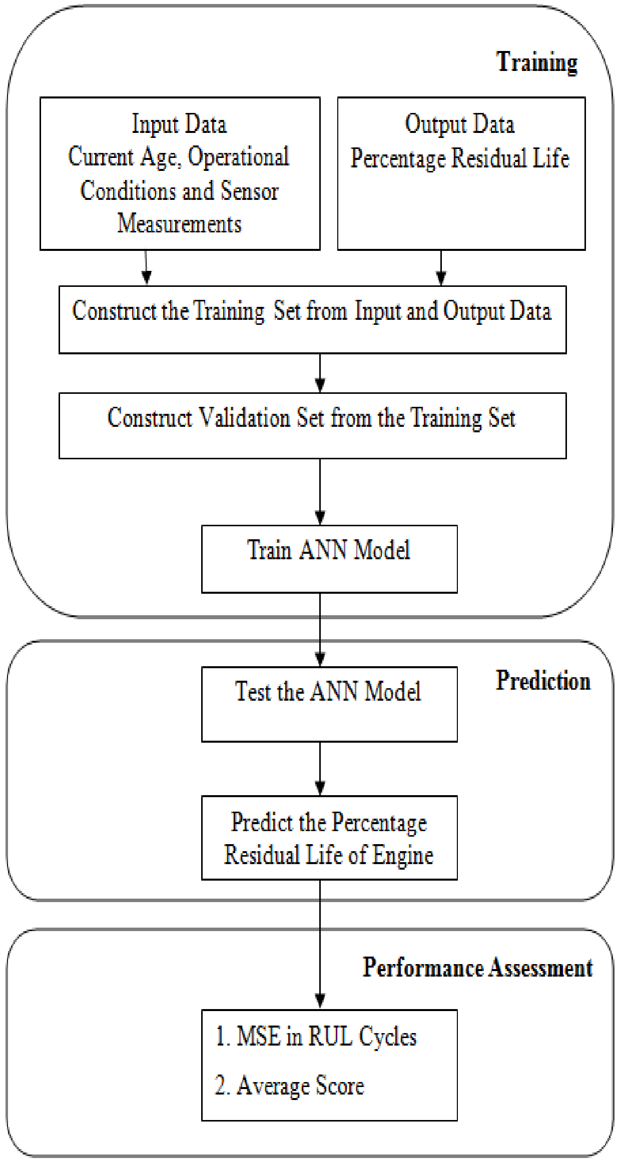


Figure 3.2 Flow chart of the proposed method for aircraft engine RUL estimation

3.3 Results and Discussion

The system monitored data includes operational data from 218 different units. In the present work variable data is divided in two subsets: training data (160 units) and test data (58 units). Table 3.2 presents the results of the ANN model.

Table 3.2 Results of ANN model

Validation Error	0.00451
No. of Neurons	13
MSE in RUL Cycles	1256
Average Score	130

Study of the Effect of Initial Wear: As the data was subjected to unknown initial wear, it is important to study the effect of the same on the prediction accuracy. Statistical control chart technique is used to screen the data with abnormal initial wear. Statistical control charts are generally used to monitor variables data from production machinery and identify the presence of abnormal process behavior because of chance causes [48].

In the present case, time to failure of units is considered as the variable monitored through control chart. $\bar{x}$ and R chart is used in the present study. Figure 3.3 shows $\bar{x}$ and R chart obtained for the given data. Statistical control limit on $\bar{x}$ chart are: upper control limit = 275 and lower control limit = 146. Thus after removing units that fall above or below the control limit on $\bar{x}$ chart; 187 units are obtained for further analysis. These 187 units are further divided into training set (137 units) and test set (50 units).

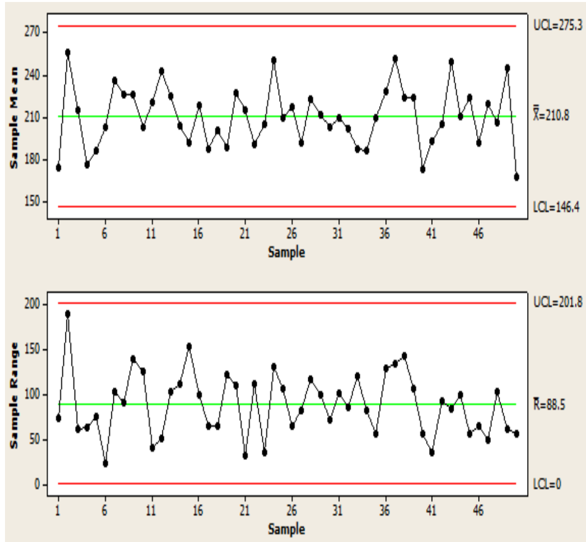


Figure 3.3 $\bar{x}$ and R chart

Table 3.3 shows the results of ANN model applied after screening of sample data. On comparing the results of table 3.2 and 3.3, it can be concluded that the prediction performance is significantly affected by the presence of the abnormal initial wear in the data. Hence, adequate measures should be taken before maintenance planning to handle such effects.

Table 3.3 Results of ANN model after screening abnormal initial wear samples

Validation Error	0.00306
No. of Neurons	13
MSE in RUL Cycles	708
Average Score	14

Guidelines to Handle the Effects of Initial Wear: As the presence of abnormal initial wear in the data may lead to poor prediction performance, the same needs to be quantify as accurately as possible. However it may not be possible many times to quantify such initial wear. In such cases updating the prediction with age of the component will be useful; as the prediction accuracy late in the life of the unit is more important than that early in its life. This will more likely affect the decision on whether or not preventive replacement should be performed at the current inspection point [37]. To investigate the prediction accuracy late in the unit life, we tested the prediction performance of units which have completed less than 50% of its life and which have completed more than 50% of its life. Table 3.4 indicates that the units which have completed less than 50% of its life have very high MSE and average score. On the other hand units which have completed more than 50% of its life have very low MSE and average score. Thus, a unit with short history tends to produce great uncertainty or variance, which results in unreasonably long or short estimation. The RUL prediction becomes more accurate when it is close to the failure time. Thus, continuously updating the RUL prediction will help in reducing the effects of abnormal initial wear on CBM planning.

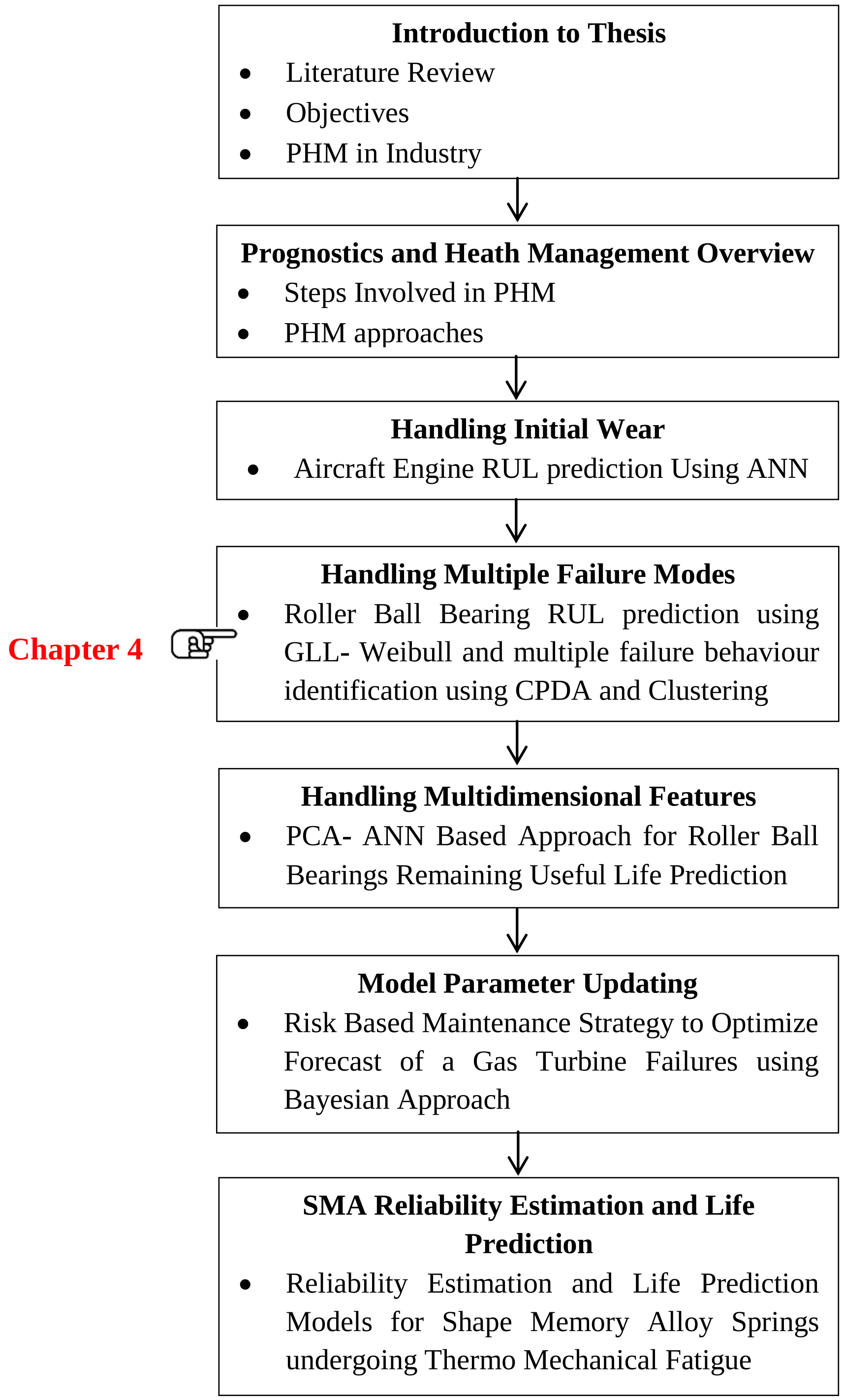
Table 3.4 Accuracy late in the life of the unit and early in its life

ANN Model 1		
MSE in RUL Cycles (>50%)	535	Count 27
AverageScore (>50%)	32	
MSE in RUL Cycles (<50%)	1885	Count 31
Average Score (<50%)	221	

3.4 Summary

This chapter has presented an ANN approach for RUL prediction of an aircraft engine under unknown initial wear. Two ANN models were developed. First model uses complete data which have unknown initial wear, while the second model is developed after removing samples with abnormal initial wear. The statistical quality control $\bar{x}$ and R chart was used to screen the samples with abnormal initial wear.

It is evident from test results that a unit with abnormal initial wear significantly affects the RUL prediction performance. It is also concluded that RUL estimation of a unit with short history tends to produce great uncertainty which leads to inaccurate prediction. Hence, updating the RUL prediction is the key to effective CBM planning.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Chapter 4

Multiple Failure Behaviour Identification and Remaining Useful Life Prediction of Ball Bearings

4.1 Problem Description

The bearing degradation data used in this research is taken from the PRONOSTIA platform (figure 4.1), which is an experimental platform used for testing and validation of diagnostic and prognostic approaches for rolling bearings. These data are used for this study with permission from IEEE PHM 2012 committee [49]. It can be seen from figure 4.1 that two accelerometers are mounted in the test platform to measure the vibration signals in horizontal and vertical direction. These accelerometers measure raw vibration signals at an interval of 10 seconds and with a sampling frequency of 25.6 kHz. It means 2560 data points are available at an interval of 10 seconds. When the amplitude of the vibration signal over passed 20g, the tested bearings were deemed failures.

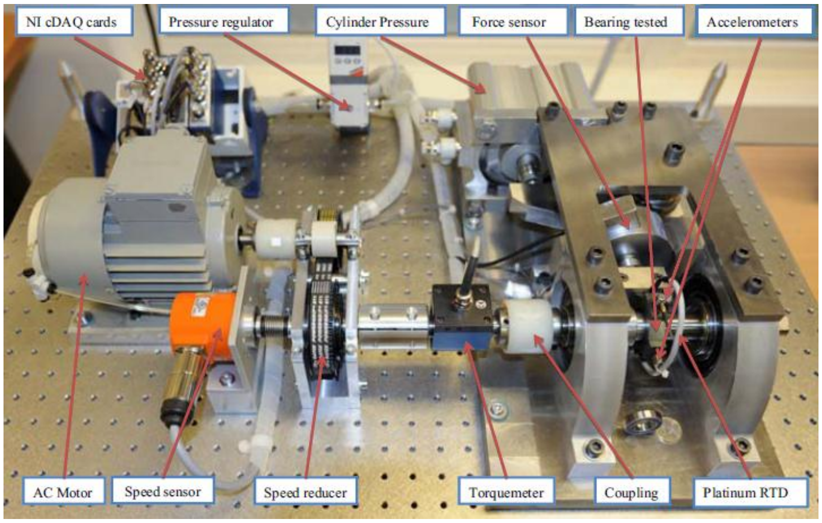


Figure 4.1 PRONOSTIA Platform

Data used in this work corresponds to the failure of the seven bearings under the operating conditions of 1800 rpm and 4000N. The failure time for each bearing is shown in table 4.1. All these bearings are run till failure, i.e., the defects are not seeded on the bearings. Thus, the bearings may fail due to any of the possible failure modes like failure of balls, rings or cage or their combinations. The presence of these failure modes resulting into multiple failure behaviour or patterns in life test data obtained from various units. Such data are very common in real industrial fleet. It is therefore required to identify the presence of multiple information in the data which is in the present case, is primarily due to presence of the multiple failure modes.

Further, small amount of training data and high variability (1h to 7h) in experimental duration poses additional challenges in failure prediction. Thus, the problem handled in this research was how to reduce the noise because of presence of the multiple failure modes and make accurate prediction of RUL.

Table 4.1 Time to failure for each bearing

Bearing ID	1	2	3	4	5	6	7
Time to failure (Second)	28030	8710	23750	14280	24630	24480	22590

4.2 Proposed Methodology for RUL Prediction

Figure 4.2 represents the flow chart of the present methodology. Experiment and data collection step is already discussed in section 4.1. The all other steps mention in the flow chart is discussed hereunder:

4.2.1 Feature Selection

The vibration data is very important to predict the health of the roller ball bearing; because both amplitude and the distribution of vibration signal change as bearing reaches close to failure. But, the raw vibration data obtained from the sensors is not suitable to represent the bearing degradation. Features are generally extracted from the raw data to get the relevant information about component degradation. Previous studies show that Root Mean Square (RMS), peak, kurtosis, skewness and crest factor are the major time domain features to represent any component failure using vibration signals [11, 12].The first two parameters reflect the vibration amplitude and energy in time domain; next three parameters represent the time series distribution of the signal in time domain. Table 4.2 contains the mathematical description of all the features.

From table 4.2, the parameter peak is used to represent the maximum excursion of the signal from the zero or equilibrium point. RMS is used to detect the imbalance in rotating machinery. However, RMS is not enough sensitive to detect incipient faults in particular. Crest factor is generally used to detect the changes in signal pattern due to impulsive vibration sources such as defect on the outer race of the bearing or a tooth breakage on the gear [50]. Kurtosis describes the impulsive shape of the signal and measures the peakdness of the signal. Skewness is the measure of the asymmetry of the probability of a signal about its mean.

Thus, the features mentioned above represent bearing degradation from different perspective. However, if all these features have been taken as input parameters to the model; then it may result into model over fitting. Over fitting means during training the model performance is good but during testing model performance is significantly worse. It generally occurs because of complexity in the model i.e. such as having too many parameters relative to the number of observations. Thus, before using these features as input parameters to the model, it is desirable to select the best bearing degradation indicative features from the feature set and remove the less indicative features to improve the model accuracy.

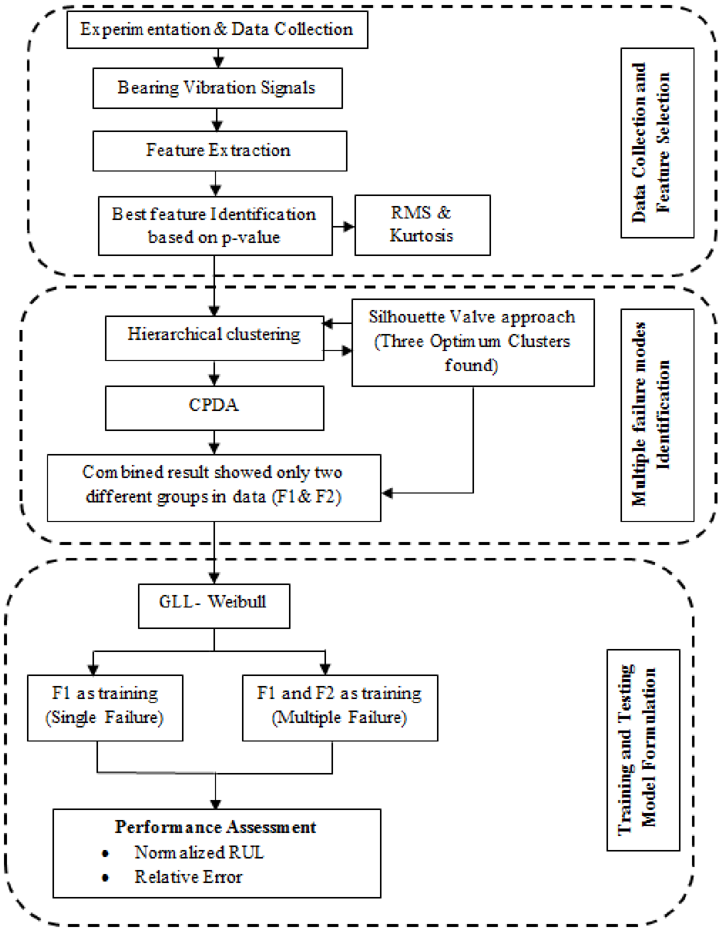


Figure 4.2 Proposed RUL prediction approach

Table 4.2 Feature parameters

$RMS\ (X_{rms}) = \sqrt{\dfrac{\sum_{i=1}^{N}(x_i)^2}{N}}$	Peak $(X_p) = \max\lvert x_i \rvert$	$Kurtosis\ (X_k) = \dfrac{N\sum_{i=1}^{N}(x_i-\bar{x})^4}{(N-1){x_{std}}^4}$
$Skewness\ (X_{ske}) = \dfrac{\sum_{i=1}^{N}(x_i-\bar{x})^3}{(N-1){x_{std}}^3}$	$Crest\ factor\ (X_{cf}) = \dfrac{X_p}{X_{rms}}$	
where x_i is a signal series for i = 1, 2, 3… N and N is the number of data points. $\bar{x}$ and x_{std} are the mean and standard deviation of the signal respectively.		

Conventional regression analysis has been used to select the most appropriate features. P value has been considered for best feature selection during model formation. P value is the probability of observing a sample statistic as extreme as the test statistic. The test statistic has been considered here is chi- square test. The chi –square value is mathematically represented as:

$$Chi - square = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \tag{4.1}$$

where, O_i is the observed value of the event i and E_i is the expected value of the event i.

This test is mainly used to compare observed data with data we would expect to obtain according to a specific hypothesis. If H_0 is the null hypothesis (i.e. no relationship between input and output parameters) and H_1 is the alternate hypothesis (i.e. some relationship between input and output parameters) then p value is defined as probability of obtaining observed sample results using chi-square test when the null hypothesis is actually true. It means low value of p indicates that alternate hypothesis is true and some relationship is present between the input and output parameters.

In the present example, the features with p value less than 0.05 are considered for model formation. RMS and kurtosis were found as best features for model formation.

4.2.2 Multiple Failure Behaviour Identification

The data provided by the PRONOSTIA platform are different because it corresponds to “normally” degraded bearings. It means the bearing defects (rings, balls and cage) are not initially initiated and any type of failure (balls, rings and cage) or their combinations can occur. Therefore, it is necessary to separate out the bearings with different failure mode. Clustering and CPDA is discussed in the next section is used for the same.

4.2.2.1 Clustering Approach

Clustering is an unsupervised learning algorithm and it can be directly applied to measured vibration data. Thus, it simply eliminates the need of the training data from the defective bearing. Clustering in general groups the similar data in to same cluster and divides dissimilar data in to different clusters by using some predefined criteria. Among various types of clustering algorithms, present study is using hierarchical clustering [44]. Following are the steps generally performed for hierarchical clustering:

- At starting assume each observation as its own cluster and calculate the initial cluster distance by using squared Euclidean distance between cluster points:

$$d_{ij} = d(\{y_i\}, \{y_j\}) = ||y_i - y_j||^2 \quad (4.2)$$

- Nearest clusters are merged after calculating the distance between each cluster and all other clusters

- At each step after merging, find the pair of clusters which leads to minimum increment in total with in clusters variance.

- If there are n observations, this process is repeated n-1 times until there is only one large cluster.

As information about number of failure behaviour is not available, to get the optimum number of failure behaviour (clusters) in the data; clustering approach is optimized using silhouette width value algorithm. The algorithm is discussed here under.

4.2.2.1.1 Silhouette Width Approach

Silhouette width approach calculates the difference between within- cluster tightness and separation from the rest [51]. Mathematically silhouette width s(j) for entity i € M is calculated as:

$$s(j) = \frac{b(j) - a(j)}{\max(a(j), b(j))} \quad (4.3)$$

where, a(j) is the average dissimilarity of j with all other data and b(j) is the minimum of the averages dissimilarity of j to any other cluster.

Its value lies between -1 and 1. -1 signifies the entity is misclassified, 1 signifies that set M is well clustered and near to zero means that the entity may belong to another cluster as well. Higher average silhouette width value of individual entities represents high closeness of the entities with in a cluster and high separateness between clusters. Thus highest value of average silhouette width is desirable.

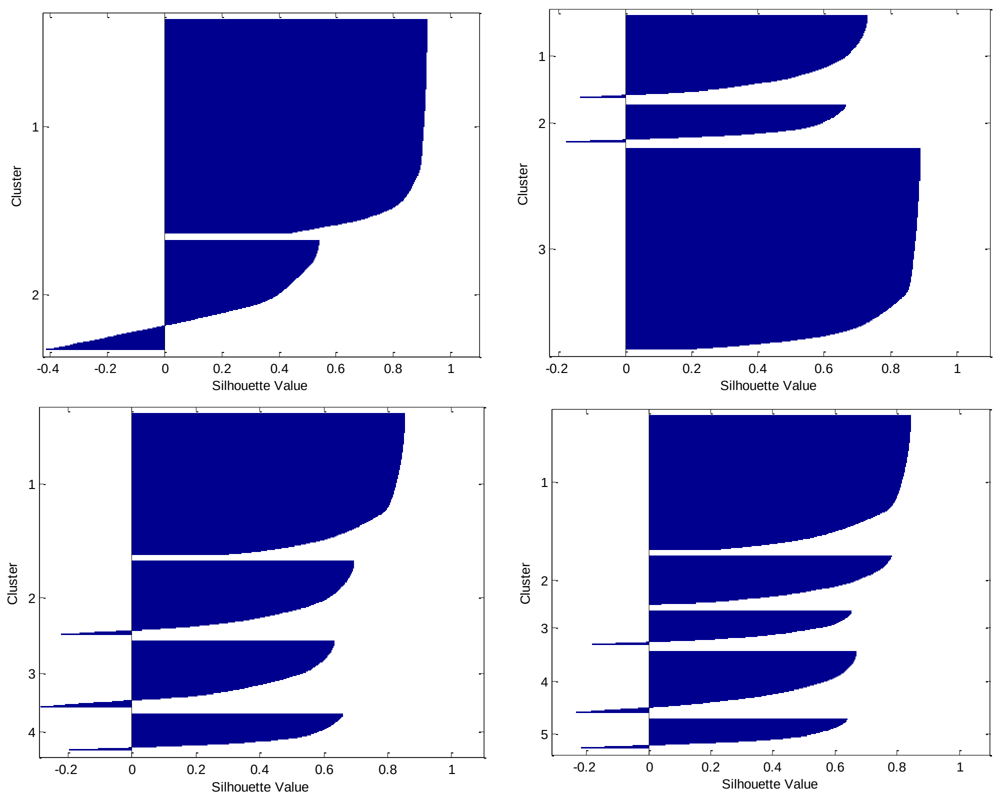


Figure 4.3 Silhouette width values for different number of clusters

For the present example, the average silhouette width values found with two, three, four and five number of clusters are 0.6637, 0.7183, 0.6055, and 0.6054 respectively. The largest average silhouette width is with three numbers of clusters. From silhouette plot also, it can be seen that in comparison of other number of clusters; with three numbers of clusters the entity in clusters are well grouped and for almost all of them silhouette width value is greater than zero. It means high tightness in the clusters and they are well separated from each other. Thus, the best number of clusters for the current data set is three.

With three numbers of clusters, figure 4.4 shows the results obtained from the hierarchical clustering. The relationship of each bearing with different clusters is clearly displayed in figure 4.4. Result indicates that bearing 1, 2, 3and 4 clearly belong to one cluster and 5 and 7 may have some overlap or confusion with cluster 2 and 3. Similarly, bearing 6 may go in cluster 1 and 2 both. To overcome this confusion Change Point Detection Algorithm (CPDA) is used.

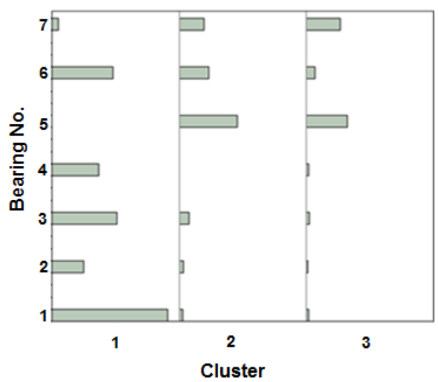


Figure 4.4 Hierarchical clustering approach

4.2.2.2 Change Point Detection Algorithm

Change point analysis is the process of detecting any kind of distributional change within a time series, i.e., point at which the statistical properties of a sequence of observations change [52].

For a finite time series data $x_1,\ x_2 \dots\dots\dots x_N$, a change point is said to occur when there exists a time, $t \in \{1 \dots\dots\dots N-1\}$ such that the statistical properties of $\{x_1 \dots\dots\dots x_t\}$ and $\{x_{t+1} \dots\dots\dots x_N\}$ are differ in some way. So, for multiple change points in data, we will have c number of change points together with their positions,$t_{1:c}\ = \{t_1 \dots\dots\dots t_N\}$. The detection of a change point can be placed as a hypothesis test. The null hypothesis H_0 corresponds to no change point (c = 0) and the alternative hypothesis H_1 is a single change point (c = 1). Consequently c change points will split the data into c + 1 segment, with the i^{th} segment containing $x_{(t_{i-1}+1):t_i}$.

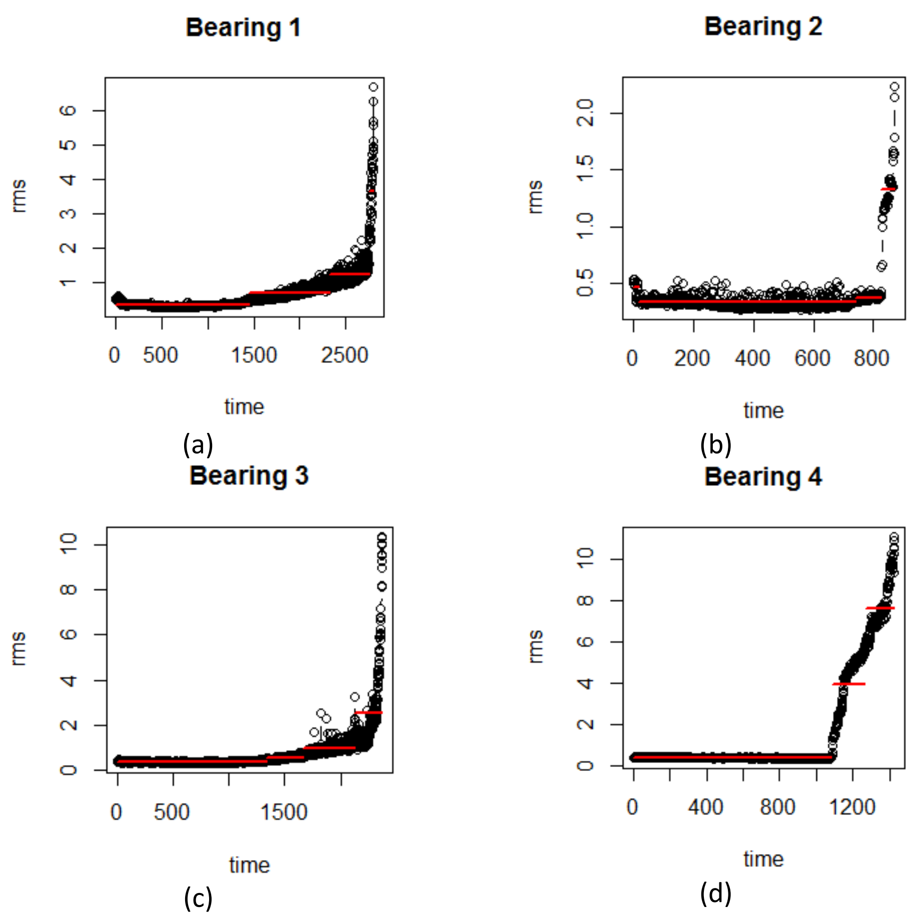
R (version 3.1.1) script is written to solve CPDA. For analysis change in mean and variance has been considered. Four change points in the bearing vibration signal are observed. Two different types of degradation pattern are found in the data set, i.e., gradual failure and abrupt failure based on the change points. Gradual failure was observed in bearing 1, 3 and 4 and abrupt failure was observed in bearing 2, 5, 6 and 7. For example, from table 4.3 and 4.4, as bearing 1, 3 and 4 approaches to the failure state, the observed vibration signals showed very high variation, i.e., variance and high amplitude, i.e., mean. These parameters (i.e. change in mean and variance) values continuously increase as we move from 2nd change point to 3rd change point and 3rd change point to 4th change point (drastic change in mean and variance both happened). 4th change point is the point of occurrence of failure. Whereas in bearing 2, 5, 6 and 7 such type of scenario is not observed and their parameter values are almost constant till third change point and suddenly large change was observed in these values from 3rd change point to 4th change point. Similar pattern can be seen from figure 4.5, where change points in time series for each bearing are highlighted by horizontal lines.

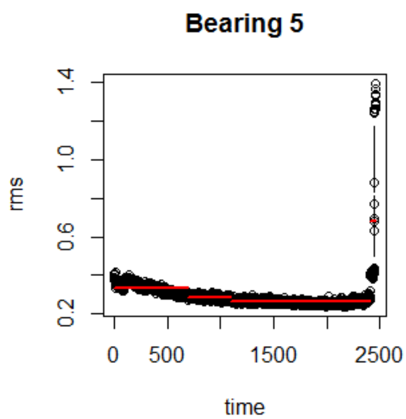
Table 4.3 CPDA mean results

Bearing ID	1st Change Point (Time)	2nd Change Point (Time)	3rd Change Point (Time)	4th Change Point (Failure Point)
1	0.366 (14500)	0.72 (23720)	1.26 (27480)	3.67 (28030)
2	0.465 (170)	0.34 (7380)	0.38 (8260)	1.32 (8710)
3	0.369 (13340)	0.55 (16680)	0.95 (21230)	2.55 (23750)
4	0.42 (2880)	0.38 (10850)	3.96 (12680)	7.61 (14280)
5	0.33 (6900)	0.28 (11020)	0.26 (24110)	0.68 (24630)
6	0.42 (5490)	0.35 (15870)	0.36 (24190)	1 (24480)
7	0.42 (2290)	0.33 (10890)	0.40 (22060)	1.50 (22590)

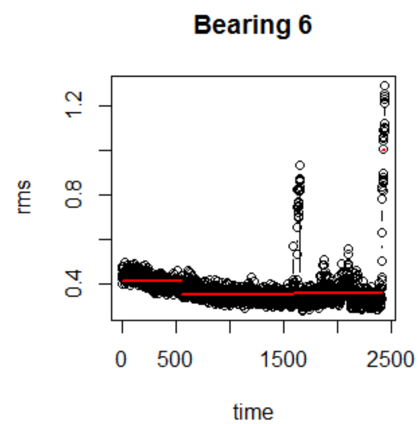
Table 4.4 CPDA variance results

Bearing ID	1st Change Point (Time)	2nd Change Point (Time)	3rd Change Point (Time)	4th Change Point (Failure Point)
1	3E-03 (14500)	2.4E-02 (23720)	4.9E-02 (27480)	1.26 (28040)
2	4.2E-02 (170)	1.9E-02 (7380)	5.1E-03 (8260)	8.2E-02 (8710)
3	7.7E-04 (13340)	6.23E-03 (16680)	4.9E-02 (21230)	3.89 (23750)
4	4.9E-04 (2880)	3.9E-04 (10850)	2.04 (12680)	1.60 (14280)
5	6.8E-04 (6900)	8.93E-05 (11020)	1.04E-04 (24110)	1.53E-01 (24630)
6	8.5E-04 (5490)	6.1E-04 (15870)	6.3E-03 (24190)	3.09E-02 (24480)
7	1.8E-03 (2290)	4.2E-04 (10890)	5.7E-04 (22060)	0.197 (22590)

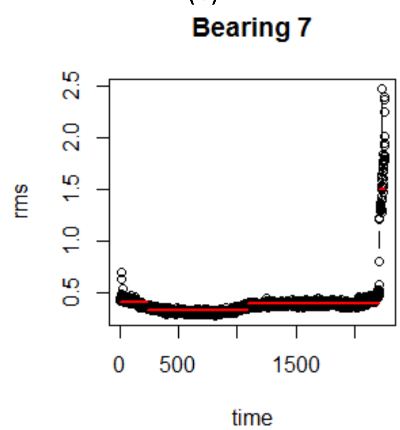




(e)



(f)



(g)

Figure 4.5 Graphical representation of CPDA mean and variance results

Table 4.5 Summarize results of clustering and CPDA

CPDA		**Clustering**	
Failure Pattern (FP)	Bearing ID	Cluster	Bearing ID
FP_1	1, 3, 4	C_1	1, 2, 3, 4 ,6
FP_2	2, 5, 6, 7	C_2	5, 6, 7
		C_3	5,7

Table 4.5 summarizes the results of CPDA and clustering approach. Combining the results of CPDA and clustering, following observations are made.

- Two distinct failure behaviour or patters (FP1 and FP2) are present in the data which may be because of the presence of two different failure modes in the test bearings. Cluster1 represents one type of failure behaviour (FP1) whereas the bearings in cluster 2 and 3 are closer to second type of failure behaviour (FP2).
- Thus, from both the approaches, it is clear that bearing 1, 3, and 4 has one type of failure behaviour (FP1) and bearing 5 and 7 show second type failure behaviour (FP2).
- Bearing 2 does not clearly classify under any of these two types of failure behaviour, as clustering approach classify it in first failure behaviour and CPDA classify the same in second type of the failure behaviour. Thus can be classified as abnormal behaviour and should be removed from the analysis. Later it is shown that removing bearing 2 from the analysis actually improves the model accuracy.
- Bearing 6 though classify under second type of failure behaviour from CPDA approach, the same also shows some closeness with first type of failure behaviour from clustering approach. Physically, this may happen if a component fails with one failure mode, while other failure mode is also initiated in it. In the next section, the implication of presence of such multiple failure behaviour, in model development is also highlighted.

4.2.3 General Log- Linear Weibull Model

Generally systems operating in harsher operating and environmental condition will fail at earlier times than those in milder environments. It means there are some additional factors that contribute to failure mode progression. These factors may be vibration, temperature, humidity, and pressure. The GLL-Weibull model was developed to estimates the effect of these different factors influencing the time to failures of a system. The output of the model is $\mathrm{F}(t|x_1, x_2 \ldots., x_n)$, which is the probability of failing at time't', given the presence of other covariates $x_1, x_2 \ldots., x_n$. It is a kind of covariate based model and generalization of Weibull – Proportional Hazard Model (Weibull-PHM).The difference between the equation of the GLL- Weibull and Weibull- PHM is that the life parameter is moved into the denominator of the exponent in GLL-Weibull (equation 4.4 and 4.6). The equation for Weibull-PHM can be expressed as:

$$F(t) = 1 - exp\left(-(t)^{\beta} \times exp^{a_o + \sum_{i=1}^{m} a_i X_i}\right) \tag{4.4}$$

where, t is the time to failure, β is the shape parameter, a_o is constant, i indexes the number of the covariates, a_i represents the coefficient for vital axis which defines the influence of the covariates on the failure process and x_i represents the vector of covariates. But for GLL-Weibull it becomes:

$$F(t) = 1 - exp\left(-\left(\frac{t}{\eta'}\right)^{\beta}\right) \tag{4.5}$$

where, η' $= exp^{a_o + \sum_{i=1}^{m} a_i X_i}$. It can be rewritten as:

$$F(t) = 1 - exp\left(-\left(\frac{t}{exp^{a_o + \sum_{i=1}^{m} a_i X_i}}\right)^{\beta}\right) \tag{4.6}$$

where, F (t) is failure probability, i.e., ratio of current time and total time. Total time means sum of current time and remaining useful life. So, RUL can be calculated as:

$$\text{RUL} = \frac{Current\ age\ of\ unit}{F(t)} - Current\ age\ of\ unit \tag{4.7}$$

Maximum likelihood estimation is commonly used for calculating the unknown parameters of GLL- Weibull. The likelihood function for GLL-Weibull is given by:

$$\text{L}\ (\beta, \eta') = \prod_{i=1}^{n} \left(\frac{\beta}{\eta'} * \left(\frac{t_i}{\eta'}\right)^{\beta - 1} * exp\left(-\left(\frac{t_i}{\eta'}\right)^{\beta}\right)\right) \tag{4.8}$$

However, the log likelihood function is more tractable as compare to likelihood function. The log-likelihood function for WPHM is:

$$\ln [L(\beta, \eta')] = n \ln(\beta) - n\,\beta \ln(\eta') + (\beta - 1) \sum_{i=1}^{n} \ln t_i - \sum_{i=1}^{n} \left(\frac{t}{\eta'}\right)^{\beta} \tag{4.9}$$

The maximization of equation 4.9 results in the estimation of the unknown parameters.

As, RMS and kurtosis were found as best features using p value, after considering these features the usual form of the GLL-Weibull used in current RUL prediction model is:

$$F(t) = 1 - exp\left(-\left(\frac{t}{\exp(a_o + a_1 * rms + a_2 * kurtosis)}\right)^{\beta}\right) \tag{4.10}$$

4.3 Results and Discussion

Based on the observations from clustering and CPDA, for bearings RUL prediction following four models were trained here using GLL-Weibull:

(a) Single failure behaviour model (M1): Trained with bearing 1 and 4. Exclude bearing 2 from the model training due to the abnormal behaviour, as discussed in section 3.2.2. The model is tested with bearing 3 and bearing 6.

(b) Single failure behaviour model (M2): Trained with bearing 1, 2, and 4, i.e. including bearing 2. The model is tested with bearing 3.

(c) Multiple failure behaviour model (M3): The failure probability density is obtained by integrating the failure probability density of the multiple failure behaviour, i.e., integrating the failure probability density of the two different failure behaviour presents in the data set. This model is developed using bearing 1, 4, 5, and 7. Exclude bearing 2 from the model training. The model is tested with bearing 3 and bearing 6.

(d) Multiple failure behaviour model (M4): This model is trained using bearing 1, 2, 4, 5, and 7, i.e., including bearing 2. The model is tested with bearing 6.

The distribution parameters for the GLL-Weibull model are found for above four cases (a, b, c and d), by using lifetime and condition monitored data. The obtained distribution parameters for each model are shown in table 4.6.

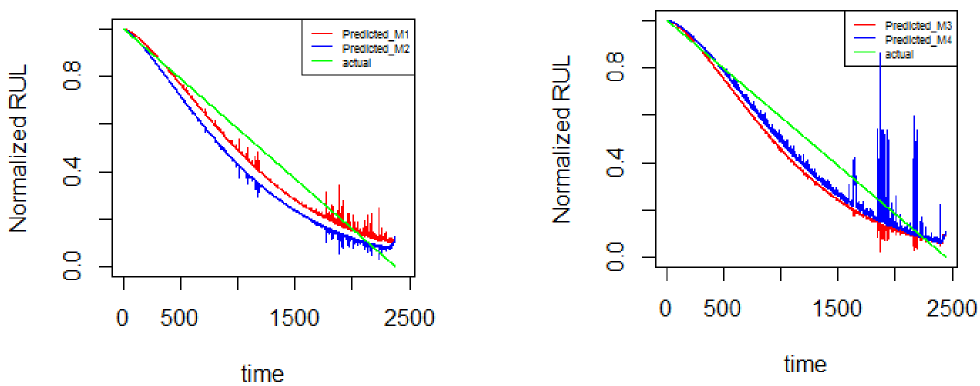
Table 4.6 Models distribution parameters

Parameters	M1	M2	M3	M4
a_o (Intercept)	9.43	9.35	9.34	9.35
a_1 (RMS)	0.0075	0.019	0.099	0.12
a_2 (Kurtosis)	0.0048	-0.004	0.0134	-0.004

As from GLL- Weibull model, a_1 and a_2 are the coefficient of the covariates, i.e., RMS and kurtosis respectively, these coefficient generally represents the influence of the covariates on the failure process. The values of the coefficients of RMS and kurtosis obtained from model 1(M1) and model 3 (M3) are positive. It means increase in the value of the RMS and kurtosis will increase the failure rate of the component. Whereas, from model 2 (M2) and model 4 (M4) RMS coefficients is positive and kurtosis coefficients is negative. It means according to M2 and M4, increase in the RMS value will increase the failure rate and increase in the kurtosis value will decrease the failure rate. But physically, as bearings approach to failure state, the RMS and kurtosis both should increases. Therefore, it can be concluded that bearing 2 has some abnormality and should be removed from the analysis. Similar results were observed in section 3.2.2. The effect of such abnormal behaviour in data, on RUL prediction can be seen from figure 4.6 and 4.7.

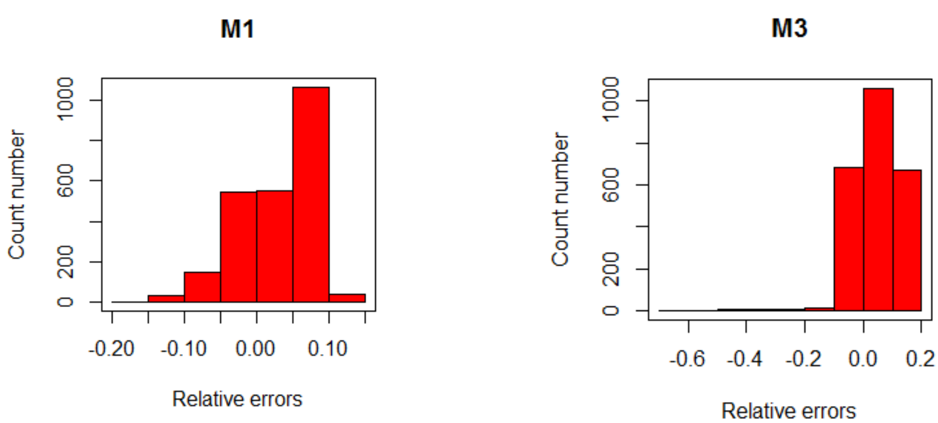
In figure 4.6 (a), the predicted RUL is closer to actual RUL from model M1 (i.e. without bearing 2) compared to model M2 (i.e. with bearing 2). Similarly in figure 4.6 (b), though both models M3 (i.e. without bearing 2) and model 4 (i.e., with bearing 2) give closer RUL predictions, the error in prediction is lesser in model M3 (i.e., without bearing 2), as more peaks are observed in case of model 4 (i.e., with bearing 2) near to the end life of bearing.

In order to get more clear picture, an error histogram is plotted as shown in figure 4.7(a)-(d). From error histogram: with model 1 (i.e., without bearing 2), only 3% of time the error in RUL prediction was more than 10%. With model 2 (i.e., with bearing 2), 47 % of time the error in RUL prediction was more than 10%. Similarly, with model 3 (i.e., without bearing 2), 29 % of time the error in RUL prediction was more than 10% and with model 4 (i.e., with bearing 2), 45 % of time the error in RUL prediction was more than 10%. It means including the bearing 2 in any of models result in high prediction error. Thus, CPDA and clustering provides an important input for RUL prediction model by identifying such abnormal data in the sample.

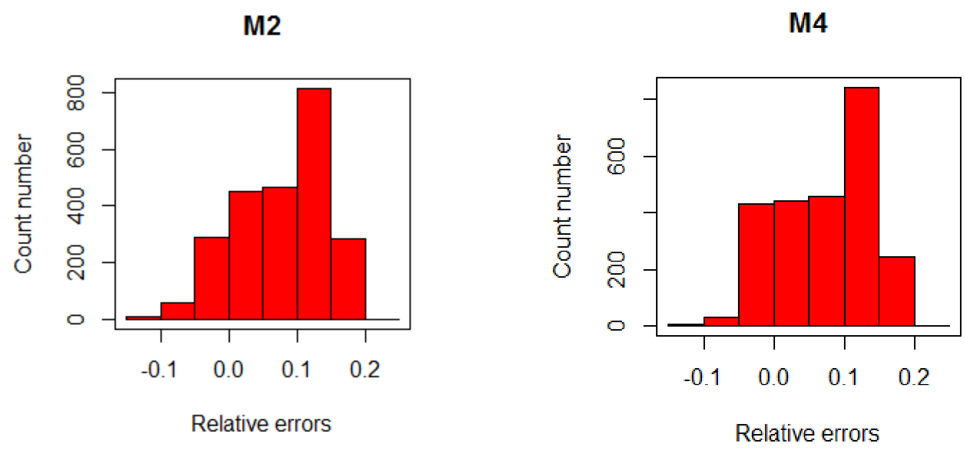


(a) (b)

Figure 4.6. Comparative RUL prediction results of (a) Bearing 3 with M1 and M2 (b) Bearing 6 with M3 and M4



(a) (b)



(c) (d)

Figure 4.7. Relative error histogram of (a) Bearing 3 (M1) (b) Bearing 6 (M3) (c) Bearing 3 (M2) (d) Bearing 6 (M4)

Finally after eliminating the bearing 2 from the model, to visualize the benefit of segregation of the bearings with different failure behaviour; model M1 (i.e. single failure behaviour model) is tested on bearing 6 (i.e. bearing having multiple failure behaviour) and model M3 (i.e. multiple failure behaviour model) is tested on bearing 3 (i.e. bearing having single failure behaviour). The figure 4.8 and 4.9 shows the results obtained from both the models on these bearings.

From figure 4.6, 4.7, 4.8, and 4.9, it can be seen that model M1 (i.e. single failure behaviour model) gives good result with bearing 3(i.e. bearing having single failure behaviour) but worse result with bearing 6 (i.e. bearing having multiple failure behaviour); whereas model M3 (.e. multiple failure behaviour model) gives good result with bearing 6 (i.e. bearing having single failure behaviour) and worse result with bearing 3 (i.e. bearing having multiple failure behaviour). Thus, both the models gave good results only with their respective failure behaviour bearings and gave worse results with other failure behaviour bearings. Therefore, identifying the presence of multiple failure behaviour helps in improving the RUL prediction accuracy.

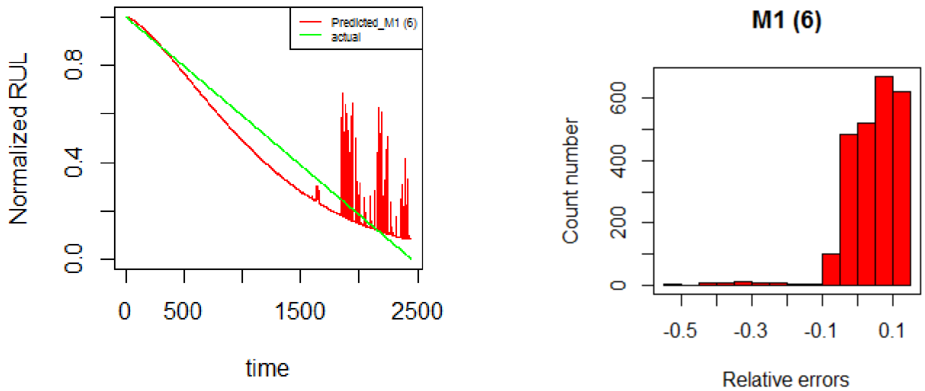


Figure 4.8. RUL prediction (a) and error histogram (b) plot for bearing 6 tested on model M1

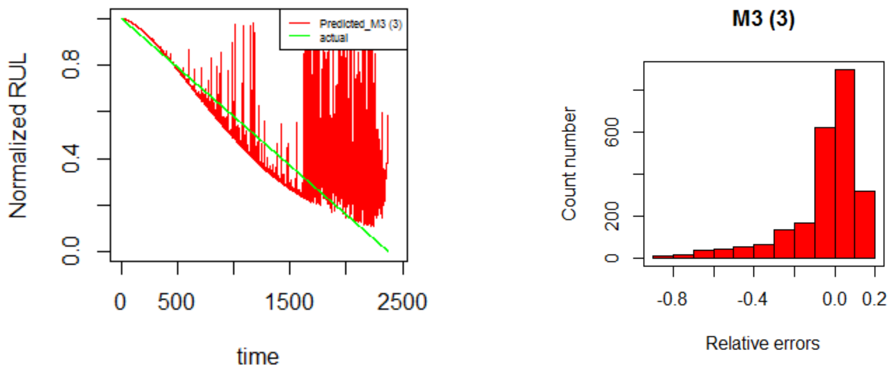
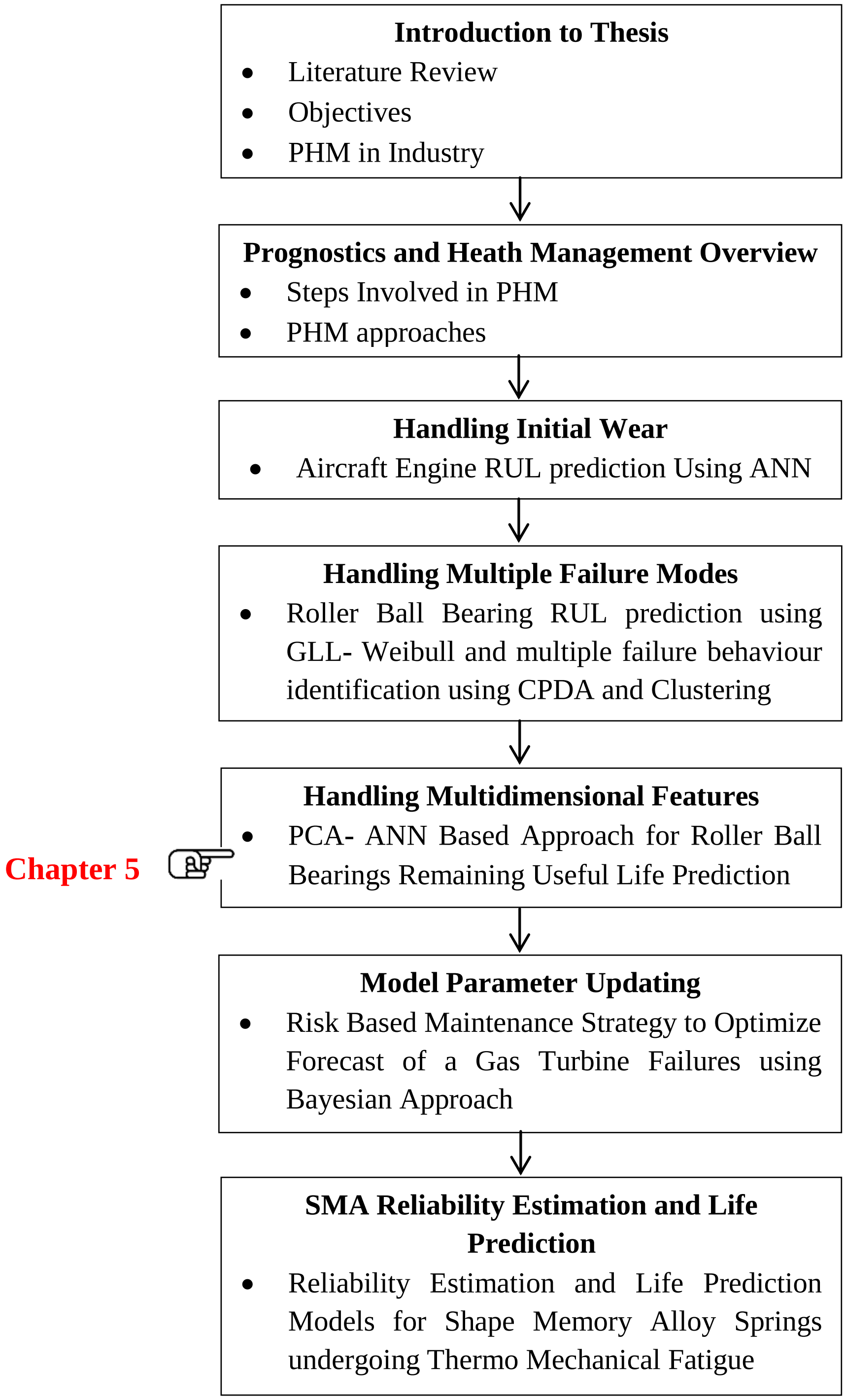


Figure 4.9. RUL prediction (a) and error histogram (b) plot for bearing 3 tested on model M3

4.4 Summary

The main focus of this chapter was to identify the multiple failure behaviour and integrate that information for efficient RUL prediction of ball bearings. Starting from review of prognostics modelling of individual failure behaviour, the present study provides an extension of prognostics analysis of a component with multiple failure behaviour. Condition monitoring variables provides the indirect information regarding the failure behaviour of each bearing. Hierarchical clustering and CPDA algorithm was used for the same. Combined results obtained from both approaches shows that before using any RUL prediction model it is desirable to use these approaches. These approaches will help in eliminating the components with abnormal behaviour in a sample and also helps in identifying the multiple failure behaviour present in the data set. Later it was found from RUL prediction model that this failure behaviour identification helped in accurate prediction of RUL. The model used for RUL prediction is GLL- Weibull distribution. The benefit of using this distribution is that the parameter values obtained from the distribution helped in eliminating the bearing which gave wrong information after including into the distribution. The lifetime and condition monitor data is used to estimate the parameters of the distribution. Different model were developed for single failure behaviour bearings and multiple failure behaviour bearings. The case study shows that proposed methodology is proved effective in RUL prediction using the developed models. The comparative study also indicates that the developed models are superior in accurately predicting RUL with respective failure ball bearings.


Introduction to Thesis
Literature Review
Objectives
PHM in Industry
Prognostics and Heath Management Overview
Steps Involved in PHM
PHM approaches
Handling Initial Wear
Aircraft Engine RUL prediction Using ANN
Handling Multiple Failure Modes
Roller Ball Bearing RUL prediction using GLL- Weibull and multiple failure behaviour identification using CPDA and Clustering
Handling Multidimensional Features
PCA- ANN Based Approach for Roller Ball Bearings Remaining Useful Life Prediction
Chapter 5
Model Parameter Updating
Risk Based Maintenance Strategy to Optimize Forecast of a Gas Turbine Failures using Bayesian Approach
SMA Reliability Estimation and Life Prediction
Reliability Estimation and Life Prediction Models for Shape Memory Alloy Springs undergoing Thermo Mechanical Fatigue

Chapter 5

PCA- ANN Based Approach for Roller Ball Bearings Remaining Useful Life Prediction

5.1 Problem Description

Roller ball bearing is one of the important components in rotating machinery. Research shows that the failures of bearings can produce around 40% of motor faults in rotating machinery [54]. The presence of these faults causes very high vibration and may affect the performance of other surrounding components. Timely prediction and elimination of these faults will help in reducing the downtime cost and economic loss to the customers [10]. Prognostic is the technology mainly used for timely prediction of these faults. Features extraction is the most critical step for implementation of prognostic approach as the effectiveness of such approach depends on the quality and sensitivity of features utilized to evaluate the condition and spread of the faults [10].

The work reported in literature is focused on selecting the best feature that can best fit to the model. However, it is always not possible to identify the features which are more sensitive to the fault propagation. In addition, even though possible; these features are still with high dimensionality and sparse information.

The main objective of this chapter is to fuse all these features in such a way that it reduce the dimensionality of the features and at the same time retain the sensitivity or variability of all the features.

For that vibration signals from PRONOSTIA [49] platform is used for the RUL prediction of the roller ball bearings. A Multi feature fusion technique PCA has been implemented here to extract out the optimum set of features for the current RUL prediction model. As the bearing vibration signal has the non-stationary and non-linear characteristics, ANN based prognostic algorithm is most widely used for bearing RUL prediction. The same is used in the present work also. To improve the accuracy of the conventional ANN model; best three principal components values obtained from the PCA and current time is used as input parameters to the model. The effectiveness of the current methodology is demonstrated over the conventional ANN.

5.2 Mixture of PCA and ANN

5.2.1 Principal Component Analysis (PCA)

PCA is a multi-feature fusion technique. This algorithm summarizes the large set of correlated variables with a smaller number of representative variables [44]. Generally three kinds of variability exist in the data. For example we have a two dimensional feature set; then there is some unique variability in first feature, variability unique to the second feature, and common variability to both the features.

The PCA approach generally transforms these two features into uncorrelated features while keeping the two sources of unique variation such that the total variation in the two features remains the same. It means PCA eliminates unnecessary correlations between variables or keeping the maximum variation among the variables with a minimum loss of information. The procedure of PCA implementation is describes in following sub section

5.2.1.1 Steps for PCA Algorithm

Suppose we have an n- dimensional data series $x^1, x^2, \dots \dots \dots \dots x^m$, where $x^i € R^n$ .Implementation of PCA will reduce this data in to k- dimensional data series $z^1, z^2, \dots \dots \dots \dots z^m$, where $z^i € R^k$. Following are the steps involved to convert this n dimensional data series into k dimensional data series.

- Before PCA implementation, it is mandatory to perform mean normalization.

$$\overline{x_j} = \sum_{i=1}^{m} x_j^i \tag{5.1}$$

Replace each x_j^i with the $x_j - \overline{x_j}$. Now each feature has the zero mean.

- If it is required, perform feature scaling. Because sometime it is possible that different features have very different scales. Scaling means the variables should be centered to have mean zero and standard deviation is one.

$$x_j^i \leftarrow \frac{x_j^i - \overline{x_j}}{x_{max} - x_{min.}} \tag{5.2}$$

- Compute the covariance matrix

$$Sigma = \frac{1}{m}\sum_{i=1}^{n}(x^i)(x^i)^T \tag{5.3}$$

Since, x^i is the matrix of order $n \times 1$. So, sigma will be the matrix of order $n \times n$

- Now use the Singular Value Decomposition (SVD) to calculate the Eigen vector of the sigma matrix.

$$[\mathrm{U}, \mathrm{S}, \mathrm{V}] = \mathrm{svd}\ (\mathrm{sigma}) \tag{5.4}$$

where, matrix U is used for the calculation of principal components and U $€\mathrm{R}^{n\times n}$. Now, let us suppose k numbers of principal components are required. Then select the first k^{th} vector of the U matrix. Now, U $€\mathrm{R}^{n\times k}$ and principal component (Z) is representing as below:

$$z = [U_{n\times k}]^T \times x \tag{5.5}$$

where, Z $€\mathrm{R}^{k}$. So, these sets of k variables are uncorrelated variables and called as principal components.

Principal component 1 is accounts for most variation in the data set. Principal component 2 is uncorrelated with the 1st and accounts for the second most variation in the data set. Similarly, k^{th}principal component is uncorrelated with principal components $1,2, \dots \dots (\mathrm{k}-1)$and account for the k^{th}most variation in the data set.

5.2.1.2. Proportion of Variance Explained and Optimum Number of Principal Components

Implementation of PCA generally loss some amount of information due to projection of the original features into few principal components. This amount of information is explained by proportion of variance.

The major objective of the PCA is to increase the total variance among the data $\frac{1}{m}\sum_{i=1}^{m}\|x^i\|^2$, while minimzing the average squared projection error $\frac{1}{m}\sum_{i=1}^{m}\|x^i - x^i_{appx.}\|^2$. Proportion of Variance Explained (PVE), mathematically can be written as:

$$PVE = 1 - \frac{\frac{1}{m}\sum_{i=1}^{m}\left\|x^i - x^i_{appx.}\right\|^2}{\frac{1}{m}\sum_{i=1}^{m}\|x^i\|^2} \tag{5.6}$$

where, $x_{appx.} = [U_{n\times k}] \times x$

This PVE also helps in selecting the optimum number of principal components required for model formation. Following are the steps involved in calculation for optimum number of principal components:

- Try PCA with k=1
- Compute $U_{reduce}, z^1, z^2, \dots \dots \dots \dots z^m$, and $x^1_{appx.}, x^2_{appx.} \dots . x^m_{appx.}$
- Now, check if

$$\left(1 - \frac{\frac{1}{m}\sum_{i=1}^{m}\left\|x^i - x^i_{appx.}\right\|^2}{\frac{1}{m}\sum_{i=1}^{m}\|x^i\|^2} \geq 0.85\right) \tag{5.7}$$

- If not, the try with k=2 and so on.

The limit defined above can be any value but at least should be greater than 0.85.

5.2.2 PCA-ANN

Due to adaptability, non-linearity, and ability of arbitrary function approximation artificial neural network is most widely used algorithm for RUL prediction [55]. Remaining useful life prediction using artificial neural network (ANN) were reported in many papers [36, 37, 55]. The difference is in present work instead of features obtained from raw vibration signal; the best principal components derive from those features using PCA are used as input parameters for the model. This helped in reducing the computational time and improving the model accuracy. This novel combination termed here after as 'PCA-ANN'. Figure 5.1 shows the basic architecture of the proposed PCA-ANN approach.

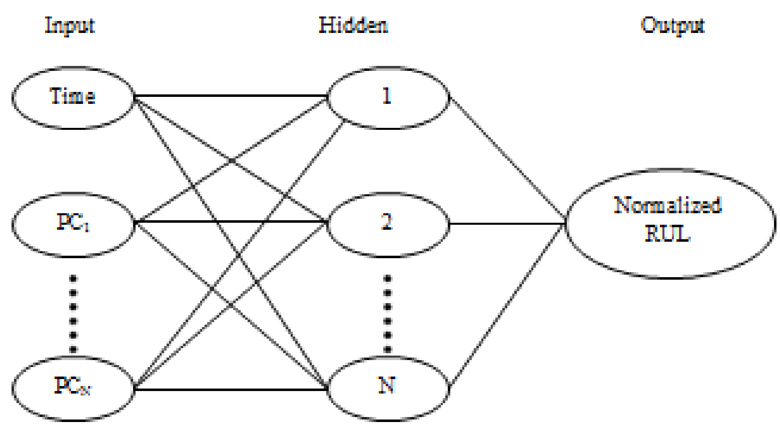


Figure 5.1 The architecture of the proposed PCA-ANN approach

The normalized RUL is taken as output parameter for the model, which mathematically is defined as:

$$\frac{Current\ RUL - Minimum\ RUL}{Maximum\ RUL - Minimum\ RUL} \tag{5.8}$$

5.3 Methodology

The RUL prediction methodology involves the training and testing of the proposed PCA-ANN model. Figure 5.2 shows the flow chart of proposed methodology. The proposed PCA-ANN approach is already discussed in previous section. The best set of features identification, comparative results and prediction performance between the conventional ANN and PCA-ANN are discussed in next section. Next subsection contains the information about the data used in this research.

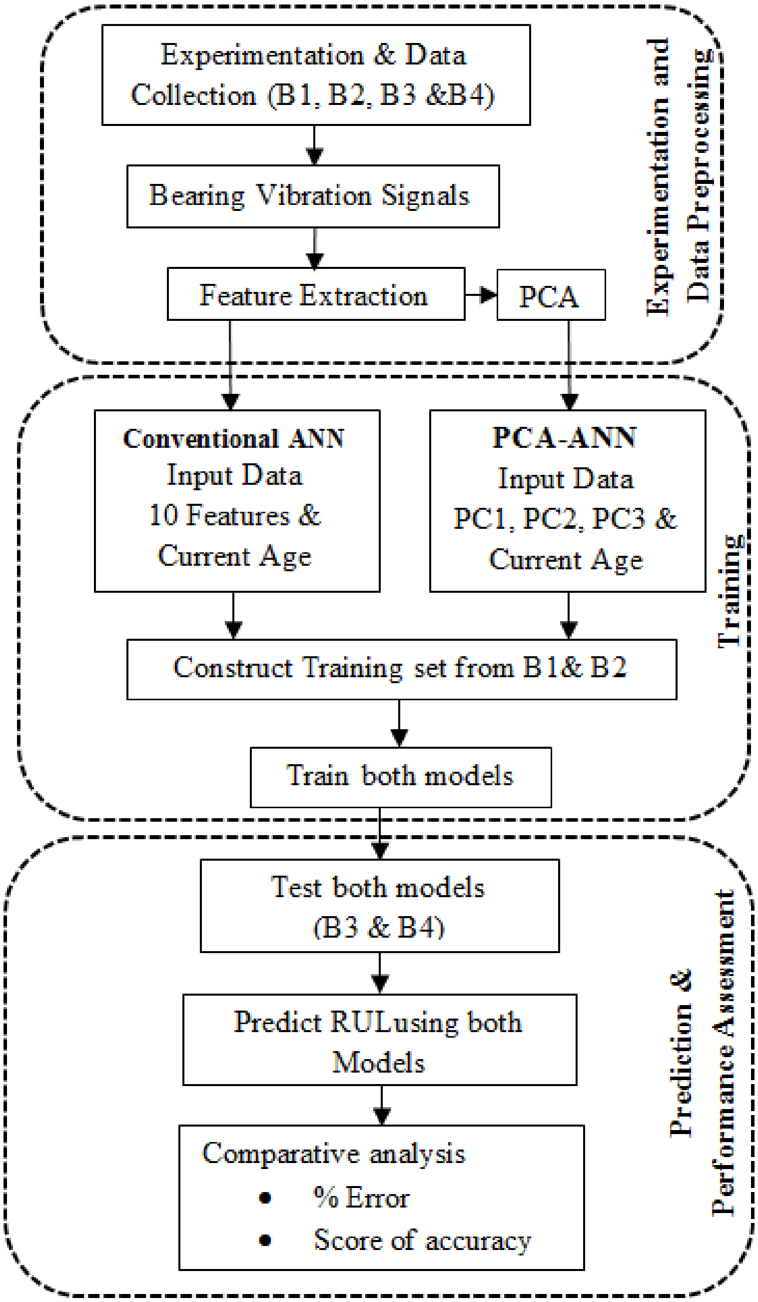


Figure 5.2 Flow chart of bearing RUL prediction procedure

5.3.1 Data Collection

For training and testing of proposed model bearing run to failure data has been taken from PRONOSTIA platform. The platform can collects both horizontal and vertical vibrations signals with a sampling frequency of 25.6 kHz i.e. 2560 samples recorded at intervals of 10 seconds. Four bearing under operating conditions of 1800 rpm and 4000N loads were analyzed here. Bearing 1 and 2 are used for training of the model whereas model was tested on bearing 3 and 4. The tested bearing data sets are truncated run to failure data sets, and an algorithm is required to estimate the remaining useful life from the truncation point to failure.

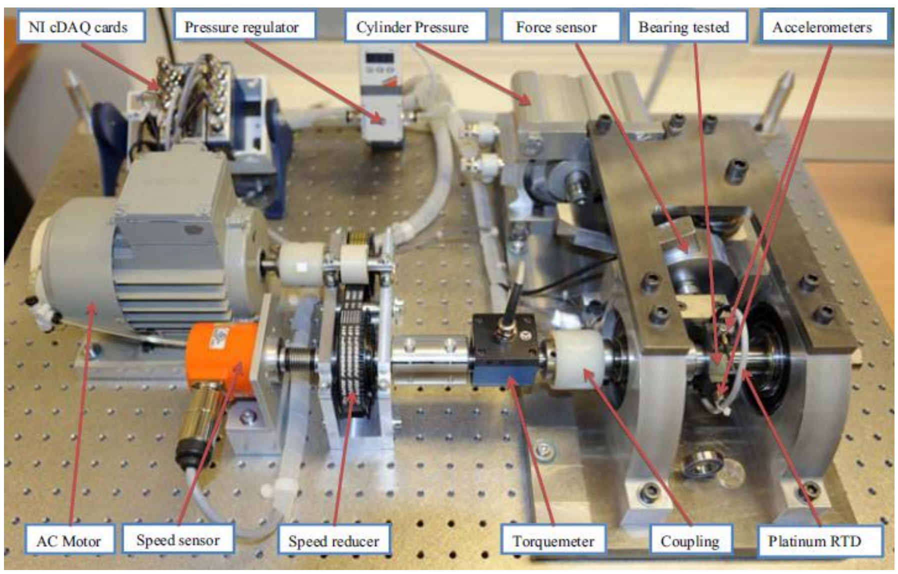


Figure 5.3 Overview of PRONOSTIA platform

5.4 Results and Discussion

5.4.1 Vibration Signal Analysis and Optimum Set of Features Identification

Proper selection of features from raw vibration data is the key step for RUL prediction. Previous studies indicate that RMS, kurtosis, peak, skewness, and crest factor are major indicator of fault propagation from vibration signal [11]. So, these five time domain features are extracted from both horizontal and vertical vibration signals. The dimensions of the extracted features are now reduced using PCA. As mentioned already, the variance should be calculated before performing

PCA; for bearing 1 the calculated variance are 0.091, 91.30, 2.43, 0.37, and 7.69 for RMS, kurtosis, crest factor, skewness, and peak respectively. It means for the current example, before performing PCA feature scaling is required. If we perform PCA on these unscaled variables, then the first principal component weight vector will have a large weighing for kurtosis, since that variable has by far the highest variance.

To check out the optimum number of principal components in the data, iteration has been performed up to 10^{th} principal component. As all of them are not so much important, first few principal components are only required to visualize or interpret the data. The scree plot has been plotted to check out the smallest number of principal components are required to explain a sizable amount of variation in data.

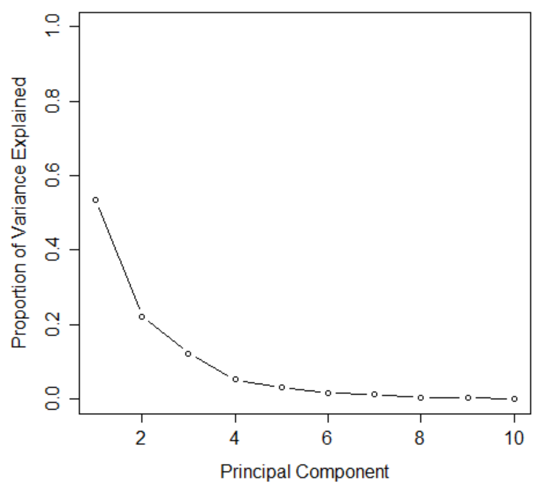


Figure 5.4 Scree plot depicting the proportion of variance explained

From figure 5.4, it can be seen that almost 90% of the variability is explained by three principal components and the fourth principal component explains less than 5% variability. Therefore, three principal components have been chosen for further analysis.

5.4.2 Model Over Fitting

Three layer (Input, hidden and output) feed forward back propagation neural network has been used for RUL prediction of roller ball bearings. Transig (Hyperbolic tangent sigmoid) is used as transfer function in the hidden and output layer of the current model. Levenberg Marquardt (LM) learning algorithm with 20 numbers of neurons in the hidden layer is used to construct the model. To see the effect of the over fitting in the model; in PCA-ANN model iteration has been made from principal component 1 to principal component 10.

MSE was calculated in each iteration. Figure 5.5 shows how the training and testing MSE is changing with number of principal components. It can be seen with lesser number of principal components; both training and testing error are high but close to each other. Whereas, with more number of principal components training error is very low but testing error is very high, which is the indication of the over fitting. The minimum testing error is obtained with three principal components. It means three is the optimum number of principal components that should be used for further model development. This results also validate the result obtained using PVE in sub section 5.4.1

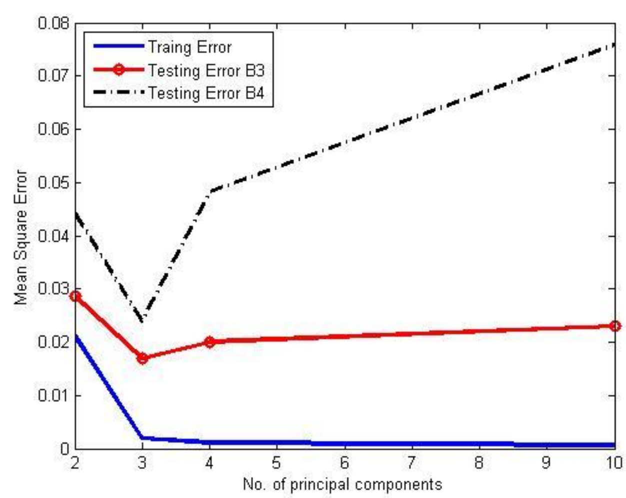


Figure 5.5 Error associated with number of principal components

5.4.3 Comparative Results between PCA-ANN Approach and Conventional ANN Approach

Following two models are developed here for RUL prediction:

a) Conventional ANN model: Developed using current age and five time domain features extracted from both horizontal and vertical vibration signals as input parameters to the model. Normalized RUL is taken as output parameter to the model.
b) PCA-ANN model: Developed using current age and best three principal components obtained from the PCA as input parameters to the model. Normalized RUL is output for the model.

In order to see the improvement in accuracy with PCA-ANN model over the conventional ANN model, following performance indices are used.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Predicted\ RUL - Actual\ RUL)^2 \tag{5.9}$$

$$\%\ Er = \frac{Actual\ RUL - Predicted\ RUL}{Actual\ RUL} \times 100 \tag{5.10}$$

$$\%\ Accuracy = 100 - |\%\ Er| \tag{5.11}$$

$$S_i = \begin{cases} exp^{-\ln(0.5).(\%Er_i/5)}\ if\ \%\ Er\ \leq 0 \\ exp^{+\ln(0.5).(\%Er_i/5)}\ if\ \%\ Er > 0 \end{cases} \tag{5.12}$$

where, MSE is the mean squared error, % Er is the % error and S_i is the score of accuracy.

First three performance indices are widely used in prognostics literature and are self-explanatory. The score of accuracy is designed in such a way that it will give exponential penalty to prediction error. It is asymmetric and gives more penalties to over prediction. Score value near to 1 indicates the highly accurate results and near to zero indicates worse result [49].

Table 5.1 shows the MSE values obtained using both the approaches. Table 5.1 clearly indicates that for conventional ANN model, testing MSE is significantly higher than training MSE which indicates over fitting. However, for the proposed PCA-ANN approach training MSE and testing MSE are almost close to each other. It means proposed approach reduces the over fitting of the model.

Table 5.1 Comparative error estimation from Conventional ANN and PCA-ANN

Approach	Training MSE	Testing MSE
Conventional ANN	0.0007	0.023 (B3) 0.0757 (B4)
PCA-ANN	0.0019	0.0170 (B3) 0.0239 (B4)

Table 5.2 indicates the all other performance indices values obtained from both the approaches. It can be seen from table 5.2 that the RUL predicted by the proposed approach is better than the conventional ANN approach. It means the proposed PCA-ANN based approach also reduces the noise and non-linear characteristics of the bearing vibration signal.

Table 5.2 RUL prediction result from Conventional ANN and PCA-ANN

Bearing ID	Actual RUL	Predicted RUL	% Error	% Accuracy	Score of accuracy
3 (PCA-ANN)	5730	5577	2.8	97.2	0.68
4 (PCA-ANN)	2890	2721	5.84	94.16	0.44
3 (Conventional ANN)	5730	1958	65.82	34.18	1×10^{-4}
4 (Conventional ANN)	2890	1532.62	46.96	53.04	1.48×10^{-3}

5.5 Summary

The novelty in this work is to improve the ANN model accuracy by obtaining the optimum set of input parameters for the model. Conclusions drawn from this work are summarized here under.

- Multi feature fusion technique PCA is used here for calculation of optimum set of features that can be input to the model. Benefit of using PCA here is that, it generally keeps the sensitivity of all the features and removes the unwanted noise and bias associated with combination of all the features.
- With increment in number of parameters to the model, it shows high testing error as compare to training error. To overcome this optimum number of principal components were found; it helps in reducing the over fitting in the model.
- Due to non-linear nature of bearing vibration signal; ANN approach is used for RUL estimation. The proposed approach is validated with experimental data of accelerated life tests of roller bearings.
- Comparative study on both the approaches reveals that proposed PCA-ANN approach is better than conventional ANN. It means the combine PCA-ANN approach is helps us in reducing the over fitting of the model.
- The RUL predicted by the proposed methodology is much better than conventional ANN approach. It means proposed approach largely able to reduce the noise and non-linear characteristics of the bearing vibration signals.
- All the prediction performances also validate the usefulness of the proposed methodology.

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- Steps Involved in PHM
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Handling Initial Wear

- Aircraft Engine RUL prediction Using ANN

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Handling Multiple Failure Modes

- Roller Ball Bearing RUL prediction using GLL- Weibull and multiple failure behaviour identification using CPDA and Clustering

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Handling Multidimensional Features

- PCA- ANN Based Approach for Roller Ball Bearings Remaining Useful Life Prediction

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Chapter 6

Model Parameter Updating

- Risk Based Maintenance Strategy to Optimize Forecast of a Gas Turbine Failures using Bayesian Approach

↓

SMA Reliability Estimation and Life Prediction

- Reliability Estimation and Life Prediction Models for Shape Memory Alloy Springs undergoing Thermo Mechanical Fatigue

Chapter 6

RBM Strategy to Optimize Forecast of a Gas Turbine Failures

6.1 Problem Description

Competition and aging of equipment's create two competing financial pressures on businesses viz., to reduce operating cost and the reduction of consequential cost of forced outages [56]. Proper maintenance of the machine helps in achieving these goals. Condition based maintenance can be used for the same. However, the effectiveness of the CBM depends on the accurate prediction of the future risk of failure of the unit.

The objective of the work reported in this chapter is to predict future risk of the failure of the unit to assist in effective implementation of the CBM strategy in the industry. A Risk Based Maintenance (RBM) methodology is developed for the same. It calculates the future risk of failure of a gas turbine power plant system so that the maintenance can be planned just before occurrence of failure.

To calculate the risk, first a General Log Linear Lognormal (GLL- Lognormal) model, which tells about damage growth of the machine, is developed. Bayesian approach is then used to update the model parameters (i.e. GLL- Lognormal) on the basis of new inspection data (i.e. crack length) and calculate the updated risk. It is recommended that risk should be continuously updated with the age of the unit to increase the effectiveness of RBM policy. The novelty in this work is that the failure probability is directly dependent on observed crack length instead of time to failures. The whole analysis is illustrated with cap effusion plate inspection data of actual gas turbine system.

6.2 Proposed Risk Based Maintenance Approach

Risk based maintenance (RBM) framework is comprised of two main phases as shown in figure 6.1. First is the risk assessment and second is maintenance planning on the basis of the calculated risk [57]. The risk assessment phase involves (i) identification of scope/case study (ii) Damage growth model (iii) Risk (normal fleet level model) (iv) Updated risk (Bayesian Approach) (v) Financial impact. These are discussed briefly in following paragraphs.

6.2.1 Case Study: Heavy Duty Gas Turbine

The purpose of Gas Turbine is to convert chemical energy of fuel into electrical energy. Mainly, gas turbine consists of air compressor, combustor, turbine and generator (figure 6.2). These four components also contain some subcomponents. For example, combustor consists of fuel nozzle, end covers, cap effusion plate, combustion liner and transition pieces. Different parts of combustor have different types of failure modes. Some of the historically observed failure modes in a combustor are liner cracks, liner bulging, thermal barrier coating spallation, fuel nozzle clogging, end cover braze leaking joint and effusion plate cracks [58]. In the present work, focus is on the failure of a cap effusion plate of a gas turbine (figure 6.3). Cap effusion plate acts a thermal barrier to reduce temperature and thermal gradients [59]. It has premixed tubes acting as shrouds for the fuel nozzle. For this study a fleet of GE gas turbine has been considered.

6.2.2 Damage Growth Model

For predicting the damage growth of the cap effusion plate General Log Linear Lognormal (GLL- Lognormal) model is used. A random variable is log normally distributed if the logarithm of the random variable follows the normal distribution. Because of this, there are many mathematical similarities between the lognormal distribution and a normal distribution. If crack length follows lognormal distribution then cumulative probability of failures is given in equation 6.1.

$$\mathrm{F}\,(\mathrm{L}) = \phi\left(\frac{\ln(L) - \mu}{\sigma}\right) \tag{6.1}$$

Lognormal distribution is a two parameter distribution. It's characterized by μ and σ, which are the mean and the standard deviation of the distribution respectively. ϕ is the standard normal cumulative density function and L is the crack length.

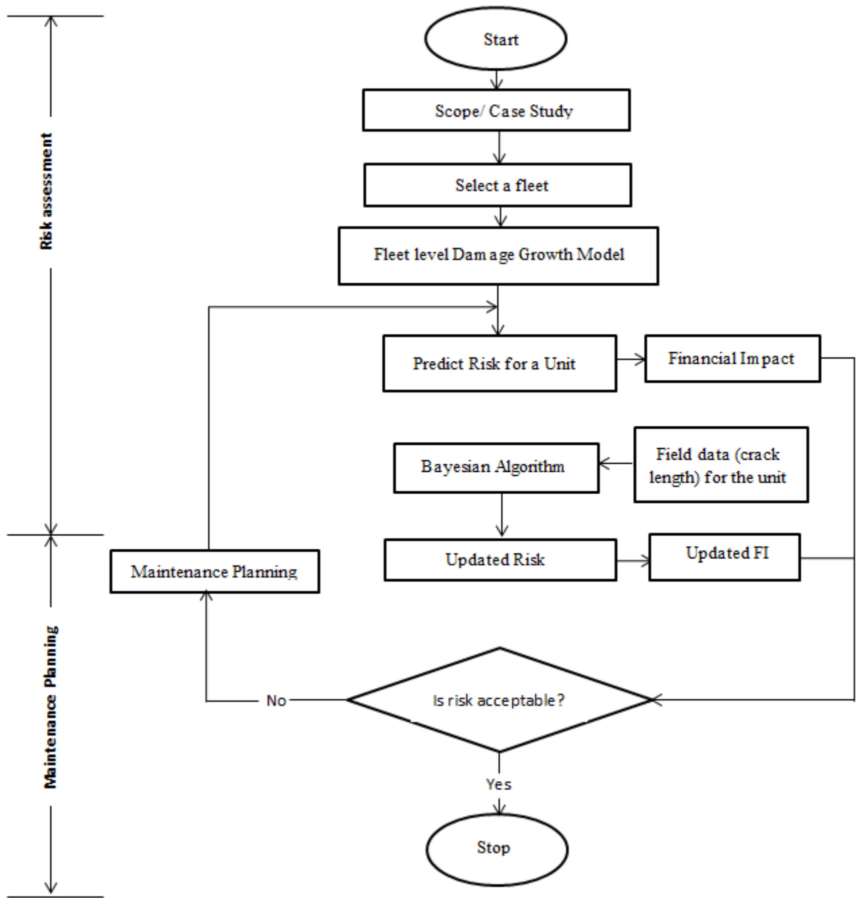

Figure 6.1 General risk – based maintenance approach

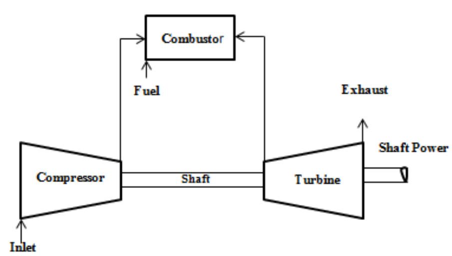

Figure 6.2 Block diagram of a Gas Turbine Power System

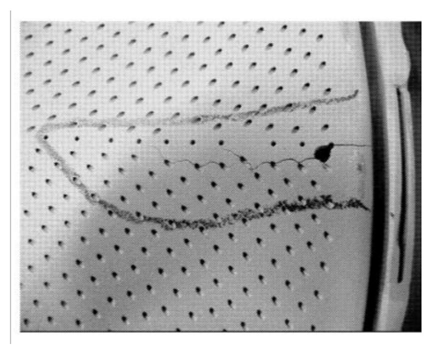

Figure 6.3 Cap effusion plate cracking [59]

The probability of failure changes with exposure as well as other factors like, environmental and operational conditions factors. The GLL was developed to estimate the effect of different factors influencing the time to failures of a system. According to GLL, the probability of failure is affected not only by the operational exposure, but also by the covariates under which it operates. The mathematical formulation of GLL- Lognormal is given in equation in 6.2.

$$F(L) = \phi\left(\frac{\ln(L) - (a_0 + a_1x_1 + \cdots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . + a_nx_n)}{\sigma}\right) \qquad (6.2)$$

Where, $\mu = (a_o+a_1x_1+a_2x_2+\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..+a_nx_n)$, a_o is intercept and a_1, a_2 are the coefficients for critical X's respectively which are correlate to failure.

As seen from equation 6.1 and 6.2 the GLL- Lognormal has all of the properties of a standard lognormal, except the lognormal mean is a linear function of critical X's which are correlated to failure. For the current model critical X's is ln(hours). The usual form of the GLL- Lognormal used in current damage accumulation model is:

$$F(l < L_{critical}) = \phi\left(\frac{\ln(L_{critical}) - (a_0 + a_1 * \ln(hours))}{\sigma}\right) \qquad (6.3)$$

Where, $L_{critical}$ is critical length above which the component is replaced.

6.2.3 Risk Calculation

The risk of failure is defined as the conditional probability of a part failing at some additional operating time Δt, given that it has survived up to time t. So, risk is calculated as:

$$\text{Risk} = P\left(t + \Delta t \,\middle|\, t\right) * 100 = \frac{P(t + \Delta t) - P(t)}{1 - P(t)} * 100 \qquad (6.4)$$

Where, P (t+Δt) and P (t) are the probabilities of a crack exceeding a given limit at time (t+Δt) and t respectively.

$$P(t) = F\left(l > L_{critical} \;\middle|\; \text{hour}\right) = 1 - \phi\left(\frac{\ln(L_{critical}) - (a_0 + a_1 * \ln(hours))}{\sigma}\right) \tag{6.5}$$

Risk brings together contributory elements of the business and multiple engineering disciplines [56]. So from business point of view financial impact is calculated using equation 6.6.

$$\text{Financial impact (\$)} = \text{Risk} \;*\; \text{Failure Consequences (\$)} \tag{6.6}$$

where, failure consequences are the downtime cost associated with the failure.

Financial impact is used to calculate the updated inspection/maintenance schedule to accommodate customer demand of extending the inspection schedule of the gas turbine by certain hours. On the basis of financial impact decision has to be made whether to go for maintenance or not or by how many hours machine can be run safely to accommodate customer demand.

6.2.4 Risk Updating using Bayesian Approach

In product reliability and availability studies, Bayesian methods offer an intelligent way of incorporating the field experience and data, resulting in an overall more precise failure probability estimation. Risk calculation using General Log Linear Lognormal is not accurate because it does not consider field data (i.e. crack length), it consider only operation exposure. Purpose of using Bayesian here is to use inspection data (observed crack length) to calculate the unit specific risk. The process of Bayesian update can be repeated continuously with each inspection. Any Bayesian update method for a damage accumulation model requires a few common elements given below:-

a) An underlying damage accumulation model characterized by some parameters that have some statistical uncertainty associated with them (i.e. GLL- Lognormal here)

b) Some prior information about the uncertainty around these parameters (Ex: σ, μ are normally distributed with known mean and variance).
c) Some field data that will be used to modify the original σ and μ (for example crack length in this chapter)

Using the Bayesian method, we calculate "Bayesian update factors" for the distribution location and scale parameters. These factors adjust the location and scale parameters to reflect inspection data (i.e. they simply "push" or "pull" distribution) and on the basis of these updated parameters future risk is calculated. Bayesian approach is derived from Bayes theorem and is shown in equation 6.7.

$$\mathrm{P\ (Hypothesis/Data)} = \frac{\mathrm{P\ (Data/Hypothesis)} * \mathrm{P(Hypothesis)}}{\mathrm{P(Data)}} \tag{6.7}$$

where, P (Hypothesis) is the prior probability of hypothesis (before taking into account new inspection data), P (Hypothesis/Data) is the conditional probability of hypothesis given new inspection data and P (Data/Hypothesis) is the conditional probability of data given hypothesis.

Thus, the observations of new inspection data update information on event of interest. In the current model hypothesis is model parameters (i.e. μ and σ) and the inspection data is the crack length. So, the Bayes theorem can be rewritten for the present case to update the risk as shown in equation 6.8.

$$\mathrm{P}\ (\mu\&\sigma/crack\ length) = \frac{\mathrm{F\ (Crack\ Length/}\mu\&\sigma) * P(\mu\&\sigma)}{\mathrm{P(crack\ length)}} \tag{6.8}$$

Where, left hand side of equation presents the posterior distribution of model parameters. It applies to predict the updated risk. In the right hand side of equation, in numerator, first factor presents the conditional probability of observed data with assumed model (lifetime distribution) given parameters and second factor presents the prior distribution of model parameters. Denominator of equation is called normalizing constant which assures that posterior distribution is valid probability distribution and integrates to 1. Normalizing constant causes computational difficulties, so Bayes formula is expressed as:

$$\text{P}\ (\mu\ \&\ \sigma\ /crack\ length)\ \alpha \text{P}\ (\text{crack length}\ /\mu\&\ \sigma) *\ P\ (\mu\ \&\ \sigma) \tag{6.9}$$

It can be written as:

Posterior **α** likelihood * prior (6.10)

And likelihood for a lognormal distribution is given in equation 6.11:

$$\begin{aligned} \text{Likelihood } &= \text{P}(l_i/\mu\&\sigma) \\ &= \prod_{i=1}^{n}\left[\frac{1}{\sigma l_i\sqrt{2\pi}} * exp\left(-\frac{1}{2}\left(\frac{\ln(l_i)-\mu}{\sigma}\right)^2\right)\right] \end{aligned} \tag{6.11}$$

6.2.4.1 Main Steps for Bayesian Update Algorithm

Consider a density function with parameters θ, written as f (θ). The observed data is in vector data. The fundamental rule for Bayesian inference is:

$$\text{f}\,(\theta/\text{DATA}) = \frac{\text{L}\ (\text{DATA}/\theta) *\ \text{f}(\theta)}{\int \text{L}(\text{DATA}/\theta)\ * \text{f}(\theta)\text{d}\theta} \tag{6.12}$$

$$= \frac{R(\theta) *\ f(\theta)}{\int R(\theta)\ * f(\theta)d\theta}$$

Where R (θ) = L (θ)/L ($\theta^{\wedge}$) is relative likelihood and f (θ) is prior density function.

a) From damage accumulation model i.e. Log normal distribution (with a known σ and μ that is not known precisely), σ and μ has a prior distribution with some mean and variance.

b) Generate the $\boldsymbol{i^{th}}$sample, θ_i, i=1…... N, from prior f (θ).The prior can be sampled from the covariance matrix used in the damage accumulation model.

c) Now calculate likelihood function with prior distribution values and sampled distribution values, and then pass the relative likelihood ratio through a statistical filter (i.e. retain the i^{th} sample value, θ_i, with probability R (θ_i). Do this by generating U_i, a random quantity from a uniform (0, 1) and retain θ if $U_i < R(\theta_i)$.)

d) It can be shown that the retained sample values, say θ_{i*}………… θ_{N*}($N^* < N$), are a random sample from posterior pdf f (θ/DATA).

e) The average of the updated distribution of σ and μ is the new best estimate of σ and μ, i.e. this is the new value of scale parameters that will be used for risk calculations

Thus, it can be concluded that Bayesian is very useful because it can build a model combining physics based models, expert opinion and data. Also, it is useful when sufficient data is not available. But to use Bayesian approach, we need to understand prior distributions and model evaluation. The overview of whole Bayesian update algorithm is shown in figure 6.4

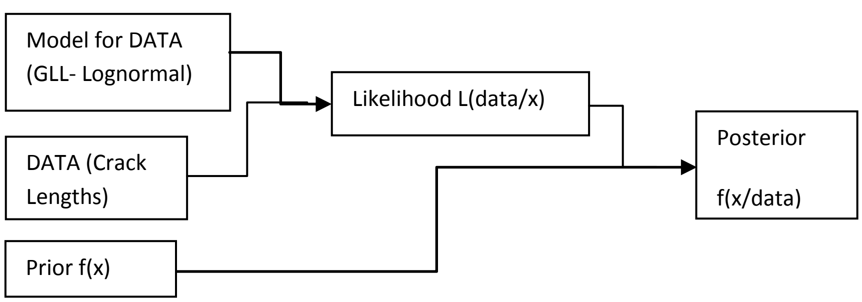

Figure 6.4 Overview of Bayesian Algorithm

6.3 Results and Discussion

The risk estimation model is constructed based on the hours and crack length of cap effusion plate using fleet of a gas turbine. JMP Pro 11 software is used to construct GLL- Lognormal. The coefficient obtained for the model are a_o= -3.1 and a_1 = 0.30 and from these coefficient the risk estimation model is created which is shown in equation 6.13.

$$P\ (t)\ = \left(1 - \ \phi\left(\frac{\ln(2.5) - (-3.1 + 0.30 * \ln(hours))}{1.13}\right)\right) * 100 \qquad (6.13)$$

Let critical crack length as 2.5 inch and consequence of failure be $1.5 Million. Now, from new inspection data set, risk can be calculated in two ways: using normal fleet level model (GLL- Lognormal) and Bayesian update. A program has been written in Matlab version 2011 to solve Bayesian approach. The results from both models are shown in table 6.1. Risk and financial impact are calculated. If we assume that the cost of planned shutdown $ 1.5 million and cost of unplanned shutdown is $150 million then from equation 6.6, the threshold level of risk is becomes 1%. It means, whenever, risk exceeds 1% then extending inspection hour or planned PM schedule is not desirable. In other words, based on the critical limit of risk as 1%, extra time a machine can be run safely can be calculated. In the present work, the same is obtained as 7725 hours and 7994 hours using simple GLL- Lognormal and Bayesian update respectively. Thus, the gas turbine can be made available based on the demand of the customer, for production for 269 more hours based on the updated risk calculation.

Risk value from both the approaches at various intervals of time is also calculated (table 6.2). It can be seen at time interval of 7900 hours the risk calculated using the conventional approach is 1.134% whereas the risk calculated from the Bayesian approach is 0.952%. It means by conventional approach turbine is above the critical limit (i.e. 1%) whereas from Bayesian approach it is away from the critical limit. Therefore, according to conventional approach turbine has to be stopped before 7900 hours but from the Bayesian approach it can run beyond 7900 hours also.

Thus, for the current problem, the Bayesian approach may give extra run hours, when requested. Owing to the strict data control policy of GE, the exact results are replaced with the current table. The results in current table are scaled version of actual results.

Table 6.1: Risk analysis results (Scaled up/notional Values)

Normal fleet level model (GLL- Lognormal)			Bayesian Update		
Hours	***Current Interval (6500)***	***Future Interval (7500)***	***Hours***	***Current Interval (6500)***	***Future Interval (7500)***
μ	-0.466	-0.423	**μ**	-0.333	-0.302
σ	1.13	1.13	**σ**	1.1253	1.1253
$F(l>L_{critical})$	11.059%	11.793%	**$F(l>L_{critical})$**	13.352%	13.948%
$P(t+dt \mid t)$ Risk	0.8251%		**$P(t+dt \mid t)$ Risk**	0.6874%	
Financial Impact	1.24 Million $		**Financial Impact**	1.03 Million $	

Table 6.2: Comparative risk analysis table at various interval of time

Time (Hours)	Risk (GLL- Lognormal)	Risk (Bayesian)
6700	0.171597	0.145435
6900	0.339758	0.287491
7100	0.504639	0.426337
7300	0.666386	0.562128
7500	0.825131	0.695009
7700	0.981002	0.825115
7900	1.134115	0.952569
8100	1.28458	1.077488

6.4 Summary

The chapter presents an approach to optimize the RBM methodology using Bayesian algorithm on GE gas turbine. This approach not only increases the availability but also reduces maintenance cost. It is also found that forecast of risk using Bayesian is better than normal fleet level model because it consider field experience and data. Finally, it concluded that proposed Risk Based Maintenance

(RBM) approach using Bayesian update can be used to increase the availability and optimize the high value critical assets (i.e. Gas Turbine) while reducing overall maintenance costs.

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SMA Reliability Estimation and Life Prediction

- Reliability Estimation and Life Prediction Models for Shape Memory Alloy Springs undergoing Thermo Mechanical Fatigue

Chapter 7 ☞

Chapter 7

Reliability Estimation and Life Prediction Models for Shape Memory Alloy Springs undergoing Thermo Mechanical Fatigue

7.1 Problem Description

Need of miniaturisation is shifted the use of conventional actuators with smart actuators. Conventional actuators generally produce the power in proportion to their volume; which reduce their application in miniature and micro applications. Shape Memory Alloys (SMAs) is one of the most promising materials used in this kind of actuator. Due to light weight, high power to weight ratio, noiseless operation, ease of actuation and muscle like movement; this material is seen as an alternative to conventional actuators such as pneumatic and hydraulic [60]. As an actuator SMA has the wide range of application. For example, in medical they used in orthodontic wire, biliary stent, regional chemotherapy, endoscopic guide wire; in automobiles they used for oil controller and steam tap; in construction they have the application in underground ventilation and static rock breaker; and in aerospace they are used in cryofit, frangibot and in pin puller [61].

It was found that with continuous input stimulus or because of aging effect; the degradation in the mechanical properties of the SMA material occurs. This results in steady departure from their initial performance specifications. Reliability is the concern if SMA based devices used in any critical application and a key factor for successful commercialization of these devices. It is a key parameter for the eventual prevalence of SMA as either sub- components or as a standalone product and it also contributes to improve the device performance. The work reported in literature on SMA life analysis is discussed in the following paragraph.

Bertacchini et al. (2003) presented the fatigue behaviour of the SMA wire undergoing thermo mechanical cyclic loading. It was observed that with aging of SMA wire; spallation oxidation occurring at its surface, which damages its properties. This cause the formation of micro cracks and growths of these circular cracks are finally responsible for the component failure [62]. Saikrishna et al. (2012) evaluated the functional fatigue behaviour of NiTi SMA wires obtained from different sources. It was found that though wires had similar transformation temperatures and mechanical properties; their functional fatigue behaviour upon thermo- mechanical cycling was at variance. This is because of difference in residual stresses in SMA wires which generally occurs either of thermo mechanical processing and/or post processing stabilization treatment [63]. Pappas et al. (2007) observed that the after a long period of activation (either cyclic or continuous) under constrained conditions the SMA material loses its ability to act as a force generator. Through SEM they observed that it generally occurs because of gradual slipping of martensite variants over the twin boundary regions which causes the vanishing of preferentially oriented martensite within the wire structure [64]. Eggeler et al. (2004) found two different fatigue behaviour of the SMA: structural and functional fatigue. Structural fatigue means the accumulation of microstructural damage during cyclic loading. Whereas, functional fatigue means decrease in working displacement of the SMA with increasing cycle numbers which also cause the change in microstructure and leads to fatigue failure [65].

These observed information helped to introduce a reliability model for SMA which is discussed in section 7.5. So far no work has been reported on reliability analysis of shape memory alloy. The work presented in the current chapter will help research engineers to develop a high performance and high reliable SMA device in future.

For reliability estimation, the root cause of the failure was understood and experiments were performed in accelerated conditions to obtain the life time data in a shorter period of time. The test plan starts with applying drive conditions (e.g. voltage) and environment conditions (e.g. mechanical load). From obtained data, degradation model is developed using GLL- Weibull distribution and its parameter is continuously updated with the life of the spring to improve accuracy in life prediction. The Bayesian approach is used for the same. The deterioration of material with number of cycles was also investigated using TGA and SEM.

This whole analysis will help in understand the internal (i.e. technology and design related) and external variables (i.e. operating and environmental conditions) affecting the life of the SMA.

7.2 SMA Overview

Certain metallic material has the properties to regain back their original shape from an apparent plastic deformation on the application of heat. The material which shows this kind of behaviour is known as Shape Memory Alloy (SMA). The unique property of the SMA results from a crystalline phase change known as "thermo-elastic martensitic transformation". Practically SMA has two different phases with three different crystal structures (i.e. twinned martensite, detwinned martensite and austenite) [60]. Below transformation temperature it exists in martensite phase and above transformation temperature it exists in austenite phase. This shape memory effect is characterized in two different categories: one way shape memory effect and two way shape memory effect.

In one way; below transformation temperature its microstructure is characterized by "self-accommodating twins". During this state SMA is quite soft and deformed to any shape by detwinning. When it heated above the transformation temperature; the transformation will take place from detwinned martensite to austenite. At this state SMA regain its original shape and convert the material into its high strength austenitic condition.   In one way, cooling from austenite phase does not cause any macroscopic change in shape and a deformation is required to create the low temperature shape.

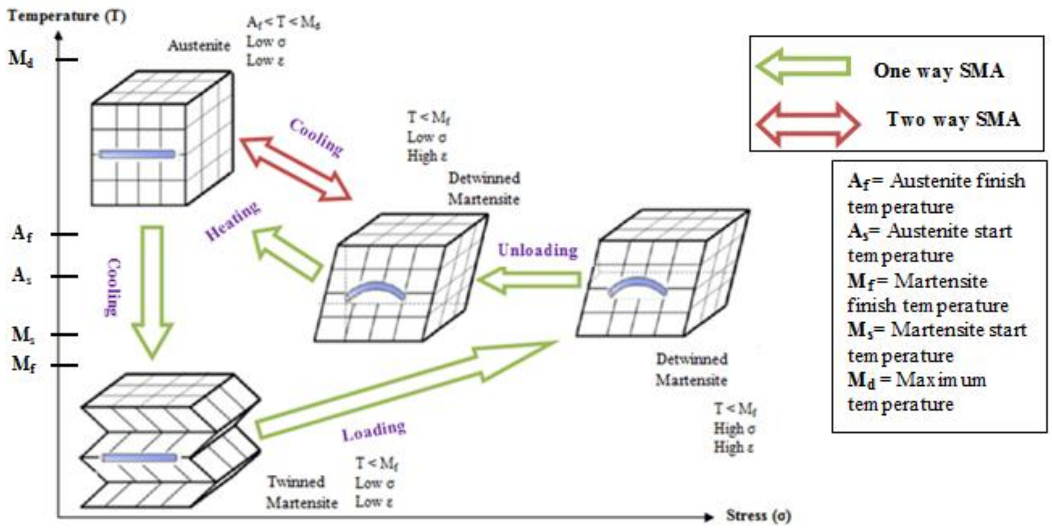


Figure 7.1 Shape memory alloy behaviour [60]

In two way; the material can remember two different shapes: one at low temperature and another at higher temperature, i.e., they have the ability to 'memorise' both low temperature shape and as well as high temperature shape. Figure 7.1 is showing the different types of behaviour of the SMA. From figure 7.1; M_d is the highest temperature above which SMA is permanently deformed like any ordinary metallic material. So, during experimentation the actuation temperature given to the SMA should not go beyond M_d.

7.3 Experimental Platform and Data Collection

The SMA fatigue behaviour is generally characterized in three different ways [66]. First, fatigue by fracture due to stress or strain cycling at constant temperature. Second, change in physical, mechanical and memory properties due to pure thermal cycling through the transformation region. Third, change in physical, mechanical and memory properties is due to combination of thermal cycling through the transformation region with constant stress or strain loading.

In most of the mechanical application third kind of fatigue behaviour is common and same is considered here. For that, an experimental set up was designed and developed to carry out the data from starting point to till failure. Figure 7.2 and 7.3 represents the photograph and schematic overview of the experimental set up.

The set up used a Laser Displacement Sensor (LDS); J- type thermocouple; Programmable Power Supply (PPS); external weight applied to the spring with the help of pulley and SMA spring.

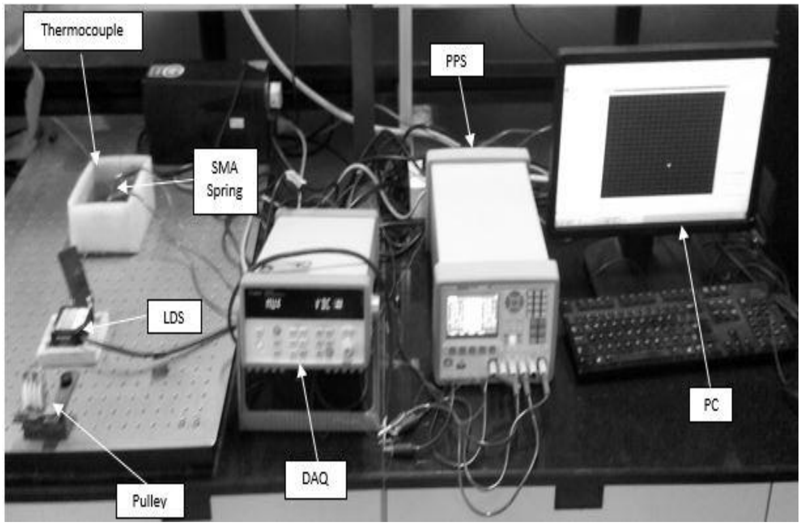


Figure 7.2 Experimental set up to characterize SMA spring actuators

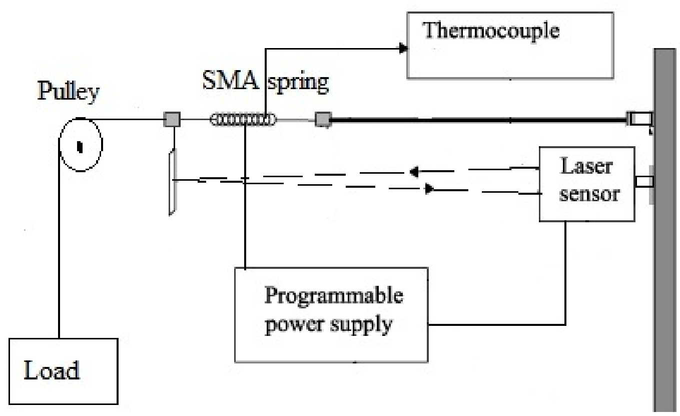


Figure 7.3 Schematic overview of the set up for reliability assessment

The Ni-Ti SMA spring was procured to investigate the life characteristics of the spring. The specification of the spring used for the current case study is given in table 7.1. It was one way trained and contract upon actuation, i.e., application of voltage. External load has been applied to keep the spring in the extended position. The specific energy required for the phase transformation of the spring is supplied through PPS. PPS also helps in controlling the heating and cooling cycles of the springs.

Table 7.1 Specification of the Ni-Ti SMA spring

Wire Diameter (mm)	Mean Diameter of the coil (mm)	Number of turns	Solid length (mm)	Actuation Temperature (^{o} C)
0.77	5.69	18	13.86	70-80

At beginning of the experiment; weight is applied to the spring and keep the spring in extended position. After applying a voltage V_c to the spring through PPS; spring recover its original length against the gravity by lifting the weights. After recovery; voltage has been cut off and allows the spring to cool at room temperature. During cooling, the external weight applied to the spring forced to spring back to the deformed shape. Number of iteration has been performed to calculate the time for heating and cooling of the SMA spring. It was found that for particular spring specification; it takes 20 seconds to complete back to its original position (i.e. heating) and 70 seconds for complete extension (i.e. cooling). The heating and cooling phase of the spring is named as actuation and release of the spring respectively. The combined actuation and release is the one cycle for reliability testing of the spring. The reduction in elongation over the number of cycles is the representation of the failure. The elongation of the spring was measured with the help of the LDS. J- Type thermocouple was attached to measure the temperature during actuation and release of the spring.

The designed experimental set up has the following advantages for reliability analysis:

a) The voltage can be supplied to the spring from 0 V to 6 V. So, accelerated life analysis can be made through supplying of different voltages to the spring.

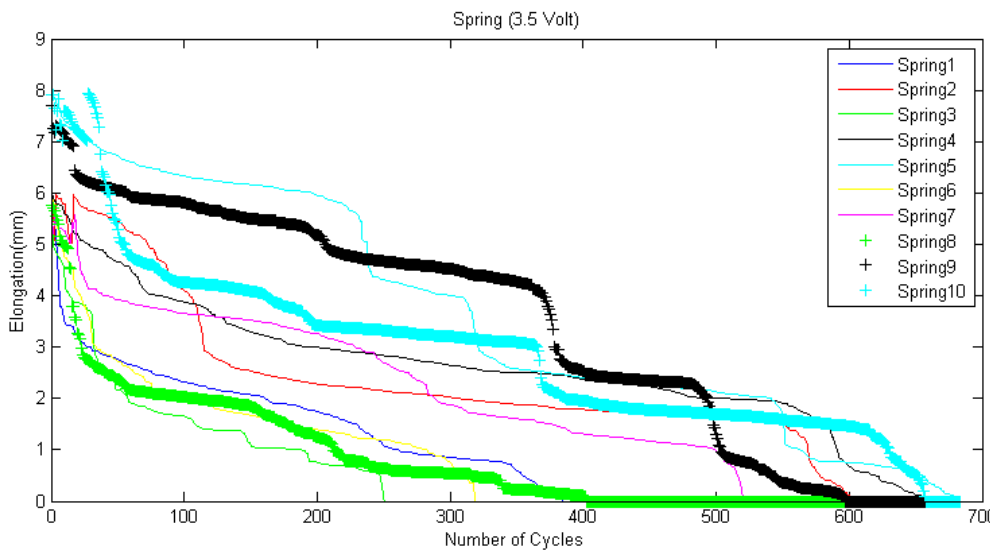
b) Mechanical load applied to the spring can be varying from 0 N to 20 N. By considering mechanical load as a stress factor for the spring failure an accelerated life analysis can be done.

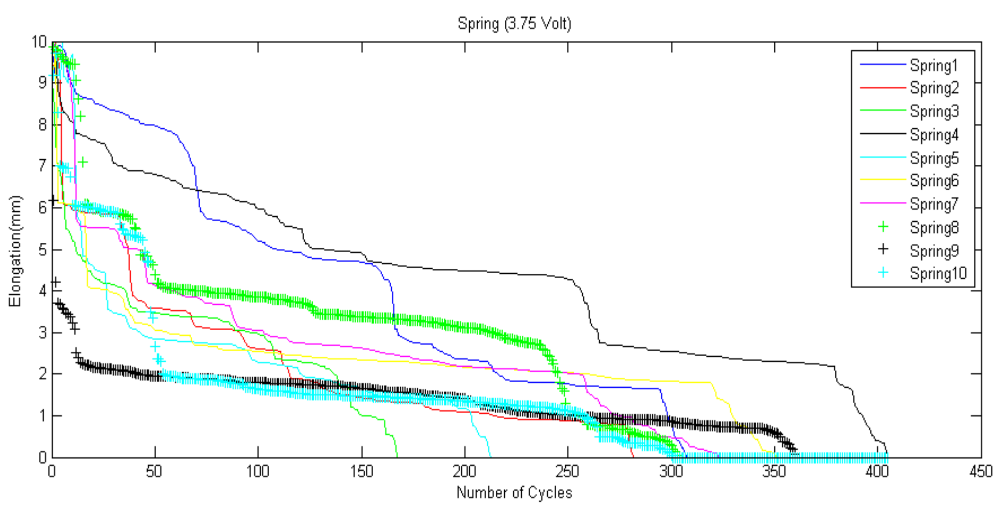
c) Spring of different stiffness parameter can be used for the analysis. So, model can be developed by considering stiffness as a stress factor.

d) Stimulus (i.e. voltage) and weight can be applied in steps for accelerated step reliability analysis.

7.4 Experimental Results

In this study, experiments were performed at three different voltage waveforms of 3.5 V, 3.75 V and 4 V and at an external load of 4 N. The spring was assumed to failed when the elongation reaches to 0.1 mm (i.e. critical elongation =0.1 mm). Ten spring's run to failure experiment were performed at each voltage, i.e., 30 experiments. Figure 7.4 shows the reduction in elongation with number of cycle's at all three different voltages.





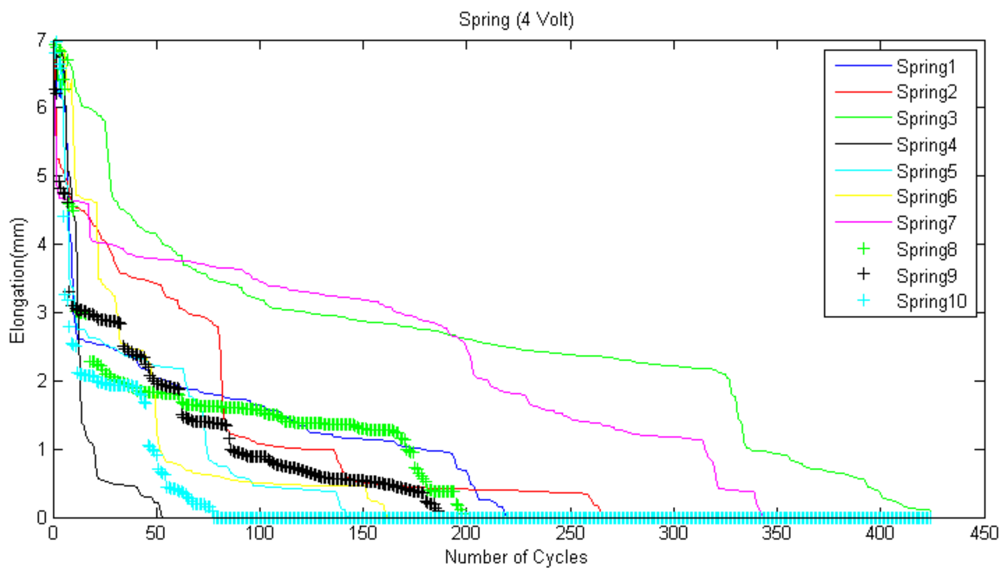


Figure 7.4 Plot showing reduction in elongation with number of cycles

From figure 7.4, at each experimental condition; it was observed that recovery stress or strain in spring is continuously changing with number of cycles and this behavior gets stabilize only after some number of cycles. The time to failure obtained for each spring is shown in table 7.2.

Table 7.2 SMA springs fatigue lifetime data

Spring ID	1	2	3	4	5	6	7	8	9	10
Time to Failure (3.5 V) (Cycles)	384	601	250	655	683	319	520	402	596	657
Time to Failure (3.75 V) (Cycles)	307	281	167	405	212	350	322	303	360	300
Time to Failure (4 V) (Cycles)	218	265	424	52	142	161	342	198	186	77

7.4.1 Failure Diagnosis Analysis using SEM and TGA

The cause of the spring failure is degradation in mechanical properties; same is investigated using Scanning Electron Microscopy (SEM) and Thermogravimetric Analysis (TGA). SEM is generally used to carry out the surface morphology of the object. TGA is monitors the mass of a substance due to gas release or absorption as a function of temperature as the specimen subjected to a control temperature program in a controlled atmosphere [67].

Three different analyses have been carried out here: virgin spring (i.e. run for zero number of cycles), deformed spring (i.e. run for 100 number of cycles) and failed spring (i.e. run till failure). Figure 7.5 shows the obtained image using SEM for all three cases.

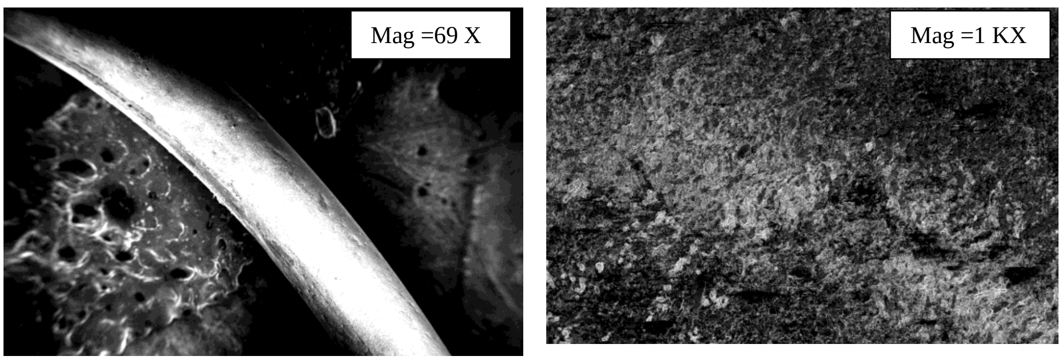
From figure 7.5 (a), uniform surface morphology throughout the length of the virgin spring is observed and with cycles of operation spring is lead to cross the elastic deformation (figure 7.5 (b) and figure 7.5 (c)). It means with aging, material is not able to retain residual strain in it and results in generation of pores with number of cycles. These pores are generally formed because of during application of stimulus SMA is generally at higher temperature and oxygen is entrapped into it and which ultimately makes the material brittle and leads to failure of the spring. The same phenomenon has been investigated using TGA analysis.

The TGA plot (figure 7.6) shows the percent mass as a function of sample temperature. During analysis the samples are put inside the furnace in an inert atmosphere. All samples were heated to 300º C from room temperature with a heating rate of 10º C/ minute. From TGA plot, it can be seen that the failed spring loses the material concentration with the temperature which indicates the accelerated melting in comparison of virgin spring. Because in failed spring, oxygen gets entrapped inside the alloy, which ultimately leads to break the bond between Ni and Ti and material gets removed at high temperature during TGA from failed spring. Furthermore, Ti is responsible for the oxidation formation inside the alloy; because Ti has the great affinity to react with the oxygen as comparison to Ni. In addition, from periodic table, as we go across a period, the nuclear charge will increase; whereas the energy level will stay same in same period. It means there is a stronger and stronger attraction for the electrons for the metal which is farther in periodic table as compare to the nearest metal. Thus, it is more and more difficult to lose electrons and consequently the reactivity of the metal decreases as we go from left to right across the periodic table.

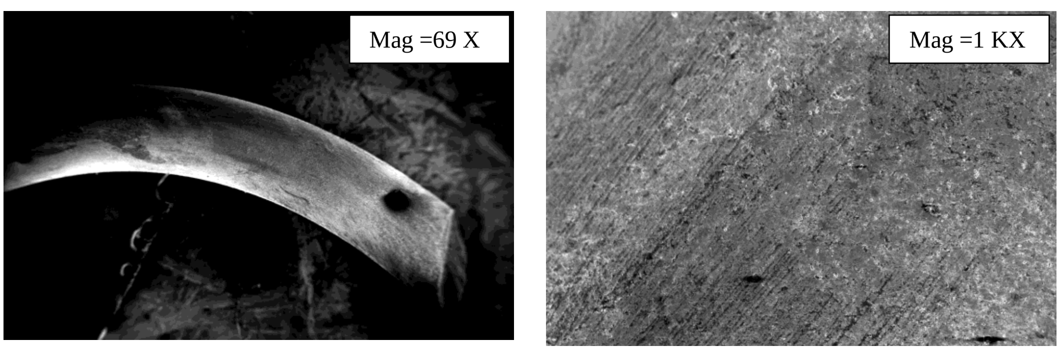
As, Ti has atomic number 22 and Ni has atomic number 28, it means based on the reason explained in above paragraph Ti is more reactive than Ni. Consequently Ti has great affinity to react with the oxygen and generally forms TiO_2 or TiO_4.

So, from TGA and SEM it can be conclude that failed spring has the higher oxygen entrapment which results in retardation in actuation of the SMA spring.

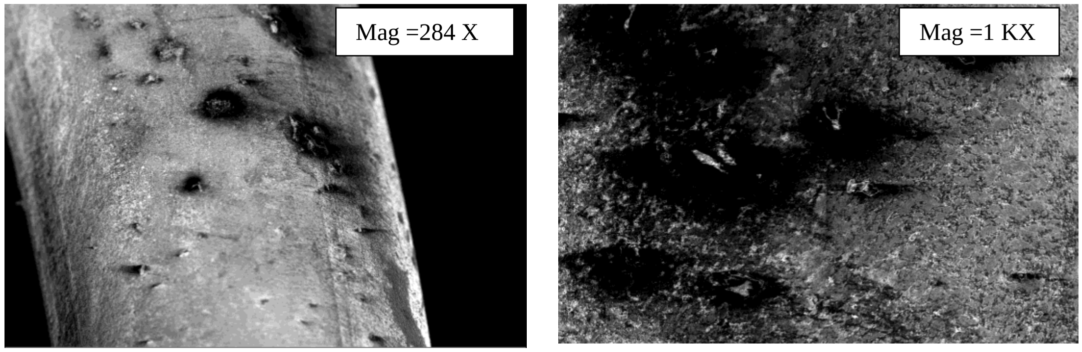
The specification of the instrument used for SEM and TGA analysis is given in appendix-C.



(a)



(b)



(c)

SEM image of the surface of the SMA spring (a) virgin spring (b) deformed spring (c) failed spring

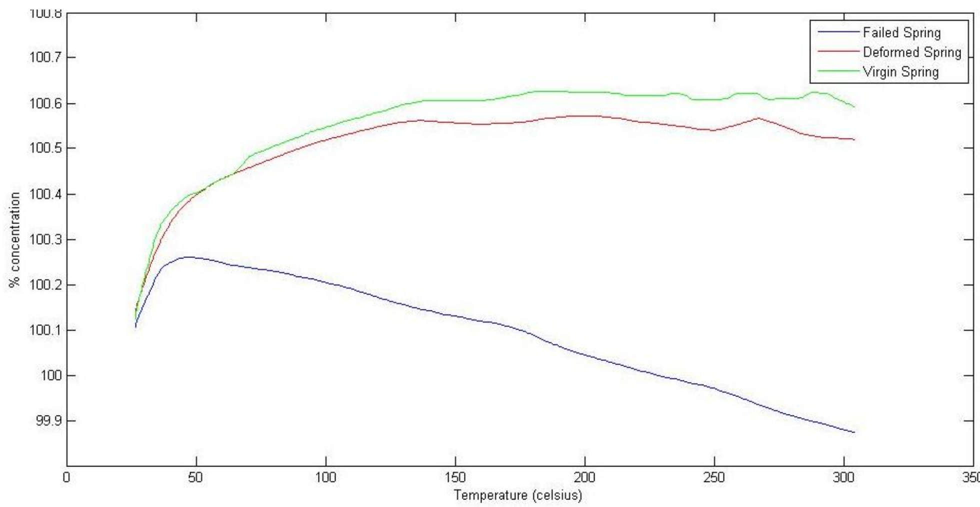


Figure 7.6 TGA results comparison between virgin, deformed and failed spring

7.5 Model Development for Proposed Methodology

The current life prediction methodology is divided in two phases: offline and online. In offline phase, reliability prediction model is developed that can best fit to the available data set. In online phase, model parameter will get updated based on new available online information.

Offline Phase:

In Offline phase the approach builds a reliability model based on the observed data. It relies on availability of failure data that will be used to develop probability distributions relating to operating parameters such as cycles of operation or crack length or wear. These probability distributions are then used to assess probability of failure for a machine or life prediction of the machine. In general, reliability based methods can be categorized in following two groups:

7.5.1 Time based Reliability Models:

This kind of models considers the failure as a probabilistic function of time. Many parametric models such as Weibull, Log-Normal, Normal, Exponential, Poisson distributions are generally used to model the component reliability. The most widely used is Weibull because of its ability to accommodate different types of behavior such as infant mortality (i.e.$\beta < 1$), constant failure rate (i.e. $\beta = 1$; exponential distributions) and increasing failure rate (i.e. $\beta > 1$; behave as normal distributions when $\beta > 3$). The reliability function for Weibull distribution is mathematically defined as follows:

$$R(t) = \exp\left(-\left(\frac{t}{\eta}\right)^{\beta}\right) \tag{7.1}$$

where, η is the characteristics life parameter; which defines as the time at which probability of failure is $63\,\%$, β is the shape parameter and 't' is the time to failure.

7.5.2 Covariate based Reliability Models:

In conventional reliability analysis only cycles of operations is considered as a factor which represent the failure. However, in many industrial applications, the degradation of a component is caused by one or more factors that are called covariates [17]. For example, degradation of a ball bearing can be affected by material properties, temperature, running speed and load applied on the bearing. Time based reliability model doesn't consider these additional factors. Covariate based reliability models are generally used to incorporate these additional factors in to failure distributions.

In present case study the covariates and factor representations of spring failure, i.e., life parameter are found by using cause and effect relationship. During experimentation stimulus, i.e., voltage is found as major cause of spring failure which was later validated using Inverse Power Law (IPL) discussed in section 7.6, i.e., with higher stimulus lesser will be life and vice versa. In effect of which very large reduction in elongation at less cycles of operation was observed at higher voltage. In section 7.4, from SEM and TGA analysis, it was also observed that after a long period of activation under constraint conditions SMA material loses it properties, i.e., cycles of operation is secondary cause of failure.

As voltage and cycles of operation are the cause of the failure; it means they should be considered as covariates. Whereas, reduction in elongation is the effect produce because of these cause; so it should be used as a life parameter based on which spring failure will be decided. The following steps have been used for covariate based reliability model formation for the current case study.

Step 1: *Sort the elongation in a descending order, i.e.,* $E \sim \{E_1, E_2, \dots \dots., E_n\}$

Step 2: *Determine the best distribution based on the log- likelihood value i.e. Normal, Log-normal, and Weibull etc.*

For the current example, Weibull model was found to be best model to characterize the spring failure. So, Generalized Log Linear Weibull (GLL-Weibull) model has been used for reliability estimation.

Step 3: *Estimate the model parameters i.e.*

$$\eta = \exp(a_0 + \ a_1 x_1 \dots \dots \dots \dots \dots a_n x_n) \; and \; \beta \tag{7.2}$$

where, a_o is constant and a_1, a_2 are the coefficient for vital axis which defines the influence of the covariates on the failure process and x_1, x_2, x_3.......x_n are the vector of covariates.

Step 4: *By considering elongation as the life parameter, the reliability formula mathematically can be expressed as:*

$$P(E_{critical} \geq E) = exp\left(-\left(\frac{Elongation}{\exp(a_0 + \ a_1 x_1 \dots \dots \dots \dots \dots a_n x_n)}\right)^{\beta}\right) \tag{7.3}$$

where, $E_{critical}$ is the critical elongation below which the SMA has to be replaced.

Step 5: *However, in this study spring reliability means its working displacement should be greater than critical elongation. Then its reliability function mathematically can be expressed as:*

$$R(E_{critical} \leq E\,) = 1 - exp\left(-\left(\frac{E}{\exp(a_0 +\ a_1 x_1 \dots\dots\dots\dots\dots a_n x_n)}\right)^{\beta}\right) \quad (7.4)$$

Online Phase:

Online phase for reliability estimation is already discussed in section 1.2.3. The Bayesian approach is used for updating the model parameters in online phase. Mathematically, steps involved for online model formation are discussed hereunder:

Steps for Bayesian Algorithm:

Step 1: *From offline model i.e. GLL- Weibull model (with* η *that is not known precisely and has a prior distribution with some mean and variance. For example, from equation 7.12:*

$$\eta_{\mathrm{fleet}} = \exp(5.73 - 0.003 \times number\ of\ cycles - 1.1\ \times Voltage) \quad (7.5)$$

$$\beta_{\mathrm{fleet}} = 2.0184 \quad (7.6)$$

$$\eta_{\mathrm{std}} = \mathrm{covariance}\ \times \eta_{\mathrm{fleet}} \quad (7.7)$$

Where, $\mathrm{covariance} = \sqrt{\frac{\Gamma[(\beta+2)/\beta]}{(\Gamma[(\beta+1)/\beta])^2} - 1}$

Step 2: *Collect the new unit inspect data,i.e, elongation, number of cycles, and voltage*

Step 3: *Use the Monte Carlo simulation to update the model parameters.*

a) Generate the random sample from prior pdf. The prior will be sample from the covariance matrix used in offline model.

b) Calculate the likelihood function with the prior distribution parameters and sampled distribution parameters.

c) Calculate the relative likelihood ratio and pass it through a statistical filter. The values which pass the filter; retain those values.

d) The retained sample values are the representation of the posterior pdf f (η/ Data).

e) The average of these sample values will be the best estimate of η and new value of η will be used for further reliability calculation.

The whole Monte Carlo simulation used for updating of model parameter is mathematically mentioned in table 7.3 and the architecture for the same is represent in figure 7.7.

Table 7.3: Monte Carlo simulation for Bayesian algorithm

for j=1:2500

$\eta' = \eta_{std}$*rand (2500, 1) +η_{fleet} (Generate random sample for η)

for i=1:n

$$likelihood\ prior = L(\beta,\eta) = \prod_{i=1}^{n}\left(\frac{\beta_{fleet}}{\eta_{fleet}} * \left(\frac{t_i}{\eta_{fleet}}\right)^{\beta_{fleet}-1} * exp\left(-\left(\frac{t_i}{\eta_{fleet}}\right)^{\beta_{fleet}}\right)\right)$$

$$likelihood\ posterior = [L(\ \beta^{fleet},\eta')]_j$$

$$= \prod_{i=1}^{n}\left(\frac{\beta^{\ fleet}}{\eta'} * \left(\frac{t_i}{\eta'}\right)^{\beta^{fleet}\ -1} * exp\left(-\left(\frac{t_i}{\eta'}\right)^{\beta^{fleet}}\right)\right)$$

Relative likelihood ratio = $\frac{Likelihood\ Posterior}{Likelihood\ Prior}$

u = rand (2500, 1) (Uniform random number generation)

if u(j) < Relative likelihood (Statistical filter)

Posterior eta (k) = η' (j)

end

end

end

$\eta_{update} = mean$ (Posterior eta) (Best estimate of η)

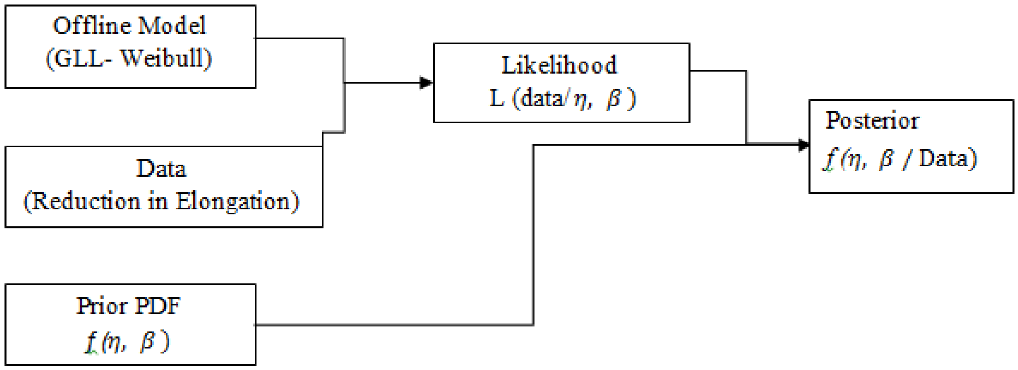


Figure 7.7 Bayesian model parameter updating approach architecture

From above conclusion can be made that the Bayesian approach is a powerful tool in reliability estimation as it incorporated the field experience, data and expert opinion at a single place. To show the significance of the proposed methodology over the conventional methodology the life prediction results are compared which are discussed in next section (figure 7.8).

7.6 Results and Discussion

Accelerated test conditions are typically set up by testing the products at higher stress level than normal, and some parameters are always chosen as the accelerated stress, i.e., temperature, pressure, load, voltage, current etc. to fail the product more quickly without introducing unrealistic failure mechanism [68]. During experimentation it was observed that SMA spring exhibits early failure at higher stimulus, i.e. voltage or temperature. So, voltage is assumed as an accelerated stress and to validate accelerated life testing analysis has been made using Inverse Power Law (IPL), i.e., non-thermal stress [68, 69]. It mathematically can be expressed as:

$$L\,(V) = \frac{1}{KV^n} \tag{7.8}$$

where, L represents a quantifiable life measure, i.e., characteristics life, mean life etc. V represents the stress level and K & n are the model parameters to be determined.

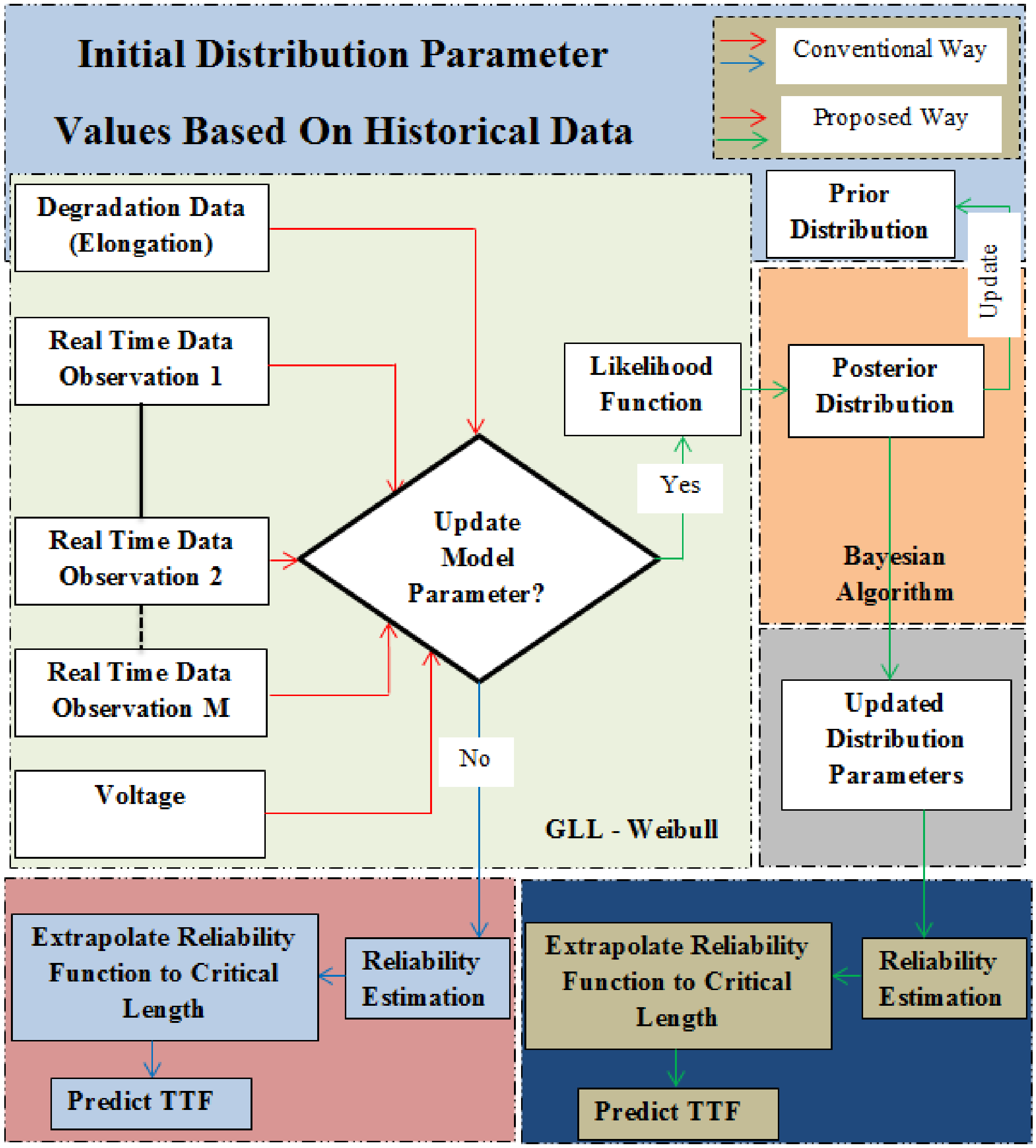


Figure 7.8 Comparative flow chart of the conventional methodology and proposed methodology

For the current analysis, based on likelihood values Weibull distribution was found as best distribution. It means $L\,(V)$ becomes the characteristics life parameter, i.e., η for the model. Therefore, IPL- Weibull can be derived by setting $\eta = L\,(V)$, yielding the following IPL- Weibull PDF:

$$f\,(t, V) = \beta\, K\, V^{n}\, (K\, V^{n}\, t)^{\beta-1}\, e^{-(K\, V^{n}\, t)^{\beta}} \qquad (7.9)$$

As SMA spring degradation data is available; degradation analysis has been performed to remove the uncertainty in the results. The three unknown parameters from the PDF equations for the current data are found as: $K = 7.38E - 07; n = 6.23$ and $\beta = 2.55$.

Figure 7.9 shows the spring life v/s stress plot obtained during accelerated life testing analysis. The center triangle in the figure represents the mean life of the spring at corresponding voltage. It can be seen from the plot that with the increasing stress spring mean life is decreasing, which is quite obvious as obtained during experimentation also. It means voltage is an accelerating stress here.

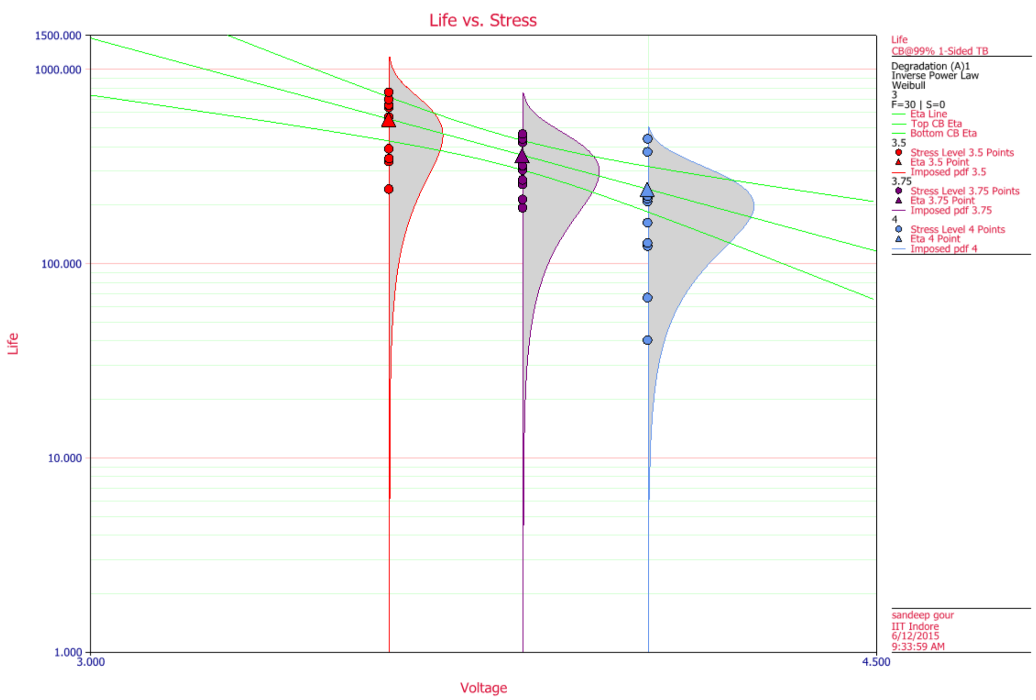


Figure 7.9 Spring life v/s stress plot

As from cause and effect relationship two cause of spring failure was observed, i.e., voltage and cycle of operation. So, to show the significance of considering external parameters in model, two different models are developed. First model (i.e. model 2) considers cycles of operation as a covariates and second model (i.e. model 3) considers cycles of operation and voltage as a covariates. In addition, a third model (i.e. model 1) is developed (i.e., time based reliability model) to show the significance of covariate based reliability model over the time based reliability model.

The steps involved in each model for predicting the life of the spring is mention here under:

- Calculate the unknown parameters for each model, i.e., η and β for time based model and β and a_o, a_1 etc. for covariate based model.
- Based on these parameters calculate the reliability using mathematical equation mentioned in section 7.5.
- As critical elongation is 0.1 mm, now perform reverse calculation by consider elongation as 0.1 mm and used η, β and reliability got from previous steps.
- Perform this step after completion of each 50 (i.e. can be any value) number of cycles and stop it where the obtained TTF values is coming less than actually it run for that number of cycles or reliability value reaches 1%.
- The obtained TTF value from the previous step is the final TTF value of the spring obtained from the model.

Model 1: Time based reliability model

The first five spring TTF values at a voltage of 3.5 V are used for the estimation of the model parameters. The obtained parameters are $\eta = 573.62$ and $\beta = 3.7$; based on these parameters the reliability function can be expressed as:

$$R(t) = \exp\left(-\left(\frac{t}{573.62}\right)^{3.7}\right) \tag{7.10}$$

By assuming 1% as the critical limit of the reliability; the obtained TTF will be 866.72 cycles. For each spring this model will give always the TTF value of 866.72 cycles. However, TTF can differ for similar components operating under the similar conditions. This can be also seen from the TTF values shown in table

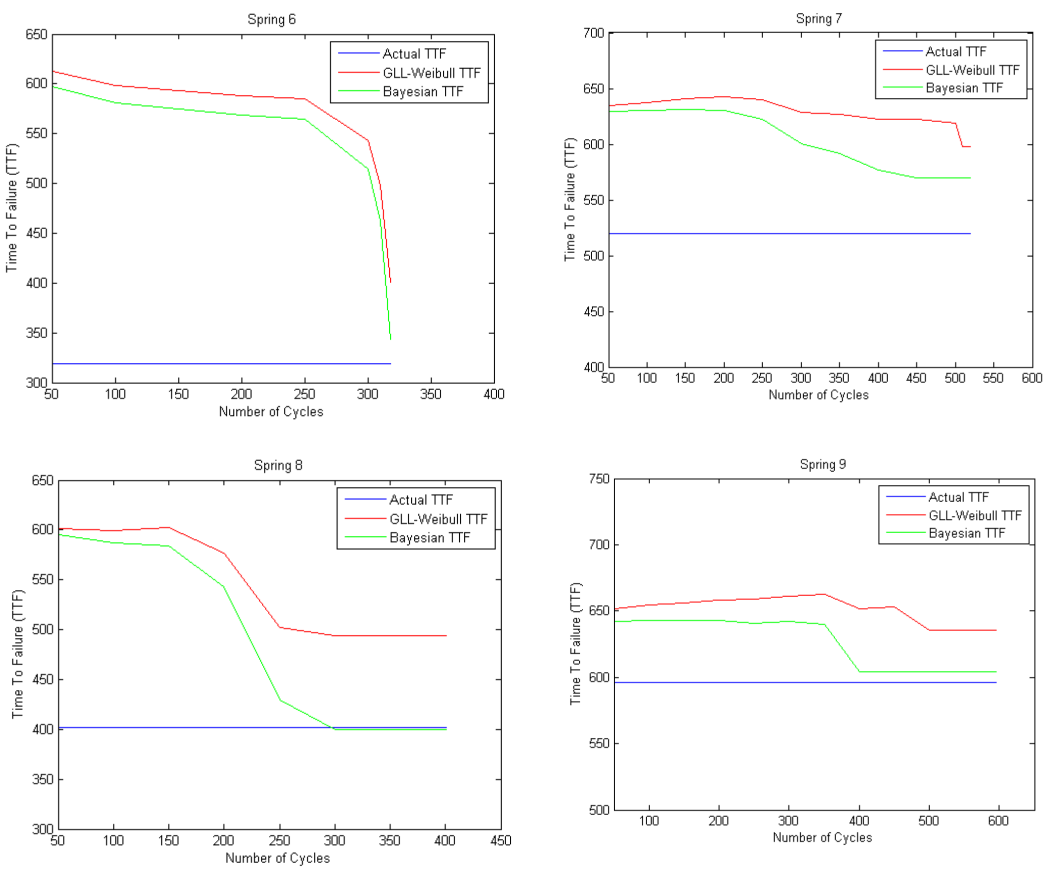
7.2. Working with such kind of problem, covariate based reliability model is developed to obtained the accurate prediction of TTF.

Model 2: Covariate based reliability model (Considered number of cycles as a covariate)

In this model first five spring elongation data at a voltage of 3.5 V along with number of cycles is used to estimate the model parameters. The obtained parameter values are $a_o = 1.71;\ a_1 = -0.0025; and\ \beta = 2.33$; based on these parameters the reliability function can be expressed as:

$$R(E_{critical} \leq E\ ) = 1 - exp\left(-\left(\frac{Elongation}{\exp(1.71 - 0.0025 \times number\ of\ cycles\ )}\right)^{2.33}\right) \quad (7.11)$$

For model testing another five springs at 3.5 V is considered and their life was predicted. The tested springs results are indicate by the green line in figure 7.10.



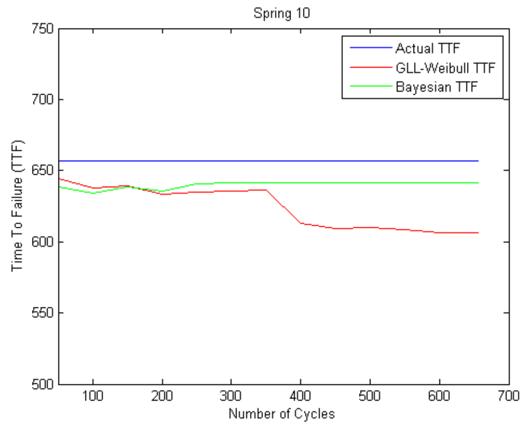


Figure 7.10 Model 2 life prediction results for different test histories using GLL- Weibull and Bayesian

Model 3: Covariate based reliability model (Considered voltage and number of cycles as a covariate)

Instead of developing the different models at different environmental conditions; this model tries to integrate the different operating and environmental stress variation. So, as compared to previous model this model will considered voltage as additional covariates. First five spring's elongation data along with number of cycle's at all three different voltages is used for estimating the model parameter, i.e. 15 test histories is used for model formation. The obtained parameter values are $a_o = 5.73$; $a_1 = -0.003$; $a_2 = -1.1$ *and* $\beta = 2.0184$; based on these parameters the reliability function can be expressed as:

$$R(E_{critical} \leq E\ ) = \qquad (7.12)$$

$$1 - exp\left(-\left(\frac{Elongation}{\exp(5.73 - 0.003 \times number\ of\ cycles - 1.1\ \times Voltage)}\right)^{2.0184}\right)$$

Another fifteen springs are used for testing of the model. The life prediction results using this model is indicate by the green line in the figure 7.11.

In model 2 and model 3; negative values of coefficient of covariates implies that increase in the value of that covariates will reduce the life of the component, which is experimentally true also.

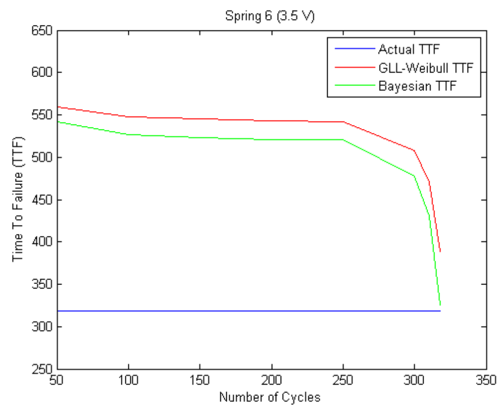
However, the results obtained from the model are still far from the actual TTF, this may because of didn't consider the uncertainty with the data, i.e., covariates values can be differ for similar components operating under similar conditions. This uncertainty is modeled here by using Bayesian approach.

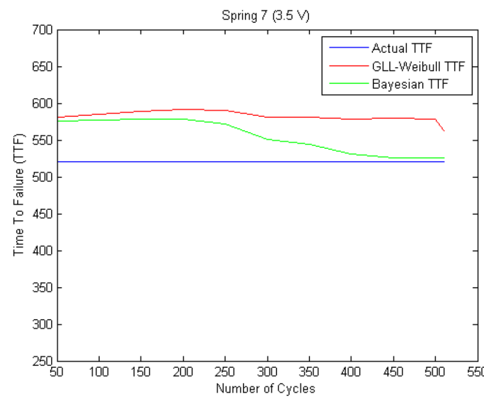
Figure 7.10 (i.e. model 2) and 7.11 (i.e. model 3) shows the life prediction results for different test histories using Bayesian and GLL- Weibull. The life prediction values for different test histories obtained from both the approaches are also mentioned in appendix- A and appendix- B using model 2 and model 3 respectively.

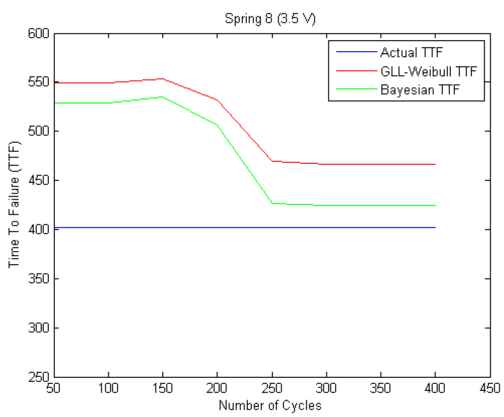
Finally, following conclusions can be made from this overall analysis:

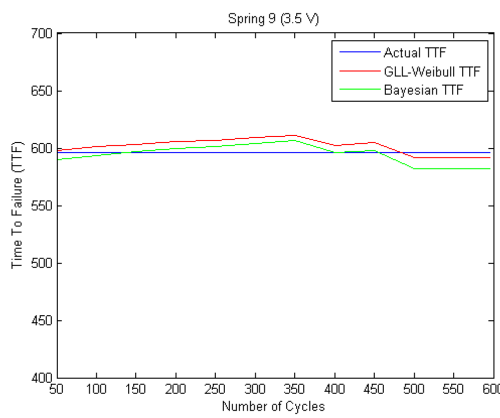
- IPL validates the assumption of considering voltage as a stress factor and it was found that higher the voltage lesser will be the life of the spring. This may be because of at higher voltage; the temperature of the SMA spring goes very high (i.e. >140 º C at 3.5 V; >160º C at 3.75 V; >180º C at 4 V) as compare to actuation temperature (i.e. 70º C). At higher temperature chances of oxygen entrapment is high which cause the spring early failure at higher voltage.
- From figure 7.10 and 7.11 it can be seen that the life prediction results obtained using Bayesian approach are better than GLL- Weibull distribution; it means uncertainty associated with data is overcome by Bayesian.
- At 3.5 V of stimulus; the results obtained from model 2 and model 3 are approximate same. It means that it is always better to keep the external factors (i.e., the factors which affecting the life of the component) in the model otherwise separate model has to be formed for each different operating conditions. For example, in present case study if voltage is not

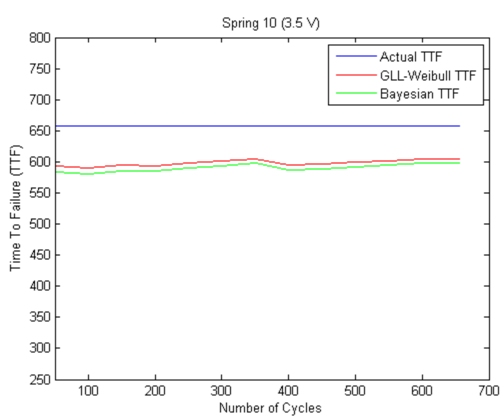
considered as a covariates in the model then three different models are required to predict the life of the spring at three different voltages. But by keeping voltage as additional covariates, only one model is required to predict the life of the spring operating at any voltage. It eliminates the need of three different models and also reduces the time required to develop the model.

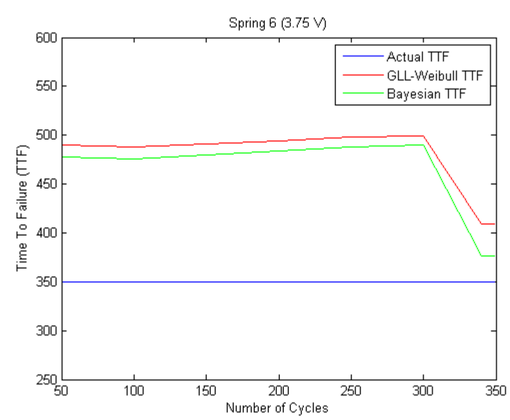


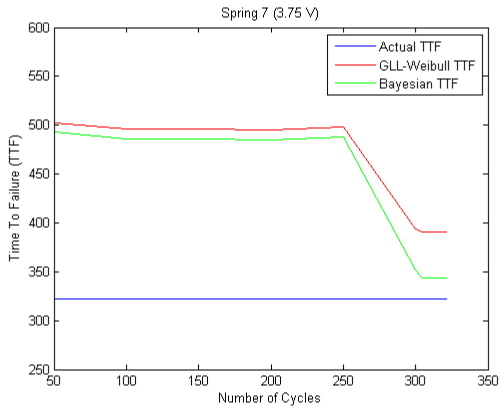


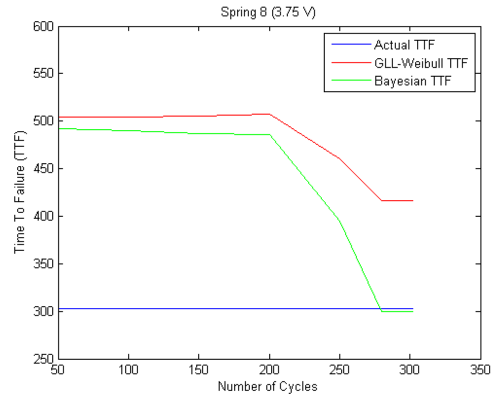


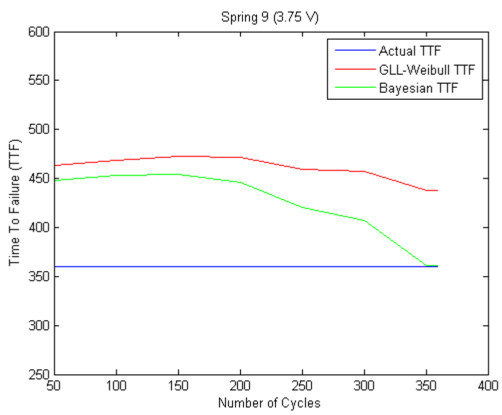


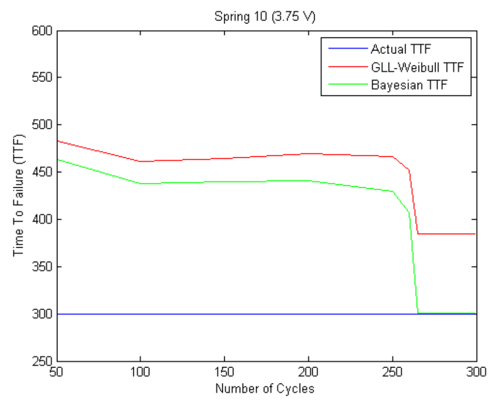


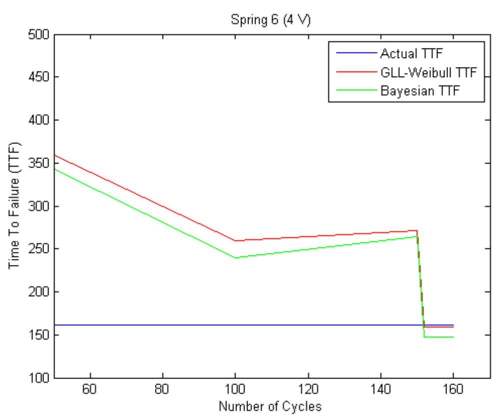


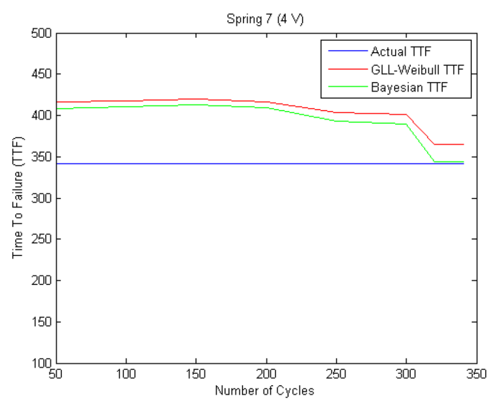

Spring 7 (3.75 V)
Actual TTF
GLL-Weibull TTF
Bayesian TTF
Time To Failure (TTF)
Number of Cycles


Spring 8 (3.75 V)
Actual TTF
GLL-Weibull TTF
Bayesian TTF
Time To Failure (TTF)
Number of Cycles


Spring 9 (3.75 V)
Actual TTF
GLL-Weibull TTF
Bayesian TTF
Time To Failure (TTF)
Number of Cycles


Spring 10 (3.75 V)
Actual TTF
GLL-Weibull TTF
Bayesian TTF
Time To Failure (TTF)
Number of Cycles


Spring 6 (4 V)
Actual TTF
GLL-Weibull TTF
Bayesian TTF
Time To Failure (TTF)
Number of Cycles


Spring 7 (4 V)
Actual TTF
GLL-Weibull TTF
Bayesian TTF
Time To Failure (TTF)
Number of Cycles

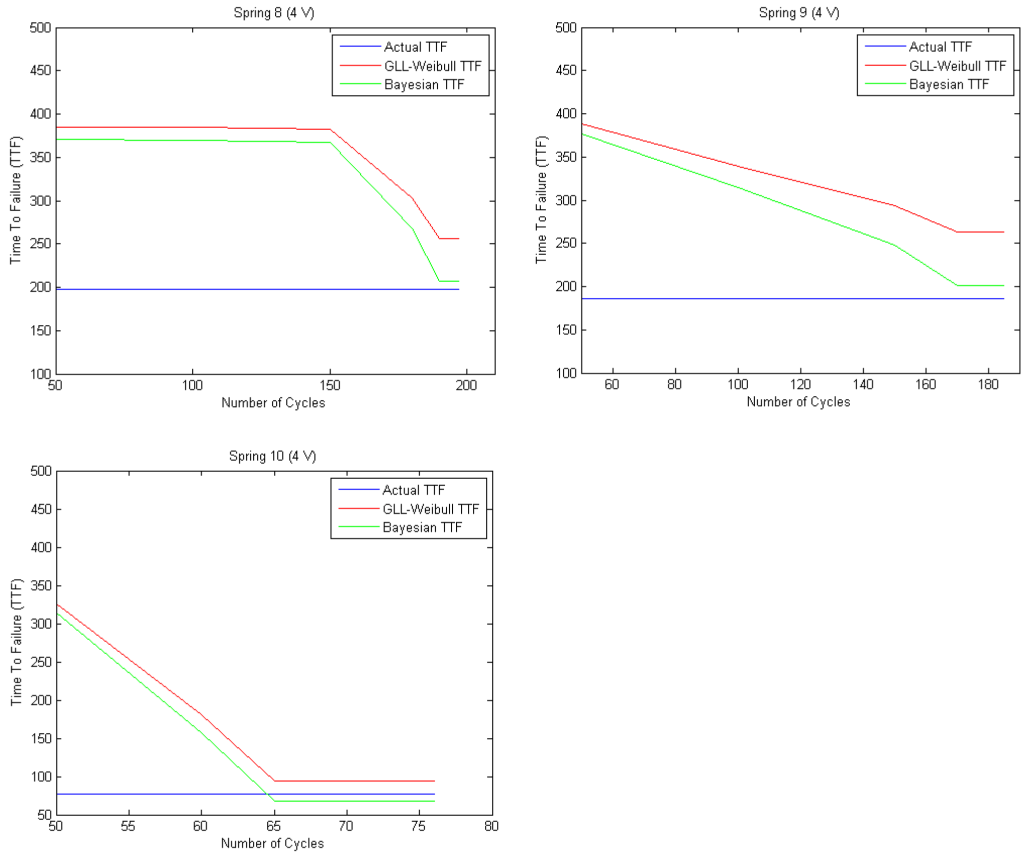


Figure 7.11 Model 3 life prediction results for different test histories using GLL- Weibull and Bayesian

7.7 Summary

With the increasing availability and complicated nature of real world data has made it look over the uncertainties associated with the data. Therefore, an algorithm is required which allow to model the uncertainties, allow integrating data from various sources, and explicitly indicate the statistically dependence and independence. The present work tries to consider all these requirements; so that a good life prediction model can be developed. First, it was assumed that voltage would be a good stress factor to perform the experiment at accelerated conditions. To validate it experiments were performed at three different voltage waveforms and obtained life cycle data is fitted using Inverse Power Law (IPL). From the analysis it was found that voltage is statistically dependent on the failure of the spring. Now, GLL- Weibull model is used as a life prediction model to integrate the information from various sources, i.e., number of cycles, voltage, and reduction in elongation. The uncertainty associated with the model is modelled by using Bayesian approach and its performance is compared with that of an existing non- Bayesian model, i.e., GLL- Weibull and normal Weibull. The proposed approach provides approximate accurate results with very less amount of uncertainty and demonstrates several advantages to integrate the data from multiple sources to address realistic life prediction challenges.

Chapter 8

Conclusions

8.1 Summary

The main aim of this thesis was to develop the prognostics algorithm for various systems or components such as gas turbine system, aircraft engine, roller ball bearings and SMA spring. The thesis has discussed the data driven prognostics approaches for prognostics of these components or systems. As discussed in chapter 1, in last few years this area has made considerable research interest but still there are some areas which require needs of development in prognostics model to increase the accuracy in RUL prediction. The key of the thesis is to developed robust algorithms capable of operating in real word environments. In specific from the literature following gaps are identified:

Gap 1: There is a lack of focus on considering the effect of the data noise in the model.

Gap 2: More work is required to handle the multidimensional features extracted from the raw data.

Gap 3: Updating of model parameters with the age of the component or system is required to consider the effect of uncertainty associated with the real world environment.

Gap 4: No work is done to estimate the life of the smart materials, i.e., Shape Memory Alloy.

8.2 Contributions of the Thesis

Keeping in mind above gaps, following are the original contributions made by this thesis to bridge the gaps:

1. Model is developed using Artificial Neural Network (ANN) for an aircraft engine. Presence of unknown initial wear in the samples is the source of the data noise here. $\bar{x}$ and R control chart is used to screen the samples

with abnormal initial wear. To calculate the remaining useful life of an aircraft engine two artificial neural network (ANN) based models are developed. First ANN model developed with the help of complete data; while second ANN model developed after removing samples with abnormal initial wear in the samples. It is concluded that a unit with abnormal initial wear significantly affects the RUL prediction performance.

2. Mechanical components are prone to failures due to several failure modes; resulting into multiple failure behaviour or patterns in life test data obtained from various units. If such failure patterns or behaviour are not identified and treated appropriately, the same may act as one of the sources for data noise and may result into poor prediction accuracy. Clustering and Change Point Detection Algorithm (CPDA) is used for identification of presence of multiple failure behaviour or patterns in the data. Silhouette width value is used to find out optimum number of clusters, i.e., failure patterns. Combined output of Clustering and CPDA is used for developing RUL prediction models. Separate models for single and multiple failure patterns are constructed using General Log- Linear Weibull (GLL- Weibull) distribution. Results show that identification of failure behaviour helps in accurate prediction of RUL.
3. PCA-ANN based approach is developed to manage the multiple dimensional features in the data set. First, five time domain features were extracted from vibration signals and then PCA is applied because extracted features still with high dimensionality and spare information. The extracted best three principal components and current age are used for ANN model construction. The proposed methodology is validated with an accelerated bearing run to failure experiment. A comparative study is presented between proposed PCA-ANN and conventional ANN approach, and the results demonstrate the effectiveness of the proposed methodology for accurate remaining useful life prediction.

4. Risk Based Maintenance (RBM) approach is developed for calculation of future risk of a gas turbine. It calculates the future risk of failure of a gas turbine power plant system so that the maintenance can be planned just before occurrence of failure. To calculate the risk, first a General Log-Linear Weibull (GLL- Weibull) model, which tells about damage growth of the machine, is developed. Bayesian approach is then used to update the model parameters (i.e. GLL- Weibull parameters) on the basis of new inspection data (i.e. crack length) and calculate the updated risk.
5. The SMA springs reliability was estimated by using life testing data from a sample of the springs. For that, first a novel accelerated run to failure experimental set up was developed to collect the life test data of Nickel–Titanium (Ni-Ti) SMA springs. Two operating parameters can be change to run the experiment on accelerated conditions: External weight applied to spring and voltage supplied for thermal heating of the spring. Voltage is assumed as an accelerating stress factor for present case study and Inverse Power Law (IPL) is used to validate it. It was observed that functional fatigue of the material leads to its failure, i.e., decrease in elongation with number of cycles. Based on the applied stimulus, elongation and cycles of operation; the spring life estimating model was developed by using Generalized Log- Linear Weibull (GLL-Weibull) distribution. It is recommended that parameters of the distribution should be continuously updated with the age of the spring. Bayesian approach is used to update the distribution parameters based on new available information (e.g. elongation). Comparative study has been made between the results obtained using simple Weibull, GLL-Weibull and Bayesian approach. It was found that integration of GLL- Weibull distribution with Bayesian approach helped in accurately life prediction of the SMA spring. In addition, degradation in the mechanical properties of the SMA material with number of cycles was investigated using Thermogravimetric Analysis (TGA) and Scanning Electronic Microscopy (SEM).

In overall, it can be concludes that data noise, multidimensional features extracted from the raw data and updating of model parameters with component or system age are the key issues and should be considered during any RUL prediction model development. Removal of data noise helped in eliminating the components with abnormal bahaviour. It is also recommended that before model development it is always better to understand the failure behaviour of the component. Furthermore, reducing the size of the features extracted from the raw data helped in reducing the noise and over fitting during model training. In addition, after model development its parameter should be updated with the age of the component to reduce the effect of the uncertainty associated with real world environment. At the end, as no work is done on SMA reliability, work reported here will help research engineers to develop high reliable and high performance SMA device in future.

From above discussions, it can be said that the developed methodologies has a number of desirable properties, which can be applied across different application domains. I hope this thesis can be bridge for readers to solve more PHM challenges.

In addition, the research accomplished in thesis should be continued in the directions mentioned in next section.

8.3 Future Scope of the Study

Many different types of machinery health diagnosis and prognostics technologies have been invented and presented in research papers, but only a few have found their way to industrial applications. Following are the areas which need to be considered further during PHM model development to improve the system performance.

- It was found from literature and Industrial interactions that most of the diagnostics and prognostics model are either based on single component or considering single failure at a time. But the prediction result of one component or one failure mode might not be sufficient to predict overall machinery failures. For example, the degradation of a component may initiate or accelerate the failure of another component or one failure mode may initiate another. So models should be instituted which can combine the multiple failure mode information and integrate component level failure information. It will help in predicting the overall machine health condition.

- Most of the real life systems are equipped with many sensors. Identifying an appropriate and optimal set of sensors and information fusion for diagnostics and prognostics is key for successful implementation of PHM in any industry. Research is required to develop such capabilities.
- Finally, it is realized that systematic framework for implementation of Prognostics and Health Management (PHM) approach in industries is missing, which can make use of multiple information, update prediction as soon as new data is available, use fuzzy information, controller alarm information's, etc. A tentative system for such approach is thought of and is shown in figure 8.1.

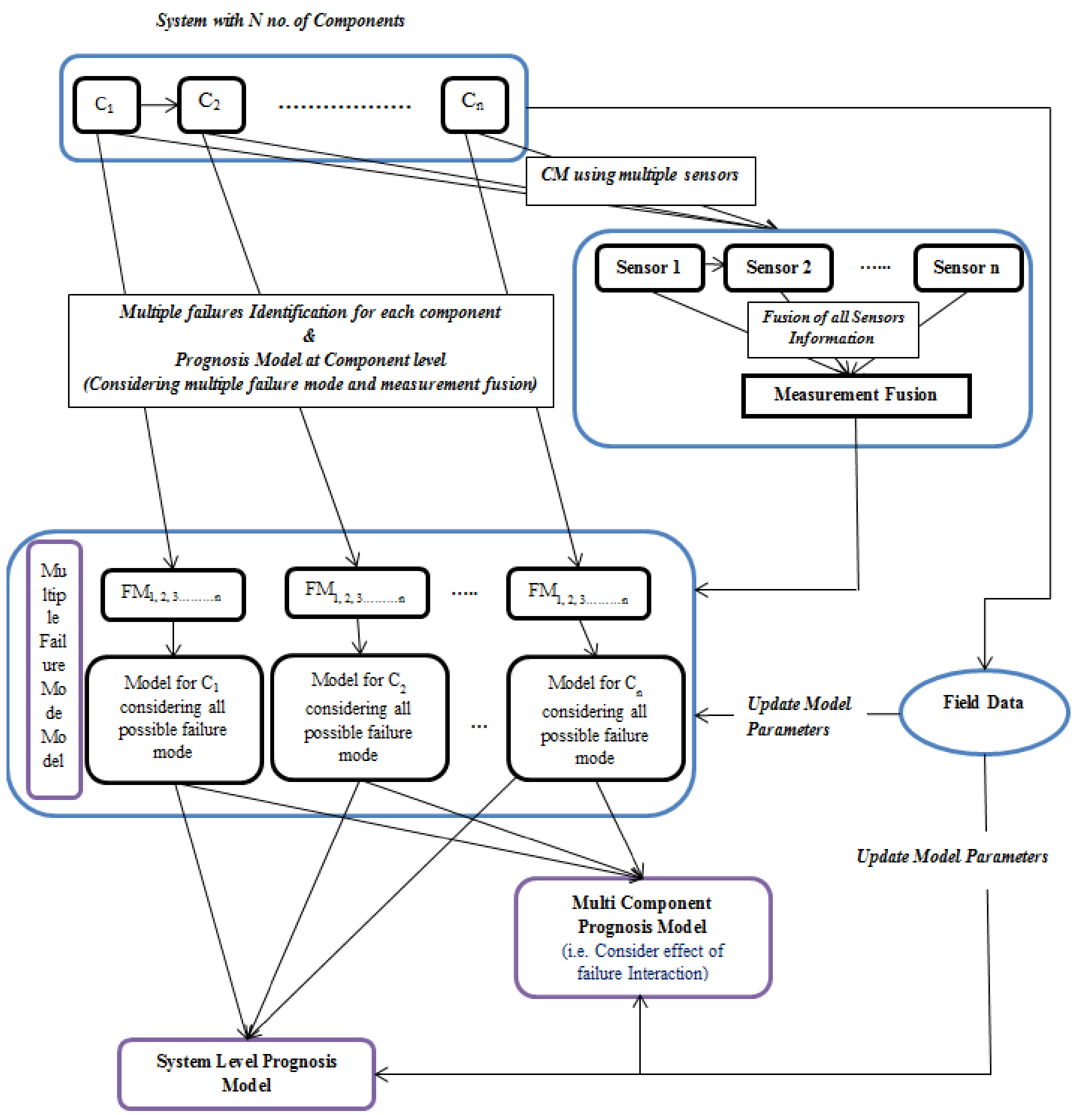


Figure 8.1 Flow chart of the proposed methodology for future research

APPENDICES

A. The life prediction results for different test histories using Bayesian and GLL- Weibull (For number of cycles as a stress parameter)

B. The life prediction results for different test histories using Bayesian and GLL- Weibull (For number of cycles and voltage as a stress parameter)

C. Details of the instrument used for characterization of Shape Memory Alloy

- Scanning Electron Microscope
- Thermogravimetric Analyzer

APPENDIX-A

Spring ID	Number of cycles	TTF (GLL- Weibull)	TTF (Bayesian)	Actual TTF
6	50	612.2620671	597.5716815	319
	100	597.9509394	580.9524719	
	150	592.9576006	574.3570852	
	200	588.2846029	568.7174253	
	250	584.9395016	564.9979148	
	300	542.8926228	514.8679929	
	310	498.2055925	461.8052352	
	318	400.833988	343.1862694	
7	50	634.3657863	629.5191009	520
	100	637.0465556	629.8824736	
	150	640.8958643	631.1473882	
	200	642.8716208	630.2510969	
	250	640.1976538	622.7080429	
	300	628.228781	600.2964682	
	350	626.6770118	591.7099707	
	400	622.1144839	576.916349	
	450	622.5329686	569.7156678	
	500	619.0216796	569.7156678	
	510	597.6144114	569.7156678	
	519	597.6144114	569.7156678	
8	50	601.8985129	595.3086227	402
	100	599.2069724	587.1491309	
	150	602.0518765	584.0542118	
	200	576.389014	543.5328029	
	250	501.7303242	429.7657002	
	300	494.0054125	400.0357671	
	350	494.0054125	400.0357671	
	400	494.0054125	400.0357671	
	50	651.7725031	642.041099	
	100	654.3616244	642.8391006	
	150	656.3669316	642.7724717	
	200	658.0659652	642.8502896	

9	250	658.670842	640.7977489	596
	300	660.9035334	641.8431121	
	350	662.4281304	639.850842	
	400	651.8061514	603.9009215	
	450	653.4381185	603.9009215	
	500	635.6324364	603.9009215	
	550	635.6324364	603.9009215	
	580	635.6324364	603.9009215	
	595	635.6324364	603.9009215	
10	50	644.8026429	638.7782319	657
	100	638.1508163	634.2295084	
	150	638.9371597	638.4683048	
	200	633.2814199	635.9264484	
	250	634.6382226	640.4114201	
	300	635.5210214	641.1731908	
	350	636.4365861	641.2456668	
	400	612.6153292	641.2456668	
	450	609.4056019	641.2456668	
	500	609.7329764	641.2456668	
	550	608.4455758	641.2456668	
	600	606.0224294	641.2456668	
	650	606.0224294	641.2456668	
	656	606.0224294	641.2456668	

APPENDIX-B

Spring ID (Voltage)	Number of cycles	TTF (GLL- Weibull)	TTF (Bayesian)	Actual TTF
6 (3.5 V)	50	559.4992448	541.7748587	319
	100	547.6674409	526.6740292	
	150	545.0258621	523.4695726	
	200	542.8465785	520.7272643	
	250	541.9854932	520.5670994	
	300	508.0937983	477.6195754	
	310	470.6231669	430.3534767	
	318	388.6346696	324.966033	
7 (3.5 V)	50	580.8696983	576.0785098	520
	100	584.5553468	576.6189442	
	150	589.1672309	578.5297509	
	200	591.8989969	577.9210455	
	250	590.4445515	571.4896118	
	300	581.1268178	551.2364736	
	350	580.9808362	543.8982155	
	400	578.4155851	531.2969645	
	450	579.9638584	525.4080385	
	500	578.4162147	525.4080385	
	510	562.1245747	525.4080385	
	519	562.1245747	525.4080385	
8 (3.5 V)	50	549.4794898	528.859068	402
	100	548.8525463	528.5880725	
	150	553.3998363	534.8437211	
	200	532.1570882	506.5863817	
	250	469.0145701	426.096195	
	300	466.2547859	424.2635443	
	350	466.2547859	424.2635443	
	400	466.2547859	424.2635443	
	50	597.6989669	589.6762675	
	100	600.8926422	593.7807378	
	150	603.4129301	596.7928472	
	200	605.5527806	599.5919034	

9 (3.5 V)	250	606.6447549	600.9419276	596
	300	609.0907651	603.925329	
	350	610.8403933	606.1683109	
	400	602.6167278	595.8313222	
	450	604.547131	598.1101915	
	500	591.3107536	581.7643009	
	550	591.3107536	581.7643009	
	580	591.3107536	581.7643009	
	595	591.3107536	581.7643009	
10 (3.5 V)	50	593.2350468	584.1758063	657
	100	590.7320479	580.842973	
	150	594.6158277	585.9015695	
	200	593.6856834	584.6122952	
	250	597.6577099	589.7934232	
	300	600.9646443	593.8284788	
	350	603.9780176	597.4901339	
	400	594.9530495	586.2427132	
	450	596.7280025	588.316138	
	500	599.8835002	592.3339418	
	550	602.1911751	595.3629204	
	600	603.9890891	597.581854	
	650	603.9890891	597.581854	
	656	603.9890891	597.581854	
6 (3.75 V)	50	489.8860926	477.7403872	350
	100	488.4042553	475.8517125	
	150	491.4633478	479.9124022	
	200	494.5207257	483.8354326	
	250	497.9321525	488.1382931	
	300	499.6418464	490.2273769	
	340	409.0082261	376.7328394	
	349	409.0082261	376.7328394	
7 (3.75 V)	50	502.0787484	492.8835733	322
	100	496.380058	485.9230667	
	150	496.2474963	485.6413793	
	200	495.1611348	484.372851	
	250	497.6823916	487.574763	

	300	394.0554811	351.5445952	
	305	390.3387246	344.0426624	
	321	390.3387246	344.0426624	
8 (3.75 V)	50	504.1397911	492.4753148	303
	100	504.8008797	489.7065628	
	150	505.2857177	486.7976516	
	200	507.4899856	486.1410292	
	250	460.7300469	394.4429086	
	270	430.543542	330.6943338	
	280	416.5693946	300.0213823	
	302	416.5693946	300.0213823	
9 (3.75 V)	50	463.6351917	448.4449384	360
	100	468.1505002	452.867357	
	150	472.7357457	453.786489	
	200	471.4033091	445.5749287	
	250	459.1361586	420.1570303	
	300	457.7026089	407.1481985	
	350	438.1208826	360.9701725	
	359	438.1208826	360.9701725	
10 (3.75 V)	50	483.1713668	463.8454943	300
	100	461.4661301	437.6396356	
	150	464.4484611	439.994893	
	200	469.0070958	441.2343234	
	250	466.0340496	429.4560979	
	260	451.9550266	406.7778866	
	265	384.3785108	300.3700426	
	299	384.3785108	300.3700426	
6 (4 V)	50	359.5659502	342.4554013	161
	100	259.3681919	239.7739994	
	150	271.3007115	264.8853716	
	152	159.6380652	147.2628929	
	160	159.6380652	147.2628929	
7 (4 V)	50	416.0465985	408.5045604	342
	100	417.6328302	410.5609873	
	150	419.4396577	412.9263811	
	200	416.8213723	409.4874677	

	250	403.2328674	392.6139663	
	300	400.8420607	389.1678545	
	320	365.0798804	343.8869097	
	341	365.0798804	343.8869097	
8 (4 V)	50	385.2107494	370.1770792	198
	100	385.1876461	370.1275984	
	150	382.453109	366.8744413	
	180	302.9350981	267.5975823	
	190	256.1970207	206.6571999	
	197	256.1970207	206.6571999	
9 (4 V)	50	388.8991678	377.0735907	186
	100	338.7457938	314.6253976	
	150	293.3970018	247.3964624	
	170	263.1450967	200.6934793	
	185	263.1450967	200.6934793	
10 (4 V)	50	325.8875309	314.4312612	77
	60	180.8185065	157.519143	
	65	93.45385989	67.31870134	
	76	93.45385989	67.31870134	

APPENDIX-C

- **Scanning Electron Microscope**

Make	Carl Zesis NTS GmbH, Germany
Model	SUPRA 55
Resolution	1.0 nm @ 15 kV
	1.7 nm @ 1 kV
	4.0 nm @ 0.1 kV
Acceleration Voltage	0.1 -30 kV
Magnification	12x – 900,000x
Stages	5- axes Motorized Eucentric Specimen Stage X = 130 mm, Y = 130 mm and Z= 50mm, T = -3º to 70º C, R = 360º

- **Thermogravimetric Analyzer**

Make	Mettler Toledo, USA
Model	TGA/ DSC 1
Temperature Range	Max 1100º C
Heating Rate	0.02 to 250 K/min
Cooling time	20 min (1100…100º C)
Vacuum	>10mbar
Measurement Range	≤ 1g/ ≤ 5g
Power Supply	230 V, 60Hz

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