DEPARTMENT OF ELECTRONIC & ELECTRICAL ENGINEERING

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ACCOMMODATING MAINTENANCE IN PROGNOSTICS

A thesis presented in fulfilment of the requirement for the degree of

Engineering Doctorate

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: Omer Panni

Date: 23rd September 2020

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I would like to dedicate this project in the memory of my lost child (baby boy). You are always with me and I will always love you.

ABSTRACT

Steam turbines are an important asset of nuclear power plants, and are required to operate reliably and efficiently. Unplanned outages have a significant impact on the ability of the plant to generate electricity. Therefore, condition-based maintenance (CBM) can be used for predictive and proactive maintenance to avoid unplanned outages while reducing operating costs and increasing the reliability and availability of the plant. In CBM, the information gathered can be interpreted for prognostics (the prediction of failure time or remaining useful life (RUL)).

The aim of this project was to address two areas of challenges in prognostics, the selection of predictive technique and accommodation of post-maintenance effects, to improve the efficacy of prognostics. The selection of an appropriate predictive algorithm is a key activity for an effective development of prognostics. In this research, a formal approach for the evaluation and selection of predictive techniques is developed to facilitate a methodic selection process of predictive techniques by engineering experts. This approach is then implemented for a case study provided by the engineering experts. Therefore, as a result of formal evaluation, a probabilistic technique the Bayesian Linear Regression (BLR) and a non-probabilistic technique the Support Vector Regression (SVR) were selected for prognostics implementation.

In this project, the knowledge of prognostics implementation is extended by including post maintenance affects into prognostics. Maintenance aims to restore a machine into a state where it is safe and reliable to operate while recovering the health of the machine. However, such activities result in introduction of uncertainties that are associated with predictions due to deviations in degradation model. Thus, affecting accuracy and efficacy of predictions. Therefore, such vulnerabilities must be addressed by incorporating the information from maintenance events for accurate and reliable predictions. This thesis presents two frameworks which are adapted for probabilistic and non-probabilistic prognostic techniques to accommodate maintenance. Two case studies: a real-world case study from a nuclear power plant in the UK and a synthetic case study which was generated based on the characteristics of a real-world case study are used for the implementation and validation of the frameworks. The results of the implementation hold a promise for predicting remaining useful life while accommodating maintenance

repairs. Therefore, ensuring increased asset availability with higher reliability, maintenance cost effectiveness and operational safety.

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General Abbreviations

ANFS	Adaptive Neuro Fuzzy System
ApEn	Approximate Entropy
ANNs	Artificial Neural Networks
ACF	Autocorrelation Function
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BLR	Bayesian Linear Regression
CPA	Change Point Analysis
CPD	Change Point Detection
CBM	Condition Based Maintenance
CUMSUM	Cumulative Sum of Differences
ETG	Electric Turning Gear
ERNN	Elman Recurrent Neural Network
EKF	Extended Kalman Filter
FFBPNN	Feed Forward Back Propagation Neural Network
FFNN	Feed Forward Neural Network
GPR	Gaussian Process Regression
HMS	Health Management System
HMM	Hidden Markov Model
HSMM	Hidden Semi-Markov Model
HHMM	Hierarchical Hidden Markov Model
HP	High Pressure
IP	Intermediate Pressure
KF	Kalman Filter
KBS	Knowledge Based System

LS	Least Square
LR	Linear Regression
LP	Low Pressure
MA	Moving Average
MFFBPNN	Multilayer Feed Forward Back Propagation Neural Network
NPPs	Nuclear Power Plants
ORH	Optimum Regression Hyperplane
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
PF	Particle Filter
PM	Preventive Maintenance
PHM	Prognostics Health Management
RBPF	Rao-Blackwellized Particle Filter
RM	Reactive Maintenance
RVM	Relevance Vector Machine
RUL	Remaining Useful Life
RMS	Root Mean Square
SIR	Sample Importance Resampling
STS	Steam-to-Set
SSR	Sum of Squared Residual
SVM	Support Vector Machine
SVR	Support Vector Regression
SKF	Switching Kalman Filter
TOF	Time of Failure
UKF	Unscented Kalman Filter

CHAPTER 1: INTRODUCTION

1.1. Introduction to Research

Nuclear power is a sustainable source of energy. There are 442 reactors operating in 31 countries producing around 11% of the world's electricity. Alone in the UK, where it is considered an integral part of base load power generation, about 21% of the electricity comes from 15 nuclear reactors at 8 sites. However, almost half of its capacity is to be retired by 2025. The UK government has stated its desire for nuclear power to remain significant part of a balanced generation mix. It has proposed meeting this by extending the operational life of nuclear power plants (NPPs) while stimulating a renaissance in building NPPs so that it contributes to all three objectives of 'trilemma' of secure supply, decarbonisation, and affordability [1].

Electricity from nuclear power plants is used mostly for base-load because it is reliable and safe. One major factor affecting the nuclear power plant is producing electricity in a cost-effective manner without compromising safety. Therefore, the risk of early closure, unplanned shutdown, or restrictions to operation are mitigated through planned maintenance strategy, equipment reliability and plant life extension programmes in order to achieve reliable and safe operation of NPPs. Maintenance strategies broadly fall into three main categories of preventive maintenance (PM), reactive maintenance (RM) and condition based maintenance (CBM).

In PM strategy, maintenance is scheduled periodically for each system or component regardless of any degradation or abnormal behavior in order to prevent any sustained damages. In this type of maintenance approach, faults can be identified at an early stage through regular inspections to keep damages to equipment minimal. However, very often components are replaced before they even reach their time of failure (TOF). Figure 1.1 shows the costs that are associated with the PM strategy. The PM maintenance strategy results in high maintenance costs to achieve reduction in operational costs due to failures occurring in operation.

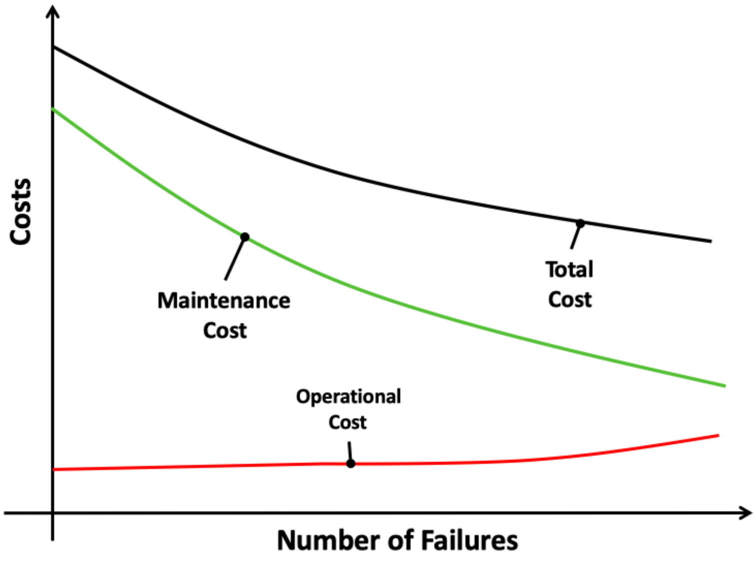


Figure 1.1 - Costs associated with Preventive Maintenance strategy

In RM strategy, a component is allowed to reach TOF and maintenance is only performed when failure occurs. Figure 1.2 shows the costs that are associated with the RM strategy. The RM strategy may reduce costs associated with unnecessary inspections and maintenance, but greatly increases the risk of catastrophic failure occurring within the machine which may lead to higher costs that are incurred for component repairs and replacements.

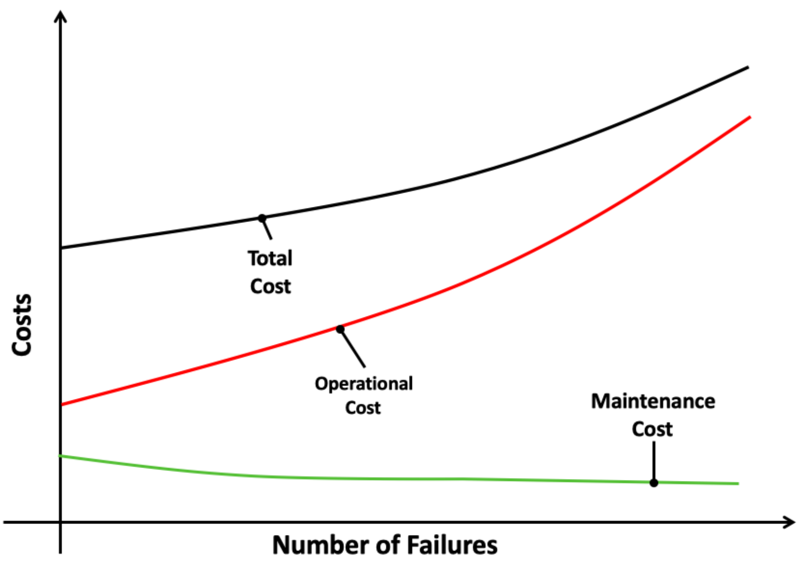


Figure 1.2 - Costs associated with Reactive Maintenance strategy

CBM strategies involve performing maintenance when necessary based on the condition of an equipment. CBM incorporates continuous monitoring of state of an equipment.

Compared to both preventive and reactive maintenance strategies, CBM aims to minimise operational and maintenance costs as illustrated in Figure 1.3. In CBM, the information gathered on the state of the equipment is used for diagnostics (detection, isolation, and identification of faults) and prognostics (the prediction of failure time) [2].

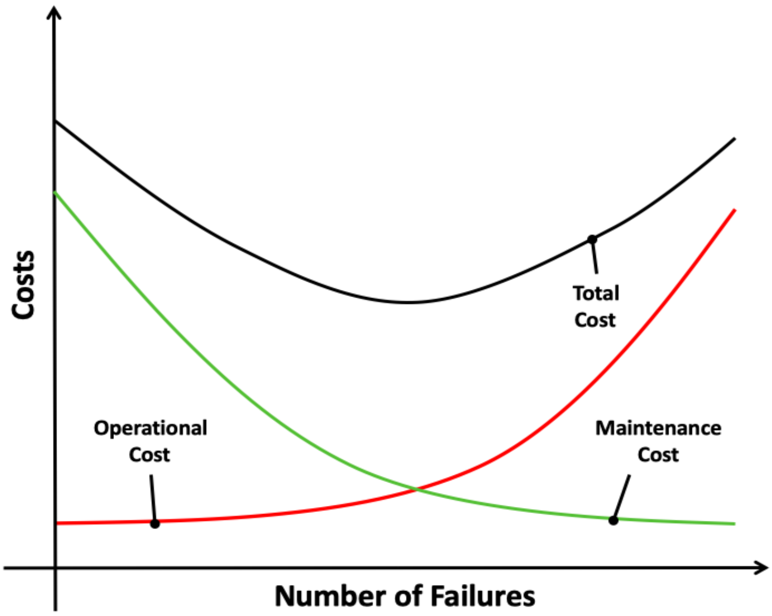


Figure 1.3 - Costs associated with CBM strategies, adapted from [3] and [4]

Prognostics is defined as the detection of precursors faults or conditions leading to a failure, and predicting when an equipment or component is likely to fail [5]. Prognostics has also been defined as an estimation of remaining useful life (RUL), where RUL is the time until a component or an equipment no longer meets its design function [6]. Prognostics is considered as an ultimate CBM regime that can increase safety and reliability and reduce unplanned plant shutdowns while facilitating operations planning and timely maintenance. Prognostics can be classified into three types. Type 1 or Reliability-based prognostics depends on historical failure time data. Type 2 or Stressor-based prognostics takes operational and environmental conditions into account. Type 3 or degradation-based prognostics measures degradation state of an equipment or component for the estimation of RUL [4].

1.2. Motivation for Research

Prognostics has the potential to significantly reduce operational and maintenance cost while increasing reliability, availability and safety. Despite of increased research and development, prognostics is still relatively new area of CBM and has yet to build its reputation compared to other areas of CBM [7]. Much work has been done to improve prognostics for estimation of RUL of engineering assets. However, there are many challenges within prognostics that still exist when implementing prognostics and need to be addressed in order to achieve reliable and meaningful results. The most notable areas of challenges in prognostics include: selection of prognostics technique; lack of run-to-failure data; management of prognostics uncertainties; effects of maintenance actions; effects of failure interactions; performance evaluation of prognostics. Out of these areas of challenges, selection of prognostics technique and effects of maintenance actions are two most underdeveloped areas of prognostics. Main drivers for selecting these two areas of prognostics was discussions with reliability engineers that desired a methodic way of selecting predictive algorithms and inclusion of changes in degradation rates due to maintenance. Therefore, in this research, these two areas of prognostics are addressed to improve the efficacy of prognostics.

Selection of an appropriate prognostics algorithm is a key activity for an effective development of prognostics in order to achieve benefit of maintenance planning and as a result cost-effective operation [8]. Recent work, [9] provides a generic design framework for selection of prognostics technique. Based on this work and wider literature review, data characteristics, and project requirements a formal evaluation and selection process for prognostics has been developed. This formal evaluation process enables selection of two prognostics techniques: Bayesian Linear Regression (BLR) and Support Vector Regression (SVR). These techniques are adapted to accommodate maintenance.

Maintenance activities affect prognostics accuracy and efficacy. Maintenance actions also do not completely restore system's health and introduces uncertainties that are associated with predictions. Therefore, in order to address such vulnerabilities of prognostics, information from maintenance events must be incorporated into prognostics for accurate predictions. One of the most notable work for incorporating maintenance in prognostics is the use of Bayesian online change point detection method to detect events. Then, this event information is used as an input to prognostics algorithm to update estimation of RUL [10].

In this research, a retrospective changepoint detection method is used to detect maintenance events which is used as an input information to adapt prognostics algorithms to accommodate maintenance. BLR as a probabilistic prognostic technique accommodates maintenance by updating parameters such as slope and intercept after maintenance has taken place. Whereas SVR as a non-probabilistic prognostic technique accommodates maintenance by using synthetic data which is generated based on the model retained prior to maintenance. A case study from the data of an operational steam turbine of a nuclear power plant in the UK was used to implement the adapted prognostic techniques. Most of the prognostic techniques are usually developed as "fit for purpose" [11]. Therefore, to ensure wider applicability and performance validation of the adapted prognostic techniques, synthetic data which closely mimics the real case study is generated and is used to implement adapted prognostic technique.

1.3. Novel Contributions

This thesis claims the following original contributions:

- Development of formal evaluation process for selecting prognostic techniques which is widely applicable to various engineering assets.
- Adaptation BLR and SVR to accommodate maintenance and estimate remaining useful life
- Implementation of Adapted-BLR and Adapted-SVR using a real-world and a synthetic data case to demonstrate improved efficacy of prognostics
- Comparison and evaluation of the Adapted-BLR and Adapted-SVR prognostic techniques for application to Nuclear Power Plants

1.4. Thesis Outline

The thesis presents solutions for selecting prognostic techniques and adapting them to accommodate maintenance. The structure of the thesis is as follows

Chapter 2

This chapter provides literature review of state-of-the-art prognostics techniques and applications in various engineering fields. The chapter also provides detailed overview of challenges that are involved during the applicability of prognostics. The opportunities that stem from prognostic implementation challenges are also discussed.

Chapter 3

This chapter describes the development of formal evaluation and selection process of prognostic techniques which uses prognostic metrics identified from the literature review, data analysis and industrial requirements of the project for selecting prognostic algorithms. The developed formal evaluation and selection process utilises look up tables which are formed based on the PHM implementation requirements and the inherent ability of the technique to score prognostic techniques for selection metrics. This chapter also presents two case studies identified from literature to validate the implementation of the formal evaluation process. After validating the process, the process is implemented for nuclear prognostics. As a result of implementation, BLR and SVR are selected for prognostics implementation.

Chapter 4

This chapter provides background review on nuclear power plant steam turbine with a description of its subsystems and components. In addition, associated steam turbine instrumentation is also discussed. An analysis on the data of nuclear steam turbine to form a case study is presented. This chapter also presents a process for generating synthetic data which is used to ensure wider applicability of adapted prognostic algorithms and to validate performance.

Chapter 5

This chapter of the thesis details the development, implementation, and adaptation of BLR as a probabilistic prognostics technique to accommodate maintenance in prognostics. This is achieved by updating the model parameters of the BLR after the maintenance. A synthetic and a real-world case studies are used to test Adapted-BLR algorithm. This chapter also provides a performance comparison of BLR and Adapted-BLR.

Chapter 6

This chapter of the thesis details the development, implementation, and adaptation of SVR as a non-probabilistic prognostics technique to accommodate maintenance in prognostics. This is achieved by using synthetic data generated based on the model retained prior to maintenance as a historic data. The adapted technique is tested using a synthetic and a real-world case study. A performance comparison of SVR and adapted SVR is detailed in this chapter.

Chapter 7

In this chapter, a discussion on the implementation of formal evaluation and selection process for prognostics is presented. The chapter also discusses Adapted-BLR and Adapted-SVR in detail while listing the strengths and weaknesses of both techniques. Results from the comparison of both adapted techniques is also discussed in this chapter.

Chapter 8

This chapter states main conclusions of this thesis and future work.

1.5. Publications

To summarise contributions, this section provides a list of the publications:

O. Panni, G. West, V. Catterson, S. McArthur, D. Shi and I. Mogridge, "Implementation of a Bayesian Linear Regression Framework for Nuclear Prognostics," in *European Conference of the Prognostics and Health Management Society*, 2016.

O. Panni, "Increasing Certainty in Nuclear Prognostics," in *Rolls-Royce Engineering Doctorate Conference*, Derby, 2015.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This literature review chapter provides comprehensive overview of prognostics health management (PHM) and prognostics algorithms. Available prognostic techniques and their applications from variety of industries are outlined. The main objective of this chapter is to present available state of the art prognostics techniques, thus, laying the foundation for the development of formal evaluation process of prognostic techniques which is discussed in Chapter 3 of this thesis. The formal evaluation process was used to select prognostic techniques for application to a case study from a NPP.

2.2. Prognostics Health Management (PHM)

As an integrated technology, PHM provides health overview of a system or an overall asset in order to enhance its reliability and availability by detecting current and predicting future states of a system, thus providing for mitigation of the system risks [12]. The process diagram of PHM is shown in Figure 2.1.

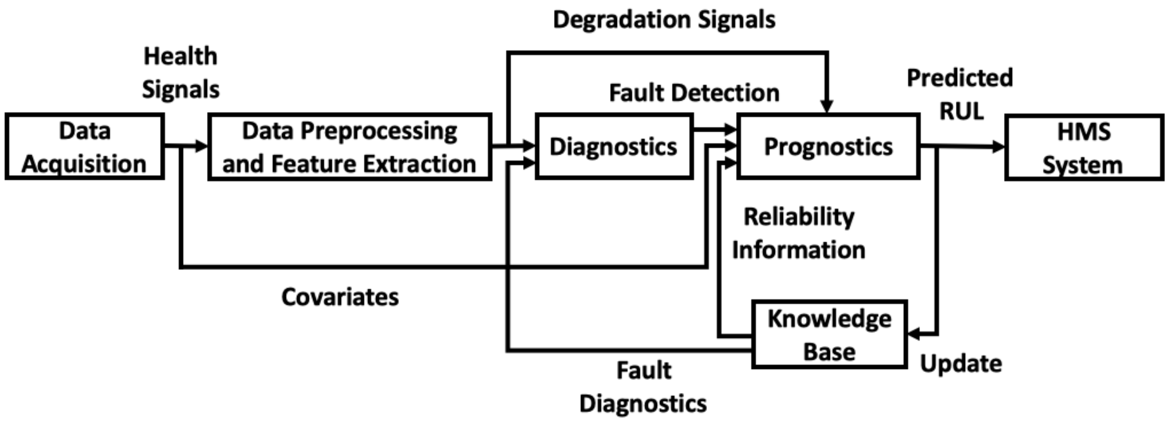


Figure 2.1 - PHM Process, adapted from [13]

The main tasks of PHM system include data acquisition, data pre-processing, feature extraction, fault detection, diagnostics and prognostics in order to support the maintenance decision making process. Each of these tasks of a PHM system are described below:

2.2.1. Data Acquisition

Data acquisition is a process of acquiring condition monitoring and covariates data. Condition monitoring data is sensory information such as temperature, vibration signals, etc. It is acquired via installed sensors from asset under investigation. The covariates data is event data (failure, breakdown, maintenance, installation, etc.), operating conditions, and environmental factors. The covariates data is collected through experts, information management system, standards, etc. and can be used to enhance RUL estimation. For example, load and speed changes were used by Gebraeel and Pan [14] to improve RUL estimation of bearings.

The main challenges of data acquisition process include right sensor selection and installation, data acquisition system selection, and data storage.

2.2.2. Data Pre-Processing and Feature Extraction

Data pre-processing and feature extraction is a process that involves cleaning the data and extracting useful data subset that best represents the system health state being monitored.

Basic operations of data cleaning process include handling missing data fields and dealing with noise and known changes in order to create a data set that is error-free for further investigation. A cleaned data set then undergoes a feature extraction process. During this process, only useful and system health representative information is extracted either by reducing the dimensions of the data or transforming the data. For example, Gebraeel et al. [15] and Widodo and Yang [16] estimated root mean square (RMS) value and kurtosis of vibration signals to characterise health condition of rolling element bearings. Walker and Coble [17] used approximate entropy (ApEn) as a health indicator for bearings to early detect degradation. Once a feature is extracted, it undergoes feature evaluation process during which monotonicity, prognosability, and trendability of the feature dataset is assessed. After the evaluation, best features are selected for further assessment.

The main challenges of data pre-processing and feature extraction include data dimensionality, data transformation, and health indicator construction.

2.2.3. Diagnostics

Diagnostics is the process of fault detection, isolation (location of fault), identification (type of fault), and assessment (severity of fault). Fault detection is performed by comparing health signals against expected profile signals or operational limits. Whereas for fault isolation, identification and assessment, feature signal is assessed. Knowledge based system can also be used for fault isolation, identification, and assessment [13]. The process of diagnostic occurs when the machine or system is either in failure or faulty state. Therefore, diagnostic results can be used for reactive and proactive maintenance.

The main challenges of diagnostic process include: fault detection, isolation, and identification; and defining failure threshold.

2.2.4. Prognostics

Prognostics is the process of estimating the RUL or time after which a system or a component fails to perform its intended design function. Prognostics process utilises prognostics algorithm on degradation signals to predict future health of a system or component.

The main challenges of prognostics process include RUL prediction horizon, prognostics metrics, impact of covariates, and uncertainty management.

2.2.5. Knowledge Based System

Knowledge based system (KBS) is a system consisting of a database and an inference engine. The database of the system contains expert knowledge, reliability, failure, and operational information about a system or a component. The inference engine applies logical rules to the database to deduce information about an asset under observation to help maintenance engineers diagnose faults. This deduced information from KBS, can be used for diagnostics and prognostics [18].

The main challenges of a KBS include knowledge elicitation bottlenecks, brittleness of rules as an approach to storing knowledge, inference efficiency problems, knowledge interpretation and maintenance of inference engine.

2.2.6. Health Management System

Health management system (HMS) integrates diagnostics/prognostics, covariates, and externals factors (i.e. safety, cost, etc.) information to provide optimised recommended actions as decision support for operations and maintenance. Recommended actions can be maintenance interventions, operational reconfigurations, or component replacements. These recommendations and actions are prioritised based on asset optimisation principles [18].

The main challenges of HMS involve profile changes and reconfigurations, and fault tolerant control system.

2.3. Prognostics Algorithms

The aim of prognostic algorithms is to estimate RUL after which a component or a system no longer meets its design function due to a fault. As a result, a component or a system is likely to fail. The estimation of RUL requires knowledge of the fault and the rate at which the component or the system will degrade over time. The rate of failure can be derived from historical data (observations or examples of run to failure) or model representing degradation process [19]. Therefore, prognostic algorithms can be categorised into three categories based on the information they use to make RUL estimates. These categories are time-to-failure analysis, stressor-based and degradation-based [20], as shown in Figure 2.2.

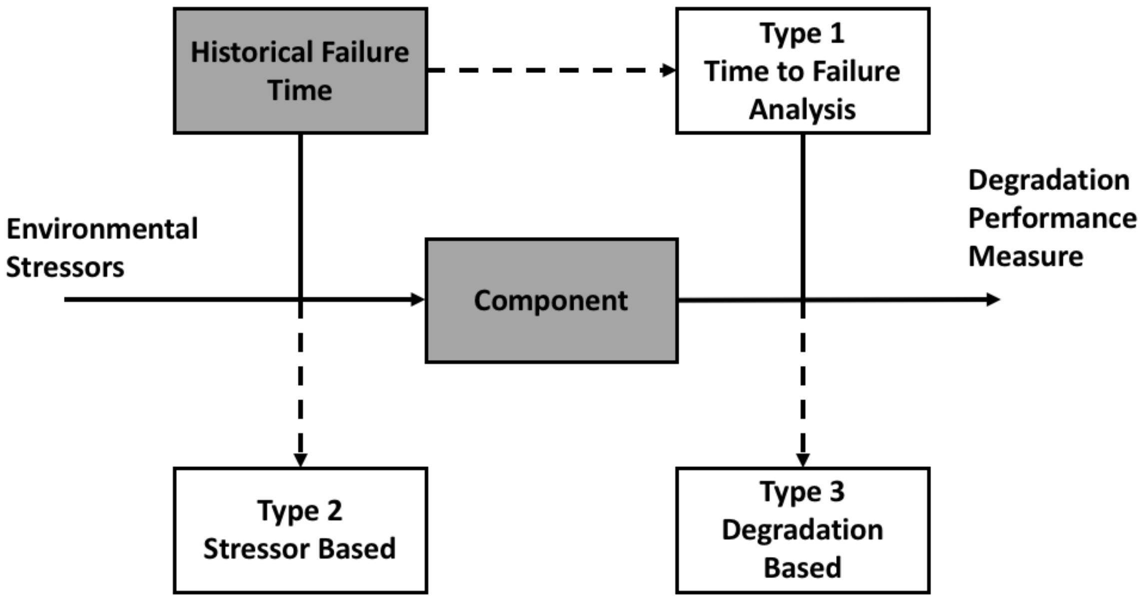


Figure 2.2 - Categories of prognostics methods, adapted from [21]

Each of these categories of prognostics algorithms is discussed in the following sections:

2.3.1. Type 1: Time to Failure Analysis

Time to failure analysis is an extension of traditional reliability analysis. Prognostics algorithms in this category use probability distributions of runtimes from historical examples of failure in similar systems to estimate TOF [21]. The Weibull distribution is the most commonly used parametric distribution, which is used to model variety of failure rates of similar systems [22]. The equation used to model failure rates is:

$$p(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} \tag{2.1}$$

where x is the failure time, α is a scale parameter, and β is a shape parameter. The scale and shape parameters of Weibull distribution allows modelling of increasing, decreasing, constant failure rates. Examples of different shape parameters exhibiting different failures rates are given in Figure 2.3.

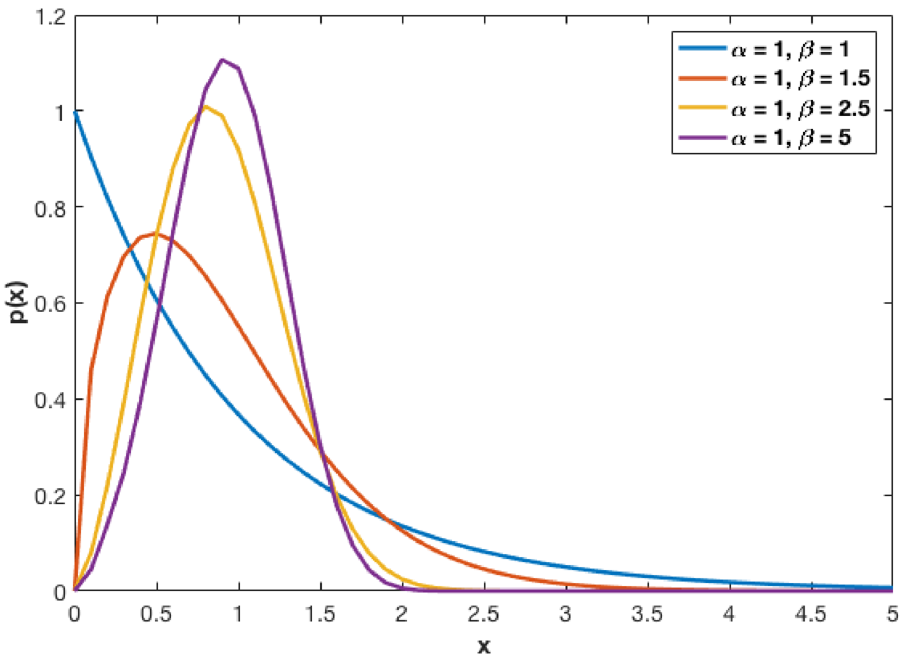


Figure 2.3 - Weibull distribution with different shape (k) parameters

Type 1 prognostics rely upon the assumption that all similar systems have operated under similar conditions, and therefore, the failure rate is similar to historic failure rates [21]. Thus, making them impractical in many industrial applications. The impact of operating conditions must be considered to improve prognostics results [23] [24].

2.3.2. Type 2: Stressor-Based

Stressor-based prognostic is an extension of type 1 prognostics. It incorporates past and future operating conditions of the system to estimate RUL. The operating conditions of the system may include speed, temperature, etc. providing usage indication of components/systems to model failure rate of an average component operating under these measured conditions [21].

Common type 2 prognostics techniques include regression analysis, Markov chain models, proportional hazards models, physics-of-failure models, and life consumption models [21].

Type 2 prognostics rely upon assumption that systems operation under same conditions will fail at similar rates and there is little unit-unit variance between systems operating under same operating conditions. Like type 1 prognostics, type 2 prognostics is also dependent on historical examples of failure. Therefore, these methods are unsuitable for new applications, where historical data of failures times will be sparsely available.

2.3.3. Type 3: Degradation Based

Degradation based prognostic algorithms predict the failure rates or remaining useful life of a system from its measured degradation parameters. Degradation parameters of a system or component provide health indication, which are used to estimate the RUL [20]. Degradation parameters of a component or a system can be measured directly or generated indirectly to infer the level of damage. Figure 2.4 shows the process of estimating the RUL using degradation parameter.

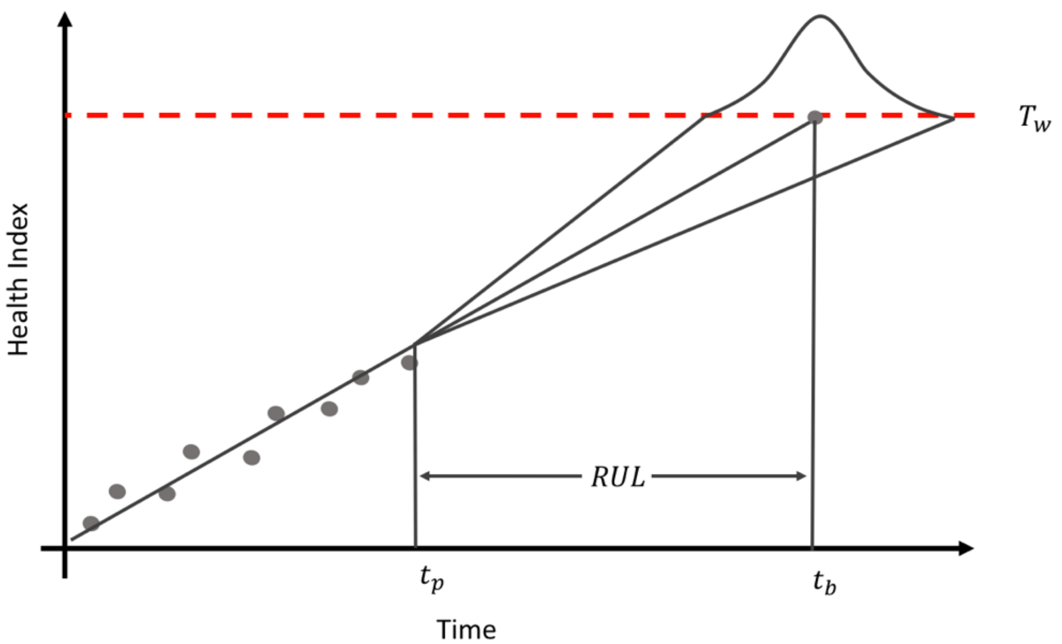


Figure 2.4 - Estimation of RUL using degradation-based prognostics

From Figure 2.4, the RUL can be estimated as:

$$RUL = t_b - t_p \tag{2.2}$$

where t_b is the future point in time at which warning threshold is breached and t_p is the point in time at which prediction are made.

Type 3 prognostics also require rate of degradation in order to extrapolate degradation parameter forward in time to a failure threshold. Type 3 prognostics can be split into three categories: model-based, data-driven, and hybrid [12] [25] [26] [27]. Degradation is inferred from model representing the underlying failure mechanism, historical data, or combination of both. Prognostics techniques in this category are most suitable for new applications as they do not rely on the availability of historic data to predict failure time. Predictions can be inferred from the current health of individual components, operating conditions, and through the measurement of a degradation parameter. Models representing similar components operating in different environment can be constructed, where model parameters can be tuned to best fit the observed trend of degradation.

The categories of degradation-based prognostic are further discussed in the remainder of this chapter with their applications and challenges involved during the implementation of prognostics techniques.

2.3.3.1. Model-Based Prognostics

Model based prognostics use physical models represented as mathematical equations to characterise the behaviour of a system [28] [29] [30]. These physical models govern system's failure degradation behaviour and therefore require complete understanding of physics-based knowledge of the specific system or the knowledge of the failure of similar components in different systems. Hence, physical models are very difficult to derive for practical applications with varying dynamic responses and complex damage evolution processes [28] [30]. However, model-based approaches are more accurate and are not dependent on the availability of run-to-failure data. They provide long prediction horizon [31] and with increasing understanding of system degradation physical models can also enhance accuracy by tuning parameters of the model to best fit the observed degradation process [28].

Figure 2.5 shows a generic methodology of model-based prognostics. In this methodology, a model representing system dynamics and the degradation process is identified. Fast and slow dynamic variables of the model represent the behaviour of the system and the degradation of the system respectively. Slow dynamic variables are used to simulate random scenarios which are compared to measurable data in order to identify the appropriate feature which is later used to estimate the RUL.

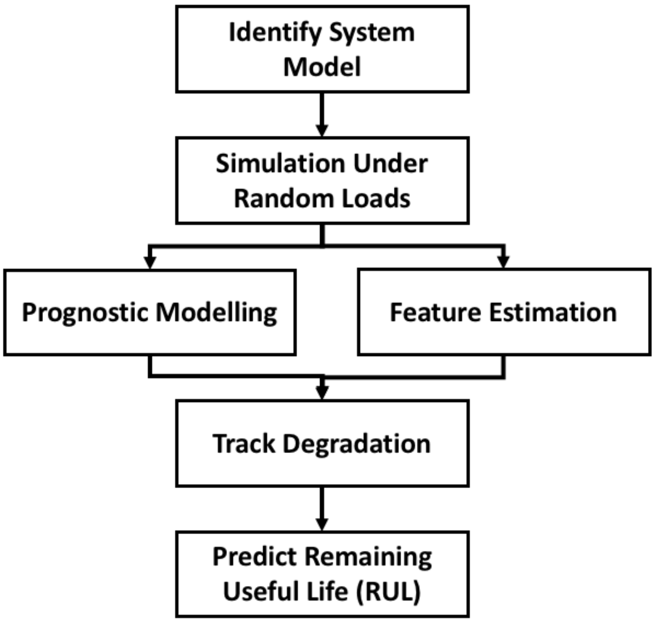


Figure 2.5 - Model-based prognostics methodology adapted from [32]

The most popular model-based prognostic approaches include Paris law, Forman Law, Fatigue Spall Initiation and Progression Model, and Parameter Estimators. For example, Paris et al. [33] modelled degradation mechanism to estimate crack growth rate for RUL estimation. Kacprzynski et al. [34] combined Paris crack propagation model and 2D Finite Element Analysis to estimate RUL based on crack growth. Li and Lee [35] extended this combined approach and developed a dynamic model to estimate RUL of gear with fatigue crack based on the estimated crack size and dynamic load on the cracked tooth. Oppenheimer and Loparo [36] used Forman law of linear elastic fracture mechanics to model rotor shaft crack growth and estimated RUL using vibration data.

Rolling bearings provide necessary support to rotating machinery by transmitting axial and radial loads from the rotating part to the structure, thus minimising friction losses in the sliding direction. Li et al. [37] predicted rolling element bearing defect growth and remaining useful life using adaptive defect propagation model that incorporates variable nature of defect propagation by a mechanistic model with time varying parameters. Qiu et al. [38] developed an integrated degradation model defining the damage as a function of the stiffness in order to estimate the RUL of the bearing. Liang et al. [39] estimated instantaneous rate of defect propagation for RUL estimation using self-adapting RUL method. Marble and Morton [40] modelled turbine engine bearing spall progression and estimated failure time and spall growth trends.

Parameter estimators such as Kalman Filter (KF), Particle Filter (PF), etc. had been applied as model based prognostic approaches depending on the sophistication of the system [41]. Most common parameter estimators are shown in Table 2.1.

Table 2.1 - Parameter estimators as model-based prognostic methods

Linear Estimators	Non-Linear Estimators
Least Square (LS) Kalman Filter (KF)	Switching Kalman Filter (SKF) Extended Kalman Filter (EKF) Particle Filter (PF)

Bayesian estimators are capable of dealing with various types of uncertainty and can be used to model linear and non-linear systems. Baraldi et al. [42] applied KF to predict RUL of a turbine blade based on creep damage. Creep is permanent deformation caused due to low loads below the elastic limit at high temperature over prolonged period of time. Turbines undergoing this degradation process can lose its blades and abrupt changes in power conversion system are experienced [43]. Lim and Mba [44] applied SKF to estimate model and the RUL of tail rotor gear box output shaft bearing using condition monitoring data. Results of this approach showed that SKF can be applied to provide decision support for maintenance. Orchard et. al. [45] compared the results of EKF and PF applied to estimate crack lengths of gear box plate using Paris Law. The results of the comparison showed that Particle Filter provides better RUL estimates.

Model-based prognostics have also been applied to electronic applications. Kwon and Yoon [46] applied PF to predict time of failure of electronic interconnections based on Paris Law which was used to model fatigue crack growth in interconnections. Lall et al. [47] explored electronic component failures due to shock and vibration loads and predicted RUL using failure model of interconnects for KF. Saha and Goebel [48] studied Li-ion battery capacity depletion and predicted RUL of the battery using empirical model for PF.

Model-based prognostics suffers from several drawbacks. In many practical applications, the process of building a representative model is very tedious and complex. It requires thorough understanding of system dynamics and the degradation process of the system.

They are only developed for specific uses addressing unique failure type and dynamic damage evolution and very difficult to adapt to a different system [49]. They require large sets of data for validation [50]. As an alternative, data-driven prognostics can be used to estimate RUL based on the historical information and degradation measurements of the equipment [51].

2.3.3.2. Data-Driven Prognostics

Data Driven prognostics use statistical or machine learning methods to model system behavior directly from historic data instead of deriving models based on system dynamics and the degradation process [52]. The observed degradation trend is then utilised to estimate RUL of the system by extrapolating the trend into future until it reaches a predefined threshold. The accuracy of data-driven prognostic methods depends on the availability of condition monitoring data [9]. These prognostic methods rely upon the assumption that there is underlying stability in the monitored system in order to utilize past patterns of degradation to predict future degradation.

Figure 2.6 shows a generic methodology for data-driven prognostics. In this methodology, raw data is used to extract feature signals which are used to identify a model representing the degradation process. This degradation model is then used to estimate the RUL.

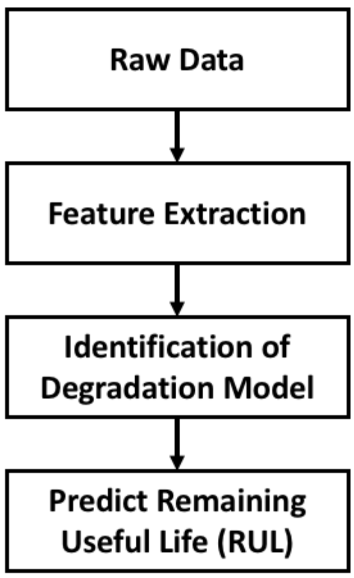


Figure 2.6 - Data-driven prognostics methodology

Data-driven prognostic approaches can be classified into conventional and machine learning methods. Conventional methods such as Autoregressive Integrated Moving Average (ARIMA) has been applied for rotating machinery prognostics to model non-stationary time series signals and estimate RUL. For example, Marinai et al. [54] applied ARIMA with regression analysis to estimate RUL of turbo fan engine based on turbine gas temperature margins. Wu et al. [55] compared the results of improved ARIMA with the traditional Box-Jenkins ARIMA using simulated vibration data. The results validated that the improved prediction method performed marginally better than the standard ARIMA. However, long term predictions still suffered due to observational and dynamic noise and the sensitivity to initial conditions. Therefore, Liu et al. [56] proposed a novel Match Matrix algorithm to address long term prediction inaccuracy. Match Matrix compares current degradation time series data with the historical degradation time series data to estimate similarity distance. If the similarity distance is large, then historical times series data can be used for modelling and estimating RUL for the current developing degradation.

Artificial Neural Networks (ANNs) are the most commonly applied machine learning prognostic technique [57]. An ANN consists of a layer of input nodes, one or more layers of hidden nodes, and a layer of output node. An ANN learns a trend and pattern by adjusting weights which are connections between the nodes. Different types and structures of ANNs have been widely applied in rotating machines to estimate RUL. For example, Mahamad et al. [58] applied Feed Forward Neural Network (FFNN) to estimate RUL of bearings using RMS and kurtosis of the vibration signal. Gebraeel and Lawley [59] estimated RUL of bearings using Feed Forward Back Propagation Neural Network (FFBPNN). Whereas, Rodríguez et al. [60] used FFBPNN to estimate the RUL of steam turbine blades. Yu et al. [61] presented an Elman Recurrent Neural Network (ERNN) Model to predict behaviour of a boring process during its full life cycle. Mazhar et al. [62] estimated the remaining life of used components in consumer products by using multilayer feedforward back propagation neural network (MFFBPNN). Other notable applications of ANNs include Electro-hydraulic servo valve of aircraft actuator components [63], planetary gear plate of a helicopter transmission [64], planetary gear train of motor-pump in power station [65], grinding mill liners [66], and Li-ion batteries [67]. ANNs are typically data hungry machine learning techniques and require considerable amount of historical failure examples for training. They do not cope very well when subjected to future failure examples that do not exhibit similar behaviour of the training dataset [68]. Most of the ANNs do not provide confidence limits with RUL predictions. Confidence limits are highly desirable feature of RUL estimates as they provide the means for uncertainty management.

Gaussian Process Regression (GPR) is a non-linear and non-parametric Bayesian regression technique which places prior distribution over the space of functions and estimates posterior degradation by constraining prior distribution to fit the training dataset [69]. The uncertainty associated with predictions is managed by providing variance around mean predictions. Baraldi et al. [70] estimated RUL of filters that are used to clean sea water entering the condenser of the BWR reactor. Similarly, Richardson et al. [71] applied GPR to estimate RUL of Li-ion batteries using capacity vs cycle dataset.

Support Vector Regression (SVR) is a variant of Support Vector Machine (SVM) and is used to predict RUL using time series data. SVR achieves this by extrapolating an optimal regression hyperplane (ORH) in order to best fit the training data and extract feature model which is used to make predictions for the test data. The application of SVR include bearings [72], batteries [73], steam turbine rotor [74], and HP LNG pump [75]. Despite of SVR being a state-of-the-art technique it suffers from lack of probabilistic interpretation of its outputs, therefore, Relevance Vector Machine (RVM) was developed which attempts to address this issue in a Bayesian framework while utilising fewer kernel functions [76]. Zio and Di Maio [77] applied RVM for degradation model identification, degradation state regression and RUL estimation of a component undergoing crack growth. The RVM is able to account for the inherent uncertainties through its Bayesian interpretation, but this advantage can be a drawback if training dataset is small or if the test dataset is significantly different.

A hidden Markov model (HMM) is a statistical Markov model in which the system being modelled is assumed to be a Markov process with unobserved (hidden) states. The objective of HMM in prognostics is to predict the evolution of the state of health of a system from its current state to its failure based on the model and the measurements. Baruah and Chinnam [78] predicted the RUL of machining drill based on thrust-force and torque signals. The results indicate that HMMs can provide reasonable prediction accuracy however they do suffer from computational burden because of competitive learning process. Standard HMMs also do not have intrinsic transition probabilities between health states, therefore, they require additional techniques in order to estimate health state transition probabilities to be used for RUL estimation. To overcome these difficulties, Camci and Chinnam [79] used Hierarchical Hidden Markov Model (HHMMs) which is variant of HMM, to capture health state transition probabilities while estimating RUL of the drill-bits on a CNC machine. Another variation of HMMs is Hidden Semi-Markov Model (HSMMs) which uses grid-based techniques to estimate health-state related probability distributions [80] to be used for RUL estimation. Dong and He [81] introduced new integrated HSMM approach to estimate the RUL of hydraulic pumps using multi-sensor data. Other applications of HMMs include bearings [82] [83] and turbo fan engines [84].

Other data-driven techniques that have been applied in prognostics include linear and quadratic regression [85], Regression Trees [86] [87], Fuzzy Logic and Neuro-Fuzzy Network [88], Dempster-Shafer Theory [89], and Bayesian Approaches [13], [15]. Each approach has its own advantages. In general, the strength of data-driven approaches is transformation of data into useful information for prognostics decision making. Data driven approaches require sufficient run-to-failure data with all failure-modes of interest in order to learn and capture degradation mechanisms. This may be more practical or available solution for prognostics of complex systems in many applications.

2.3.3.3. Hybrid Prognostics

Hybrid Prognostics is an integration of prognostics approaches. It aims to leverage the strengths of different approaches while minimising their limitations in order to achieve finely tuned prognostics models for better system or component health estimation and RUL prediction. Hybrid prognostics can be classified into following two categories based on the literature survey of prognostics implementation:

- Model-Based and Data-Driven Prognostics
- Multiple Data-Driven Prognostics

In this section, these classifications are explained with their applications in prognostics.

2.3.3.3.1. Model-Based and Data-Driven Prognostics

This hybrid prognostics approach integrates model-based and data-driven prognostics in order to achieve accuracy in predictions by interfacing different types of models. For example, data-driven prognostic approaches can be used to build measurement model or equation based on which RUL can be estimated. Saha et al. [90] used RVM as data-driven technique to develop a model representing the health state of the Li-ion batteries. This model was then incorporated into a PF framework in order to estimate the RUL while using statistical estimates of noise and anticipated operational conditions. Later this work was extended by Saha et al. [91] by using Rao-Blackwellized Particle Filter (RBPF) framework. Baraldi et al. [92] proposed a novel hybrid approach in which a bagged ensemble of ANNs was used as a data-driven prognostics technique to build an empirical measurement model for a Particle filtering approach in order to estimate the RUL of bearings based on crack depth and crack propagation rate. This type of hybrid prognostics approach allows inclusion of uncertainty into predictions. However, to benefit from this approach full life cycle data should be used in order to achieve accuracy in predictions as the data collected after the detection of incipient fault is most effective for building measurement model [93].

Data-driven prognostics can also be used to replace system model of model-based prognostics in order to reduce modelling effort. This type of hybrid approach can be potentially applicable to different systems. However, this approach also heavily relies on availability and completeness of the data in order to achieve accuracy in predictions while minimising uncertainties. For example, Galloway [94] used exponential model as the system model for PF in order to estimate RUL using simulated gearbox data. The results provided predictions with higher accuracy indicating that sensible prognostic estimates can be achieved by using data driven models as a system model in model-based prognostics. This type of hybrid prognostic approach has also been applied by Chen et al. [95] [96] for crack growth prognostics. The adaptive neuro fuzzy system (ANFS) was trained on the historical data to model degradation and the PF estimated the RUL probability density function (PDF). Liu et al. [97] applied integrated prognostics approach to estimate the RUL of Li-ion batteries. Data-driven prognostic techniques (i.e. NN, NF, and Recurrent NF) were used to predict the future measurements in order to update the weights of the particles for long term RUL predictions. This type of hybrid prognostics allows accurate long-term predictions when degradation does not follow the fault growth model especially in the case of PFs as they suffer from degeneracy. However, if data-driven prognostics performs poorly in terms of predicting future measurement, it can significantly affect the performance of hybrid prognostics [93].

Model-based prognostics and data-driven prognostics had also been applied simultaneously for the RUL prediction. The model-based prognostic approach incorporates physics-based degradation model whereas data-driven prognostic utilises historical data to estimate the system state. The final RUL is calculated by fusing the prediction results of both prognostics approaches. Goebel et al. [98] fused the damage prediction results of model-based and data-driven prognostics in order to achieve reliable and robust estimation of RUL for bearings.

2.3.3.3.2. Multiple Data-Driven Prognostics

Multiple Data-Driven Prognostics combines two or more data-driven prognostics approaches in order to achieve accuracy in predictions by capturing system or component dynamics both in failure modes and operating conditions. In this type of hybrid prognostics, one data-driven technique is used to estimate health which is extrapolated using another data-driven technique to predict RUL. Yan and Lee [99] estimated RUL based on the tool wear condition. The tool wear condition was estimated by applying logistic regression with a maximum likelihood on features extracted from the vibration signals. Then tool wear condition was extrapolated using autoregressive moving average (ARMA) to predict the RUL.

In multiple data-driven prognostics, two or more data-driven prognostic approaches can be applied as competing algorithms estimating the RUL simultaneously. The results of data-driven prognostic approaches are fused together to estimate aggregated RUL while reducing prediction errors. Gebraeel et al. [100] developed a multiple data-driven prognostics technique for bearing failure prediction using feedforward back propagation neural networks. In this approach, NNs were trained on the data collected from a single bearing and a cluster of bearings. An aggregated estimate of the RUL was made by weighting the outputs of NNs.

2.4. Prognostics Challenges and Opportunities

Developing an effective prognostics system is a complex and challenging process. The main challenges that are involved in the process of implementing effective prognostics are discussed below with the opportunities that stem from these challenges:

2.4.1. Prognostics Technique Selection

As discussed, prognostic approaches can be categorised into model-based, data-driven, and hybrid approaches. Each prognostic approach has its own advantages and disadvantages. Model-based approaches tend to produce accurate results and require less data. However, model-based approaches are component or defect specific and require exhaustive modelling for POF progression which can be very hard for complex systems. On the other hand, data-driven approaches solely depend on the run-to-failure data but gathering comprehensive data may not always be possible. To overcome these weaknesses of model-based and data driven approaches, hybrid prognostics can be applied which leverages upon the strengths of model-based and data-driven approaches.

Therefore, the effective and reliable application of prognostics depends on proper selection of prognostics methods for particular application. There is no standardised applicable methodology which suggests a prognostic technique according to the user requirements. The selection of applicable prognostics technique is mainly driven by the available engineering resources (run-to-failure data or physics-based degradation model), failure threshold, generality or scope of the approach, uncertainty management, and transparency. Azipurua et al. [9] proposed prognostics selection methodologies for prognostics categories. However, these proposed methodologies need further validation and development while considering business requirements and performance evaluation (i.e. computation complexity, learning experience, cost-benefit analysis, etc.).

2.4.2. Lack of Run-to-Failure Data

Most of the prognostics approaches are dependent on historical data containing failure events. However, many industrial assets are not allowed to run-to-failure because of interactive functioning nature of components which can result in initiating failure in other components, accelerating their degradation or total breakdown of a system. In most cases, the defective unit is replaced well before it fails and as a result condition monitoring data is recorded only up to the point of maintenance. Therefore, availability of run-to-failure data for real-life prognostics implementation is almost non-existing. Thus, making it a big challenge for effective prognostics implementation which is able to provide accurate prediction results.

2.4.3. Uncertainty Management

Uncertainties can lead to inaccurate predictions. Therefore, for effective implementation of prognostics, uncertainties must be addressed. Figure 2.7 shows sources of uncertainties that can affect prediction accuracy of prognostics. These sources of uncertainties are grouped into three categories: Data uncertainties are caused by sensors collecting the data, data errors, data processing tools for feature extraction, and uncertainty estimation in the state; Modelling uncertainties deal with the factors that affect true representation of degradation process through a model and its parameters: Prediction uncertainties are induced by the factors such as loading, operating and environmental conditions of the system, prediction model quantifying combined effect of uncertainties, and prediction methods.

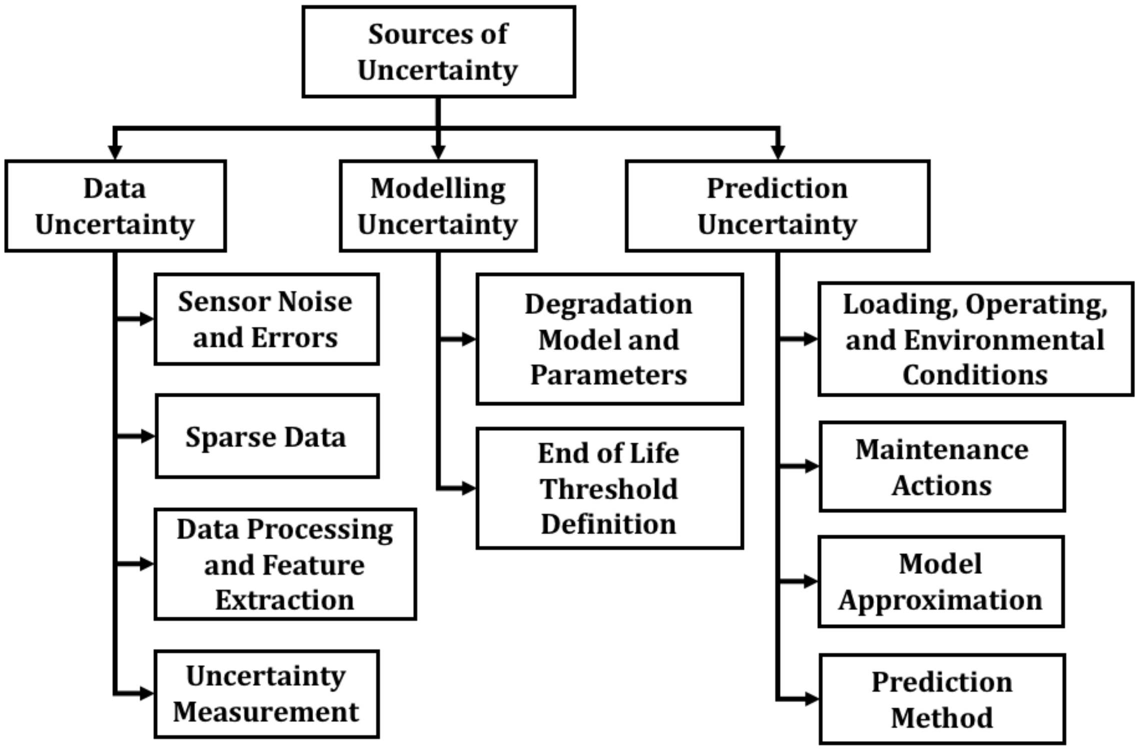


Figure 2.7 - Sources of uncertainty

Hence, developing and implementing prognostic methods that are able to deal with uncertainty and can describe uncertainty is very important. Accommodating uncertainties in prognostics is a complex process and if this problem is not addressed it can lead to the significant deviation of the prognostics results from actual situation. Examples of uncertainty quantification can be found in [101], [102], and [103].

2.4.4. Effects of Maintenance Actions

The main objective of prognostics is to provide decision support for maintenance by optimising maintenance schedules and actions. This is achieved by continuously estimating the health of the asset so that the effectiveness of maintenance can be measured. Though, maintenance actions do not restore system to "as good as new" but the changes in machine health after such actions must be incorporated into prognostics for accurate predictions. Researchers in [104], [105], [106], and [107] have used reliability models to incorporate maintenance. However, this area of research can be further improved by incorporating the effects of maintenance on the health of an asset.

2.4.5. Effects of Failure Interactions

Most of the prognostics to-date has been implemented to predict the RUL of components. However, a complex system is made up of many interactively functioning individual components and predicting the degradation of one component may not be sufficient to predict the failure of overall system due to the fact that a component may initiate or accelerate the failure of another component or vice versa. Literature in prognostics for multi-component systems is very limited. Existing examples of system-level PHM can be found in [108] and [109]. However, there still remains the challenge to be solved to develop system-level PHM addressing component degradation interactions and uncertainties at system-level PHM.

2.4.6. Performance Evaluation

There are many benefits of implementing prognostics [110]. Evaluation of overall effectiveness and technical performance of prognostics system is a challenging and multi-objective task necessary for the justification of prognostics implementation. There is no general agreement to appropriate and acceptable set of metrics to quantify the benefits of prognostics [111]. Saxena et al. [112] provided functional classification of performance metrics. The performance metrics were categorised into following three categories:

- **Algorithm Performance:** Metrics used in this class assess the accuracy, precision, and robustness of prognostics algorithm.
- **Computation Performance:** Metrics in this category highlight the computation performance of prognostics algorithms in order to assess their decision-making ability especially in the cases of critical systems.
- **Cost-Benefit-Risk Analysis:** Metrics in this category measure the economic benefits of prognostics which are influenced by the accuracy with which RUL is predicted. Operational costs can be reduced if RUL is predicted accurately, resulting in fewer component replacements and potentially fewer costly repairs.

Although efforts in [112] have been made to develop a framework of metrics to assess the performance of prognostics systems, further refinements in concepts, definitions, and implementation are expected.

2.5. Summary

This chapter presents a thorough survey on PHM literature and its importance in maintaining and managing critical engineering assets at reduced operational costs with lower risks. A detailed survey of prognostics classifications and approaches with their advantages and disadvantages is presented. This enabled the identification of major challenges for the implementation of prognostics system. One of these challenges is selecting appropriate prognostics methods. The following chapter of this thesis presents a formal evaluation and selection process for prognostic techniques. The process utilises selection metrics that are identified during the literature survey, user requirements, and engineering resources. The detailed overview of techniques that are considered for evaluation is also presented in the following chapter.

CHAPTER 3: EVALUATION AND SELECTION OF PROGNOSTIC TECHNIQUES

3.1. Introduction

This chapter presents a formal evaluation and selection process of prognostic techniques. A review of the background and theory behind the mathematical techniques which were evaluated using a formal review process is presented. To assess the feasibility of prognostic techniques, a selection of metrics identified from prognostics literature and the requirements of the project were used to facilitate evaluation and selection of prognostic techniques. The underlying idea of using this methodology is to develop a methodological approach that enables maintenance engineers to select suitable prognostic techniques for real world applications. This chapter also details the implementation of this formal review process and as a result a probabilistic and a non-probabilistic technique are selected for prognostics implementation.

3.2. Prognostic Techniques

3.2.1. Linear Regression (LR)

A linear regression (LR) model is used to describe a linear relationship between input variable x and an output or response variable y. Therefore, the form of LR model is given by

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{3.1}$$

The terms β_0 and β_1 are parameters of the model termed as intercept and slope. These parameters are usually called regression coefficients. The term ε represents the difference between the true and observed realisation of y. The term ε is often represented as Gaussian Noise expressed as $\varepsilon = \mathcal{N}(0, \sigma^2)$. The determination of LR model depends on the determination of β_0, β_1, and σ^2. The most common method of determining these values is ordinary least squares (OLS) [113] which utilises n pairs of observations $(x_i, y_i)(i = 1, 2, \dots, n)$. Therefore, the model for each observation can be written as

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i , (i = 1, 2, \dots, n) \tag{3.2}$$

The main objective of OLS regression modelling is to estimate regression coefficients such that the ordinary least square function is minimised [114]. The cost function which is the sum of squared residual (SSR) error between the true and observed values of y is given by:

$$SSR = \sum_{i=1}^{n} {\varepsilon_i}^2 = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)^2 \tag{3.3}$$

$$= \sum_{i=1}^{n} ({y_i}^2 - 2y_i(\beta_0 + \beta_1 x_i) + {\beta_0}^2 + 2\beta_0\beta_1 x_i + {\beta_1}^2 {x_i}^2) \tag{3.4}$$

To minimise SSR and determine regression coefficients, partial derivatives of SSR with respect to $\beta_0$and $\beta_1$are calculated

$$\frac{\partial SSR}{\partial \beta_0} = \sum_{i=1}^{n} (-2y_i + 2\beta_0 + 2\beta_1 x_i) \tag{3.5}$$

$$0 = \sum_{i=1}^{n} (-y_i + \hat{\beta}_0 + \hat{\beta}_1 x_i) \tag{3.6}$$

$$0 = -n\bar{y} + n\hat{\beta}_0 + \hat{\beta}_1 n\bar{x} \tag{3.7}$$

$$\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x} \tag{3.8}$$

$$\frac{\partial SSR}{\partial \beta_1} = \sum_{i=1}^{n} (-2x_i y_i + 2\beta_0 x_i + 2\beta_1 x_i^2) \tag{3.9}$$

$$0 = -\sum_{i=1}^{n} x_i y_i + \hat{\beta}_0 \sum_{i=1}^{n} x_i + \hat{\beta}_1 \sum_{i=1}^{n} x_i^2 \tag{3.10}$$

$$0 = -\sum_{i=1}^{n} x_i y_i + (\bar{y} - \hat{\beta}_1 \bar{x}) \sum_{i=1}^{n} x_i + \hat{\beta}_1 \sum_{i=1}^{n} x_i^2 \quad (3.11)$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n} x_i (y_i - \overline{y}\,)}{\sum_{i=1}^{n} x_i (x_i - \overline{x}\,)} \quad (3.12)$$

The solution of Equation 3.8 and 3.12 allows estimation of $\beta_0$and β_1. In multiple regression the matrix formula for the coefficient estimates is

$$\hat{\beta} = (X^T X\,)^{-1} X^T y \quad (3.13)$$

The main advantages of implementing linear regression include

- Easier determination of model parameters
- Mathematically explicable and provides deterministic estimation of target variables

However, the technique also suffers from disadvantages of

- Sensitivity to outliers, noise, or deviation in the data resulting in poor predictions of target variables
- RUL is estimated as a single point, thus lacking the ability to quantify uncertainty associated with the prediction of failure

3.2.2. Bayesian Linear Regression

Bayesian Linear Regression (BLR) is a statistical framework of linear regression that utilises Bayesian inference to update its model parameters. The Bayesian inference utilises Bayes theorem to update prior probability of the model parameters (the slope and the y-intercept) into posterior probability by incorporating the evidence provided by the data in the form of the likelihood function. The Bayes theorem in generalised form [115] is expressed as:

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)} \quad (3.14)$$

where $p(w|D)$ is the posterior probability distribution, $p(D|w)$ is the likelihood function, $p(w)$ is the prior probability distribution and $p(D)$ is the probability of the data. Alternatively, according to Gelman et. al [116], given the above definition of the likelihood function, Bayes theorem can be expressed as:

$$posterior \propto likelihood \times prior \tag{3.15}$$

3.2.2.1. Model Setup

According to Murphy [117], before the application of BLR, degradation is modelled as:

$$y = \phi(x)^T w + \varepsilon \tag{3.16}$$

where y is the degradation signal, ε is random error, w is vector of weights (the slope and the y-intercept) and $\phi(x)^T$ is first order polynomial basis with x denoting time. The first order polynomial basis function in reduced form can be represented as:

$$\phi(x)^T w = \begin{bmatrix} 1 & x^1 \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \end{bmatrix} \tag{3.17}$$

3.2.2.2. BLR Framework

As shown in Figure 3.1, there are four parts in the BLR framework. For the first three parts of the BLR Framework, Bayes theorem [116] is applied to update the prior probability distribution of the model parameters to form a posterior distribution with the likelihood of the observation data. Once the model parameters w (or the slope and the y-intercept) are updated, they are used to get the predicted signal over the desired time as shown by "predictive distribution" in Figure 3.1.

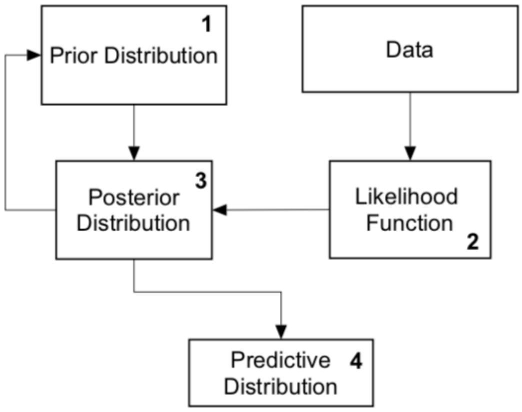


Figure 3.1 - BLR Framework

3.2.2.3. Prior Distribution

The weights are modelled as a multivariate normal distribution to capture the variable dependency (in the case of a linear model there are two dimensions to the distribution, one each for w_0 and w_1). Therefore, the prior distribution can be specified as:

$$p(w) = \mathcal{N}(w|m, S) \tag{3.18}$$

where m and S are the mean and covariance of w respectively. For further simplicity, the prior distribution can be modelled as a zero mean Gaussian distribution so that $m_0 = 0$ and $S_0 = \alpha^{-1}I$ with $\alpha \rightarrow 0$. The parameters α and I represent prior noise precision and identity matrix respectively. In zero mean Gaussian distribution form, the prior can be expressed as:

$$p(w) = \mathcal{N}(w|m_0, S_0) \tag{3.19}$$

$$p(w) = \mathcal{N}(w|0, \alpha^{-1}I) \tag{3.20}$$

Therefore, when no data is observed the posterior distribution is the same as the prior distribution. Also, when data points arrive sequentially, the posterior distribution acts as a prior distribution for the subsequent data point.

3.2.2.4. Likelihood Function

The likelihood is the conditional probability of the observed data x and the model parameters (w, β), and is given by:

$$p(y|x, w, \beta) = \mathcal{N}(\phi(x)^T w, \beta^{-1}) \tag{3.21}$$

where $\phi(x)^T$ is first order polynomial basis with x denoting time and β is called the likelihood noise precision parameter.

3.2.2.5. Posterior Distribution

According to Equation 3.20, the posterior distribution is proportional to the product of the likelihood function and the prior distribution. Mathematically it can be expressed as:

$$p(y|x, w, \alpha, \beta) \propto p(y|x, w, \beta)\, p(w|\alpha) \tag{3.22}$$

Due to the fact that the prior has been chosen to be a conjugate normal distribution, the posterior distribution is also normal and therefore can be expressed as:

$$p(y|x, w, \alpha, \beta) = \mathcal{N}\big(y\big|m(x), s^2(x)\big) \tag{3.23}$$

where $s^2(x)^{-1} = {S_0}^{-1} + \beta x^T x$ and $m(x) = s^2(x)\big({S_0}^{-1} m_0 + \beta x^T y\big)$. Since, the prior has been modelled as a zero mean Gaussian distribution, therefore, $s^2(x)^{-1} = \alpha I + \beta x^T x$ and $m(x) = \beta s^2(x) x^T y$. As mentioned earlier, due to the choice of prior, the posterior distribution acts as a prior distribution for the subsequent data point when data points arrive sequentially. The resulting posterior is also used to compute the predictive distribution.

3.2.2.6. Predictive Distribution

The posterior distribution results in update of the model parameters w, which can be used to make predictions of y at a given future point in time. Therefore, the predictive distribution is evaluated using the following equation:

$$p(y_{new}|y,\alpha,\beta) = \int p(y|x,w,\beta)p(y|x,w,\alpha,\beta) \tag{3.24}$$

This predictive distribution represents the predicted degradation signal y_{new} probabilistically. The predictive distribution can also be expressed as:

$$p(y_{new}|x,y,\alpha,\beta) = \mathcal{N}\left(y\middle|m(x)^T,x,\sigma^2{}_N(x)\right) \tag{3.25}$$

where $\sigma^2{}_N(x) = \frac{1}{\beta} + x^T s(x)x$. It should be noted that the predicted values of y_{new} correspond to a Normal distribution rather than one single value. This is fundamentally because of the uncertainty in the model parameters of w: there is uncertainty in the slope of the linear trend w_1 and in the intercept w_0. The distribution of y_{new} values is the result of combining predictions from all linear trends within the envelope of possible parameters.

The main advantages of BLR as prognostics technique includes:

- Ability to explicitly track the uncertainty in the linear model
- BLR provides analytical framework based on conjugate Gaussian distributions to estimate model parameters using available data, thus allowing estimation of posterior and predictive distributions
- RUL can be estimated from the failure/warning distributions which is obtained based on the predicted values exceeding the failure/warning threshold, thus allowing quantification of uncertainty in predictions

The main disadvantage of BLR is potential uncertainty in capturing noise characteristics due to the assumption that the variation in observed health of an asset over its lifetime is constant.

3.2.3. Auto-Regressive Integrated Moving Average (ARIMA)

Auto-regressive integrated moving average (ARIMA) is a time series modelling technique generalising ARMA model to characterise data or predict future points in the series [118]. ARIMA uses autoregressive (AR) model to forecast future points in time series based on the relationship between an observation and lagged observations p. Whereas, moving average (MA), models the dependency between an observation and a residual error from the AR model using number of elements q as a size of the moving average window. MA indicates the regression error is a linear combination of residual errors. ARIMA achieves stationarity by differencing d times (i.e. subtracting an observation x_t from an observation x_{t-1}). The AR model is represented as:

$$x_t = c + \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t, (i = 1, 2, \dots , p) \tag{3.26}$$

where x_t is a stationary series, x_{t-1} represents lagged observations, ϕ_i are parameters of the model, c is a constant, and ϵ_t is a noise. The MA is calculated as:

$$x_t = \mu + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t, (i = 1, 2, \dots , q) \tag{3.27}$$

where θ_i are the parameters of the model, μ is the expectation of x_t, and ϵ_t , ϵ_{t-1}, … , ϵ_{t-q} are noise terms. After the initial differencing step, the ARIMA process can be expressed as:

$$x_t = c + \epsilon_t + \sum_{i=1}^{p} \phi_i x_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{3.28}$$

The basic process of using ARIMA as forecasting technique outlined by [118] includes:

- Checking Stationarity: If time series data lacks stationarity, differencing is applied to transform time series data into stationary data
- Identification: Specification of appropriate number of AR terms, p, moving average terms, q, from Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) correlograms
- Forecasting: Multi-step-ahead prediction to forecast failure/warning breach time based on the forecasting model
- Verification: If predictions result in an unexpected behaviour, repeat identification and forecasting steps until the difference between the actual values and forecasted values are small enough and model fits the data well

The main advantage of implementing ARIMA as a prognostic technique is its abilities to deal with non-stationary data in order to provide short-term forecasts based on historic data while keeping number of parameters to a minimum. There are more disadvantages than advantages of implementing ARIMA as a prognostic technique. Main disadvantages include:

- Stationarity is difficult to achieve and can result in inaccurate results due to repeated differencing
- Inability to provide long term predictions
- Entire modelling procedure requires update when new data point becomes available

3.2.4. Support Vector Regression (SVR)

Support Vector Regression (SVR) is a common application form of support vector machines (SVMs) that is used to estimate functional relation between input and output variables [72]. Suppose there are k training data $(x_i, y_i),\ i = 1,2, \dots, k$, where $x_i \in R^n$ is an input vector, $y_i \in R$ is a scaler output. In case of linear regression, the regression function takes the following form

$$f(x) = \langle w, x \rangle + b \tag{3.29}$$

where $w \in R^n$ is a coefficient vector and $b \in R$ is a bias defining the regression function f. The optimal regression function can be acquired as a solution to the following optimisation problem:

$$minimise \frac{1}{2} \|w\|^2 \tag{3.30}$$

$$subject\ to \begin{cases} y_i - w.x_i - b \leq \varepsilon \\ w.x_i + b - y_i \leq \varepsilon \end{cases} \tag{3.31}$$

where ε denotes prediction precision. Equation 3.30 and 3.31 are only valid when the predition error is less than ε. Therefore, in order to cope with the data that can result in prediction error greater than ε, slack variables ξ_i, ξ_i^* and error penalty C are introduced. Hence, Equtions 3.30 and 3.31 takes the following form:

$$minimise \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{3.32}$$

$$subject\ to \begin{cases} y_i - w.x_i - b \leq \varepsilon + \xi_i \\ w.x_i + b - \ y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \tag{3.33}$$

where C penalises deviations that are larger than ε while determining the trade-off between flatness of function $f(x)$ and the number of deviations larger than ε. By applying Lagrangian multiplier, the Equation 3.32 can be converted into optimisation problem as:

$$\begin{aligned} maximise & \left\{-\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)\langle x_i, x_j\rangle \right. \\ & \left. - \varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\right\} \end{aligned} \tag{3.34}$$

$$subject\ to\ \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \text{ and } \alpha_i, \alpha_i^* \geq 0 \tag{3.35}$$

Therefore, the regression function can be expressed as:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\,\langle x_i, x\rangle\ + b \tag{3.36}$$

The regression function $f(x)$ for non-linear implementation with the application of kernal function $K(x_i, x)$ takes the following form

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\,K(x_i, x) + b \tag{3.37}$$

The kernel function $K(x_i, x)$ maps original data onto high dimensional feature space where linear regression is possible [119]. The main advantages of SVR include

- Provides robust and accurate predictions while accommodating different sizes of datasets based on maximised decision boundary
- Mathematically explicable and easy to implement while achieving good generalisation performance on a limited number of learning degradation patterns

Main disadvantages of the technique include:

- No standard way of selecting kernel functions
- RUL is estimated as a single point, thus lacking the ability to quantify uncertainty associated with the prediction of failure
- Tuning parameters is difficult to achieve and are specifically adapted for the degradation problem

3.2.5. Relevance Vector Machine (RVM)

Relevance Vector Machine (RVM) is a Bayesian representation of identical functional form to SVM [120]. As a supervised learning technique, RVM starts with a given set of input-target pairs $\{x_n, t_n\}_{n=1}^{N}$. The target values t_n are samples from a model with additive noise, such that

$$t_n = y(x_n, w) + \varepsilon_n \tag{3.38}$$

where ε_n is the noise term and is assumed to be following zero mean Gaussian $\mathcal{N}(0, \sigma^2)$ distribution, $w = (w_1, w_2, \dots, w_n)^{\mathrm{T}}$ is a weight vector. The function $y(x)$ which is used to sample target values t_n can be expressed as

$$y(x) = w_n \phi(x) = w^{\mathrm{T}} \Phi \tag{3.39}$$

where Φ is a design matrix with $\Phi = [\phi(x_1), \phi(x_2), \dots, \phi(x_n)]$, where $\phi(x_n) = [1, K(x_n, x_1), K(x_n, x_1), \dots., K(x_n, x_N)]$, where $K(x_n, x_i)$ is a kernel function. Assuming t_n is independent, the likelihood of the data can be estimated as

$$p(t|w, \sigma^2) = (2\pi\sigma^2)^{-N/2} \exp\left\{-\frac{1}{2\sigma^2} \|t - \Phi w\|\right\} \tag{3.40}$$

The maximum likelihood estimation of w and σ^2 in Equation 3.40 results in overfitting. To address this issue, a constraint is placed on the parameters by defining zero mean Gaussian distribution over w [121] such that

$$p(w|\alpha) = \prod_{i=0}^{N} \mathcal{N}(w_i|0, \alpha_i^{-1}) \tag{3.41}$$

where α is a vector of $N+1$ hyperparameters. Each individual and independent hyperparameter is associated with each individual weight w_i. These hyperparameters control the deviation of each w_i from zero. Having defined the prior, Bayes' rule is used to infer the posterior over all the weights [120] given the data as

$$p(w|t, \alpha, \sigma^2) = \frac{p(t|w, \sigma^2)p(w|\alpha)}{p(t|\alpha, \sigma^2)}$$

$$= (2\pi)^{-(N+1)/2} |\Sigma|^{-1/2} \times \exp\left\{-\frac{1}{2}(w-\mu)^{\mathrm{T}}\Sigma^{-1}(w-\mu)\right\} \tag{3.42}$$

where posterior mean μ and covariance Σ are given by

$$\mu = \Sigma\Phi^{\mathrm{T}}\mathrm{B}t \tag{3.43}$$

$$\Sigma = (\Phi^{\mathrm{T}}\mathrm{B}\Phi + \mathrm{A})^{-1} \tag{3.44}$$

with $\mathrm{A} = diag(\alpha_1, \alpha_2, \dots, \alpha_{N+1})$ and $\mathrm{B} = \sigma^2\mathrm{I}$

To estimate posterior mean and covariance, most probable values of hyperparameters α_{MP} and σ^2_{MP} are estimated by maximising the marginal likelihood. Once hyperparameters are estimated, predictions can be computed for new input data x_* in terms of the predictive distribution as

$$p(t_*|t, \alpha_{\mathrm{MP}}, \sigma^2_{\mathrm{MP}}) = \int p(t_*|w, \sigma^2_{\mathrm{MP}})p(w|t, \alpha_{\mathrm{MP}}, \sigma^2_{\mathrm{MP}})\, dw \tag{3.45}$$

The predictive distribution in Gaussian form can be represented as

$$p(t_*|t, \alpha_{\mathrm{MP}}, \sigma^2_{\mathrm{MP}}) = \mathcal{N}(t_*|y_*, \sigma^2_*) \tag{3.46}$$

where predictive mean y_* and variance σ^2_* are given by

$$y_* = \mu^{\mathrm{T}}\phi(x_*) \tag{3.47}$$

$$\sigma_*^2 = \sigma_{\mathrm{MP}}^2 + \phi(x_*)^{\mathrm{T}}\Sigma\phi(x_*) \quad (3.48)$$

The main advantages of RVM include:

- Predictions generated by RVM are probabilistic, thus providing interpretation in Bayesian framework to accommodate uncertainties that are associated with the predictions
- Ability to detect underlying trends in noisy and varying dataset
- Utilises fewer kernel functions compared to SVM as many model weights are set to zero in order to achieve sparsity

Main disadvantages of the technique include:

- Insufficient data for training or significantly different testing data affects the performance of the RVM
- Compared to SVM, training time can be longer
- Higher computational costs due to update rules for hyperparameters

3.2.6. Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) is a Bayesian technique for nonlinear regression that computes posterior degradation estimates by constraining the prior distribution to fit the available training data [122]. GPR samples function $f(x)$ from a Gaussian Process (GP) instead of postulating a parametric form for the function $f(x, w)$ and estimating the parameters w [123]. A Gaussian process (GP) is defined as a probability distribution over functions and is represented as

$$f(x) \sim GP\big(m(x), k(x, x')\big) \quad (3.49)$$

where $x, x' \in \mathrm{X}$ are random variables, $m(x)$ and $k(x, x')$ are the mean and covariance functions respectively, and can be defined as

$$m(x) = \mathrm{E}[f(x)] \quad (3.50)$$

$$k(x, x') = \mathrm{E}\left[\big(f(x) - m(x)\big)\big(f(x') - m(x')\big)^{\mathrm{T}}\right] \quad (3.51)$$

For regression GP model with noise is defined as

$$y = f(x) + \varepsilon \quad (3.52)$$

Where x is the input vector, f is the function output, and y is the observed values with noise ε which is following zero mean gaussian distribution $\mathcal{N}(0, \sigma_n^2)$. The prior distribution of y is given by

$$y \sim \mathcal{N}(m(x), K(X,X) + \sigma_n^2 I_n) \qquad (3.53)$$

The prior joint distribution of y and the prediction value of y^* is defined as

$$\begin{bmatrix} y \\ y^* \end{bmatrix} \sim \mathcal{N}\left(m(x), \begin{bmatrix} K(X,X) + \sigma_n^2 I_n & K(X,x^*) \\ K(x^*,X) & k(x^*,x^*) \end{bmatrix}\right) \qquad (3.54)$$

where $K(X,X)$ is a symmetric positive definite covariance matrix, I_n is the unity matrix, $K(X,x^*) = K(x^*,X)^{\mathrm{T}}$ is the covariance matrix of the test input x^* and the training data X, and $k(x^*,x^*)$ is the covariance matrix of test input x^*.Under the conditions of a given input x^* and the training data X, y^* can be calculated as the the posterior distribution:

$$y^* | x^*, X \sim \mathcal{N}\left(\mu_{y^*}, \sigma_{y^*}^2\right) \qquad (3.55)$$

$$\mu_{y^*} = m + K(x^*,X)[K(X,X) + \sigma_n^2 I_n]^{-1}(y - m) \qquad (3.56)$$

$$\sigma_{y^*}^2 = k(x^*,x^*) - K(x^*,X) \times [K(X,X) + \sigma_n^2 I_n]^{-1} K(X,x^*) \qquad (3.57)$$

where μ_{y^*} and $\sigma_{y^*}^2$ are the mean and variance of the prediction output y^*. The main challenge in GPR is to estimate the covariance function which encodes the assumptions about the functions to be learnt by defining the relationship between data points [124]. The main advantages of GPR include:

- Ability to accommodate uncertainties in predictions through variance around the mean prediction of the gaussian process model
- Provides both the regression function and the uncertainty estimates depending on the variance of the data
- Ability to produce accurate predictions despite of small training data

Though GPR is an attractive option for the implementation of prognostics. However, its disadvantages can limit prognostics performance. Main disadvantages of implementing GPR as a prognostic technique include:

- Difficult to choose covariance function in the absence of any knowledge about the actual process
- Only suitable for gaussian likelihood
- Provides extremely conservative confidence bounds for predictions, thus leading to unmanageable bounds when prediction horizon is long
- Assumes that the data is normally distributed, the error between each data point is correlated, and the noise in the training dataset is constant over the entire input domain

3.2.7. Kalman Filters (KFs)

The Kalman Filter (KF) is a linear recursive Bayesian technique that estimates the future state. The future estimations are made based on the measurements of the state that are observed over time and the mathematical state transition model such that the estimated state error covariance is minimum [125]. The KF assumes that the state x at time step t can be inferred from the previous step $t-1$ as in Equation 3.58, where F_t is a state transition model, B_t is a control-input model applied to inputs u_t, and $w_t$is process noise which follows zero mean gaussian distribution with covariance Q_t

$$x_t = F_t x_{t-1} + B_t u_t + w_t \tag{3.58}$$

Measurements of true state $y_t$can be expressed as

$$y_t = H_t x_t + v_t \tag{3.59}$$

where H_t is an observation model and v_t is observation noise which is also assumed to follow zero mean gaussian distribution with covariance R_t.The Kalman filter uses two steps to calculate optimal state [126]. In the first step, the state in the current point in time t is predicted using the previous state in time $(t-1)$ as shown in Equation 3.60 and 3.61

$$\tilde{x}_{t|t-1} = F_t \tilde{x}_{t-1|t-1} + B_{t-1} u_{t-1} \tag{3.60}$$

$$P_{t|t-1} = F_t P_{t-1|t-1} A_t^{\mathrm{T}} + Q_t \tag{3.61}$$

where $\tilde{x}$ denotes the state estimates and P denotes the estimates' error covariance. In the second step, the current state estimate in time t and its error covariance are updated with observations y_t as shown in Equations 3.62 to 3.64 [127]

$$\tilde{x}_{t|t} = \tilde{x}_{t|t-1} + K_t\left(y_t - H_t \tilde{x}_{t|t-1}\right) \tag{3.62}$$

$$K_t = P_{t|t-1} H_t^{\mathrm{T}} \left(H_t P_{t|t-1} H_t^{\mathrm{T}} + R_t\right)^{-1} \tag{3.63}$$

$$P_{t|t} = (\mathrm{I} - K_t H_t) P_{t|t-1} \tag{3.64}$$

where K_t is a weighting known as the Kalman gain. Prognostics in KF is performed by repeating the first step Equations 3.60 and 3.61 iteratively estimating the future degradation states until it crosses the failure or warning threshold. The RUL of the damaged equipment can then be estimated as time difference between failure or warning threshold crossing time t_{thresh} and the time of prediction t_p.

$$RUL = t_{thresh} - t_p \tag{3.65}$$

The main advantages of implementing KF as a prognostic technique include:

- Ability to estimate both the current state and the future states while accommodating incomplete and noisy measurements
- Ability to correct the state estimate with the latest observation while minimising state error covariance
- Computationally efficient and is able to deal with large datasets

Despite of KF's usefulness it also suffers from disadvantages which limits its applicability in prognostics. Main disadvantages of the technique include:

- Inability to deal with non-linear data and therefore, is only applicable to linear systems with gaussian noise model

- System and measurement model need to be defined

3.2.8. Extended Kalman Filter (EKF)

As discussed in Section 3.2.7, KF estimates the state of degradation that is represented by a linear stochastic equation. However, when the process or the relationship between the process and the measurements is non-linear Extended Kalman Filter (EKF) is used [118]. The EKF linearises non-linear functions around the current mean estimate and its covariance. The non-linear state transition and observation models must be differentiable for the EKF [118]. These models can be expressed as:

$$x_t = f(x_{t-1}, u_t) + w_t \tag{3.66}$$

$$y_t = h(x_t, v_t) \tag{3.67}$$

Here, f is the non-linear function and relates the state at the previous point in time $(t - 1)$ to the state at the current point in time t. Whereas, the non-linear function h in Equation 3.66 relates the state x_t to the measurement y_t. For f and h, the Jacobian matrices (matrices of partial derivatives) F and H are calculated respectively at each time step t with the predicted state at $(t - 1)$ as in Equation 3.68 and 3.69

$$F_t = \left(\frac{\partial f}{\partial x}\right) \mid \tilde{x}_{t-1|t-1}, u_t \tag{3.68}$$

$$H_t = \left(\frac{\partial h}{\partial x}\right) \mid \tilde{x}_{t|t-1} \tag{3.69}$$

From here, the prediction and update steps of KF are applied (as in Equations 3.60 to 3.64) [128], where Equation 3.60 becomes 3.70 to accommodate non-linear model.

$$\tilde{x}_{t|t-1} = f\left(\tilde{x}_{t-1|t-1}, u_t\right) \tag{3.70}$$

Main advantages of implementing the EKF as a prognostic technique include:

- Ability to linearise non-linear dynamic system in the context of KF
- Ability to estimate both the current state and the future states

Despite the useful linearisation ability of the EKF, technique suffers from many disadvantages which may affect the prognostics performance. Main disadvantages of the EKF include:

- Exhibits divergence when dealing with significant non linearities due to approximation errors introduced during the linearisation process
- Computationally expensive due to the calculation of Jacobian matrices

3.2.9. Unscented Kalman Filter (UKF)

Although, the EKF provides solution for the non-linear system by approximating the mean and covariance using a first order approximation of system dynamics. However, when non-linearities are significant, the EKF exhibits divergence [129]. The unscented Kalman Filter (UKF) overcomes these deficiencies by estimating the distribution of the state using a deterministic technique called Unscented Transform [130]. Weighted sample points (also known as sigma points) are sampled around the mean and are propagated through the non-linear functions to form an approximate estimate of the new mean and covariance [129] as shown in Equations 3.71 to 3.73

$$\gamma^i = f(\chi^i) \tag{3.71}$$

$$\bar{y} = \sum_i w^i \gamma^i \tag{3.72}$$

$$P_{yy} = \sum_i w^i (\gamma^i - \bar{y})(\gamma^i - \bar{y})^{\mathrm{T}} \tag{3.73}$$

Here, χ^i represent sigma points which are passed through the non-linear function f such that the new mean $\bar{y}$ and covariance P_{yy} can be estimated. The term w^i is weights of each i^{th}sigma point. The UKF then follows the same procedure as of the KF and the EKF such that the first and second stage equations can be written as

$$\tilde{\chi}^i_{t|t-1} = f(\tilde{\chi}^i_{t-1|t-1}, u_t) \tag{3.74}$$

$$\tilde{x}_{t|t-1} = \sum_i w^i \tilde{\chi}^i_{t|t-1} \tag{3.75}$$

$$\tilde{\gamma}^{i}_{t|t-1} = h(\tilde{\chi}^{i}_{t|t-1}) \tag{3.76}$$

$$\tilde{y}_{t\}t-1} = \sum_{i} w^{i}\tilde{\gamma}^{i}_{t|t-1} \tag{3.77}$$

$$P_{t|t-1} = Q_t + \sum_{i} w^{i}(\chi^{i}_{t|t-1} - \tilde{x}_{t|t-1})\left(\chi^{i}_{t|t-1} - \tilde{x}_{t|t-1}\right)^{\mathrm{T}} \tag{3.78}$$

The update stage then becomes:

$$P_{yy} = R + \sum_{i} w^{i}(\tilde{\gamma}^{i}_{t|t-1} - \tilde{y}_{t\}t-1})\left(\tilde{\gamma}^{i}_{t|t-1} - \tilde{y}_{t\}t-1}\right)^{\mathrm{T}} \tag{3.79}$$

$$P_{xy} = \sum_{i} w^{i}(\chi^{i}_{t|t-1} - \tilde{x}_{t\}t-1})\left(\tilde{\gamma}^{i}_{t|t-1} - \tilde{y}_{t\}t-1}\right)^{\mathrm{T}} \tag{3.80}$$

$$K_t = P_{xy}{P_{yy}}^{-1} \tag{3.81}$$

$$\tilde{x}_{t|t} = \tilde{x}_{t|t-1} + K_t\left(y_t - \tilde{y}_{t\}t-1}\right) \tag{3.82}$$

$$P_{t\}t} = P_{t|t-1} - K_t P_{yy} K_t^{\mathrm{T}} \tag{3.83}$$

Main advantages of implementing the UKF as a prognostic technique include:

- Ability to linearise non-linear dynamic system in the context of KF with higher accuracy compared to the EKF
- Ability to represent uncertainty on a linearised function
- More computationally efficient than the EKF as no Jacobian matrices are required to be estimated

The UKF also suffers from many disadvantages which can affect the accuracy of the algorithm as a prognostic technique. Main disadvantages include:

- Difficult to choose unscented transformation parameters in the absence of any knowledge about the process
- Only applicable to models that are driven by Gaussian noises

3.2.10. Particle Filter (PF)

The particle filter (PF) is an alternative approach and can be applied to non-linear systems with non-gaussian noise [127]. The underlying principle of the methodology is to estimate the state probability distribution by a set of particles (samples from the space of the unknowns) and their associated weightings. A non-linear process model, a set of measurements, a measurement model, and prior estimate of the state distribution are used to generate and recursively update particles. These particles can be expressed as:

$$\{x_t^i, w_t^i\}_{i=1}^{P} \tag{3.84}$$

where x_t^i and w_t^i represent the state vector estimate and weight respectively for particle i at each time step t, for P number of particles [129]. The posterior density of these samples can be calculated as

$$p(x_t|y_{0:t}) \approx \sum_{i=1}^{N} w_t^i \, \delta_{x_t^i}(d\, x_t) \tag{3.85}$$

where $\delta_{x_t^i}(dx_t)$ is the Dirac delta function at each particle state estimate x_t^i. Sample importance resampling (SIR) [131] is the most frequently used technique in prognostics [118]. It resamples particles at each time step in order to stop degeneracy. The degeneracy is a problem that causes single particles to dominate after few iterations [127]. The state estimate for each particle can be calculated as:

$$x_t^i \sim p\left(x_t \middle| x_{t-1}^i, u_{t-1}\right) \tag{3.86}$$

$$x_t^i = f\left(x_{t-1}^i, u_{t-1}\right) + \omega_{t-1}^i \tag{3.87}$$

The term x_{t-1}^i represents previous particle state estimate, ω_{t-1}^i is a sample process noise generated from a process noise PDF. Based on y_t which can be calculated as in Equation 3.88, weights are then assigned to each particle.

$$y_t = h(x_t^i, v_t^i) \tag{3.88}$$

$$w_t^i = w_{t-1}^i \, p\left(y_t | x_t^i\right) \tag{3.89}$$

The term v_t^i represents samples of observation noise generated from an observation noise PDF. Weights are then normalised such that:

$$\widehat{w}_t = \frac{w_t}{\sum_{i=1}^{N} w_t^i} \tag{3.90}$$

$$\sum_i w_t^i = 1 \tag{3.91}$$

Then, particles $\{x_t^i, w_t^i\}$ resampling is performed based on the effectiveness of the number of particles P_{eff} falling below some threshold P_T [127]. The effectiveness of the particles can be calculated as:

$$\hat{P}_{eff} = \frac{1}{\sum_{i=1}^{N} (w_t^i)^2} \tag{3.92}$$

The PF has significant advantage over KF techniques. It provides the benefit of dealing with non-linear dynamic systems with non-gaussian noise. Other main advantages of implementing the PF as a prognostic technique include:

- Ability to provide long term predictions
- Ability to provide highly accurate results due to SIR

The PF also suffers from disadvantages which can affect its prognostics performance. Main disadvantages include:

- Computational efficiency decreases with higher number of particles
- Requires large number of data points to avoid degeneracy
- Requires system dynamic and measurement model

3.3. Prognostics Techniques Selection Metrics

An effective and accurate decision support for maintenance/intervention depends on accurate RUL predictions. To achieve accurate RUL predictions, selection of suitable prognostics technique is required in order to achieve accurate estimation of future failure progression. Most of the times prognostic techniques are selected based on expert knowledge and experience which often results in overlooking other suitable techniques. Therefore, in this thesis a simplistic formal evaluation and selection process for prognostic techniques is presented which utilises metrics that are identified from data characteristics, user requirements, and advantages and disadvantages of the techniques in mathematical context (See Section 3.2). The evaluation metrics use weighting criteria for evaluating the feasibility of prognostic techniques for PHM implementation. The weighting criteria uses look up tables which combines the requirements of PHM implementation and prognostic technique characteristics while evaluating a prognostic technique. This method is an improvement to the two existing methods such as decision trees [9] and ranking [18]. Using the first method of decision trees, a practitioner is able to select a predictive technique while navigating through the tree based on the implementation requirements. The method suffers from bottle necks due to hard decision points and lacks overall feasibility assessment of a prognostic technique for the implementation. The second method ranks predictive techniques based on the merits of techniques. The method utilises subjective ranking criteria and lacks practitioner's perspective. Compared to the existing methods, the formal evaluation process through requirement driven methodology enables practitioners formally evaluate and select a predictive technique while considering the overall feasibility for prognostics implementation. The evaluation metrics that are considered for the assessment of prognostic techniques in this project are detailed below with their weighting criteria:

3.3.1. Repeatability

Repeatability deals with the ability of the technique to produce results that are fully determined by the parameter and input values. Whereas non-repeatability or stochasticity is the randomness in outputs which is due to inherent steps of the technique. For example, LR [132], SVR [72], KF [125], and UKF [128] produce repeatable results which can be used to realise parameter and input values, therefore, they are classed as deterministic approaches. Whereas rest of the techniques considered in this thesis, can be classified as stochastic techniques. For instance, particle filter is classified as a stochastic prognostic technique due to its sampling methods which may introduce randomness in the results [68]. A look up table that combines possible PHM implementation requirement and repeatability of technique is shown below:

Table 3.1 - Look-up Table: Repeatability

PHM Implementation Requirement	Repeatability of a Technique		
		Deterministic	**Stochastic**
	Deterministic	1	0
	Stochastic	0	1

Table 3.1 shows that if PHM implementation requirement matches the capability of a prognostic technique to produce repeatable or non-repeatable results, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation requirement and the repeatability of a prognostic technique, the weighting of 0 is assigned to a prognostic technique in the formal evaluation process.

3.3.2. Data Capability

Data is the information that is collected from a component or a system under observation. Data capability of a prognostic technique is the ability of a technique to deal with linear or non-linear data that has gaussian or non-gaussian noise. Most of the techniques that are considered in this thesis except LR, BLR, and KF are capable of dealing with non-linear data. A look up table that combines possible PHM implementation requirement and the ability of a technique to deal with a kind of data whether linear or non-linear is shown below:

Table 3.2 - Look-Up Table: Data Capability of a Technique

PHM Implementation Requirement	Data Capability of a Technique		
		Linear	**Non-Linear**
	Linear	1	0
	Non-Linear	0	1

Table 3.2 shows that if PHM implementation requirement matches the data dealing capability of a prognostic technique, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation

requirement and the data dealing capability of a prognostic technique, the weighting of 0 is assigned to a prognostic technique in the formal evaluation process.

3.3.3. Explicability

Explicability is the working explanation of the technique in mathematical context from input to output. The explicability of the technique can be categorised into high, medium, or low. For instance, LR is a highly explicable technique and can be explained with its mathematical equations from input to output. Similarly, techniques like BLR, ARIMA, and SVR can be explained in mathematical context. Whereas, a technique like PF requires understanding of available filtering and approximation of posterior state probability distribution function methods in order to avoid degeneracy problems. Therefore, PF can be classified as moderately explicable prognostic technique. Most of the techniques that are considered in this thesis are either classified as highly explicable or moderately explicable techniques. A look up table that combines possible PHM implementation requirement and the explicability of a prognostic technique is shown below:

Table 3.3 - Look-Up Table: Explicability of a Technique

		Explicability of a Technique		
		High	**Medium**	**Low**
PHM Implementation Requirement	**High**	1	0.5	0
	Medium	0.5	1	0.5
	Low	0	0.5	1

Table 3.3 shows that if PHM implementation requirement matches the explicability of a prognostic technique, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation requirement and the explicability of a prognostic technique, the weightings of 0.5 and 0 are assigned to a prognostic technique based on the level of mismatch in the formal evaluation process.

3.3.4. Uncertainty Representation

Uncertainty representation defines the presentation of prediction uncertainty that is associated with the estimated future failure progression. The prediction uncertainty can be represented as confidence intervals or probability distribution. Techniques such as LR [132] and ARIMA [118] present uncertainty as confidence intervals. Whereas, other techniques considered in this research present uncertainty as probability distribution. An example of a technique presenting uncertainty as probability distribution is BLR since it defines the probability distribution over the parameters and predictions [133]. A look up table that combines possible PHM implementation requirement and the uncertainty representation of a prognostic technique is shown below:

Table 3.4 - Look-Up Table: Uncertainty Representation of a Technique

<table>
<tr><th rowspan="4">PHM Implementation Requirement</th><th colspan="3">Uncertainty Representation of a Technique</th></tr>
<tr><th></th><th>Probability Distribution</th><th>Confidence Intervals</th></tr>
<tr><th>Probability Distribution</th><td>1</td><td>0</td></tr>
<tr><th>Confidence Intervals</th><td>0</td><td>1</td></tr>
</table>

Table 3.4 shows that if PHM implementation requirement matches the uncertainty representation of a prognostic technique, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation requirement and the uncertainty representation of a prognostic technique, the weighting of 0 is assigned to a prognostic technique in the formal evaluation process.

3.3.5. Implementation Complexity

Implementation complexity is the likely time that is consumed to implement prognostics technique to achieve satisfactory prediction results. The implementation complexity of a prognostic technique can be categorised as high, medium, or low. All of the techniques considered in this research are classified as techniques with low or medium implementation complexities. Techniques that do not require deeper understanding and for which there are existing resources available in the form of either literature (i.e. tutorials, etc.) or toolkits/libraries (i.e. MATLAB, python, etc.) are classified as techniques with low implementation complexity. Whereas, if implementation requires deeper understanding and resources, a technique can be classified as a technique with medium implementation complexity. For instance, for the implementation of UKF, resources exist in the form of a tutorial and toolkits. However, the practitioner is required to have a deeper understanding of a toolkit and the technique to produce meaningful results. A look up table that combines possible PHM implementation requirement and the implementation complexity of a prognostic technique is shown below:

Table 3.5 - Look-Up Table: Implementation Complexity

PHM Implementation Requirement	Implementation Complexity of a Technique			
		Low	**Medium**	**High**
	Low	1	0.5	0
	Medium	0.5	1	0.5
	High	0	0.5	1

Table 3.5 shows that if PHM implementation requirement matches the implementation complexity of a prognostic technique, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation requirement and the implementation complexity of a prognostic technique, the weightings of 0.5 and 0 are assigned to a prognostic technique based on the level of mismatch in the formal evaluation process.

3.3.6. Run Time

Run time is the running time of prognostics technique estimating the future failure progression and the RUL. This metric is evaluated based on the speed in completing the prediction tasks and therefore is categorised as high, medium, or low. The running time of a predictive technique can be a limiting factor of its real-time (i.e. safety critical) or retrospective application. Techniques such LR, BLR, and SVR have low running times [18]. Examples of techniques that have medium and high running times are KF [18]and EKF [29] [128]. A look up table that combines possible PHM implementation requirement and the run time of a prognostic technique is shown below:

Table 3.6 - Look-Up Table: Run Time

PHM Implementation Requirement	Run Time of a Technique			
		Low	**Medium**	**High**
	Low	1	0.5	0
	Medium	0.5	1	0.5
	High	0	0.5	1

Table 3.6 shows that if PHM implementation requirement matches the running time of a prognostic technique, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation requirement and the running time of a prognostic technique, the weightings of 0.5 and 0 are assigned to a prognostic technique based on the level of mismatch in the formal evaluation process.

3.3.7. Accuracy

Accuracy measures the ability of a prognostic technique to correctly estimate future failure progression. The accuracy of a prognostic techniques can be categorised as high, medium, or low. Literature indicates that the techniques that produce highly accurate results include GPR and PF [18]. Examples of techniques that produce moderately accurate and less accurate results include BLR [133] and ARIMA [118]. A look up table that combines possible PHM implementation requirement and the accuracy of a prognostic technique is shown below:

Table 3.7 - Look-Up Table: Accuracy

		Accuracy of a Technique		
PHM Implementation Requirement		**High**	**Medium**	**Low**
	High	1	0.5	0
	Medium	0.5	1	0.5
	Low	0	0.5	1

Table 3.7 shows that if PHM implementation requirement matches the accuracy of a prognostic technique, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation requirement and the accuracy of a prognostic technique, the weightings of 0.5 and 0 are assigned to a prognostic technique based on the level of mismatch in the formal evaluation process.

3.3.8. Robustness

Robustness measures the ability of prognostic technique to deal with noise and uncertainty. The robustness of prognostic techniques can be categorised as high, medium, or low. GPR and PF are classified as highly robust techniques. GPR is capable of fitting models to data and recover underlying process form noisy observed data based on a particularly effective method for placing a prior distribution over the space of functions [12] [134]. PF is capable of producing accurate results in the presence of non-gaussian noise [127]. Rest of the techniques in this thesis are either classified as moderately or less robust techniques. Examples of moderately and less robust techniques are UKF [135]and LR. A look up table that combines possible PHM implementation requirement and the robustness of a prognostic technique is shown below:

Table 3.8 - Look-Up Table: Robustness

		Robustness of a Technique		
PHM Implementation Requirement		**High**	**Medium**	**Low**
	High	1	0.5	0
	Medium	0.5	1	0.5
	Low	0	0.5	1

Table 3.8 shows that if PHM implementation requirement matches the robustness of a prognostic technique, the weighting of 1 is assigned to a prognostic technique. However, if there is a mismatch between the PHM implementation requirement and the robustness of a prognostic technique, the weightings of 0.5 and 0 are assigned to a prognostic technique based on the level of mismatch in the formal evaluation process.

3.3.9. Prediction Horizon

Prediction horizon is the ability of a prognostic technique to estimate the future failure over the residual life of the asset within the desired accuracy range. The prediction horizon for a prognostic technique can be categorised as long, medium, or short. Techniques such as BLR [133], SVR [18], RVM [136] and PF [7] have long prediction horizon. GPR is the only technique considered in this thesis that has medium prediction horizon as it provides extremely conservative confidence bounds for predictions, thus leading to unmanageable bounds when prediction horizon is long [118]. An example of a technique that has small prediction horizon is ARIMA which is a purely data driven technique and is incapable of accommodating physics of the process which results in wide uncertainty margins. Therefore, ARIMA is not suitable for long term predictions [118]. A look up table that combines possible PHM implementation requirement and the prediction horizon of a prognostic technique is shown below:

Table 3.9 - Look-Up Table: Prediction Horizon

		Prediction Horizon of a Technique		
PHM Implementation Requirement		**Long**	**Medium**	**Short**
	Long	1	0.5	0
	Medium	0.5	1	0.5
	Short	0	0.5	1

Table 3.9 shows that if PHM implementation requirement matches the prediction horizon of a prognostic technique, the weighting of 1 is assigned to a prognostic technique.

However, if there is a mismatch between the PHM implementation requirement and the prediction horizon of a prognostic technique, the weightings of 0.5 and 0 are assigned to a prognostic technique based on the level of mismatch in the formal evaluation process.

3.4. Validation of Formal Evaluation Process

In this section, two prognostic applications in the field of power systems are evaluated in order to show the applicability and validity of the formal evaluation and selection process through the analysis of different PHM implementation requirements. The assets that are examined for validation of the process include transformers and circuit breakers. These assets are selected for validation based on the discussions with the practitioners.

3.4.1. Transformer Prognostics

The transformer physical aging mechanisms can be divided into two groups of transitive and intransitive aging [137]. The transitive aging is the rapid aging of the transformer due to abnormal conditions such as highly distorted loads with harmonics, high ambient temperature, and overloading. The measurements of hot spot temperature are used to assess transitive gaining progression. The intransitive aging is the insulation deterioration of a transformer and can be assessed by using techniques such as degree of polymerization, dissolved gas analysis, detection of furanic compounds, recovery voltage measurement, and measurement of retaining tensile strength.

To estimate the RUL of transformers different prognostics techniques have been implemented. For example, the transformer's paper aging model [138] defining a gaining acceleration factor based on the hot spot temperature was used with PF to estimate the RUL of the transformer through the degree of polymerization of the paper at its most aged point [139]. The design requirements for PHM implementation [139] that are interpreted into prognostics selection metrics are shown in Table 3.10:

Table 3.10 - PHM Implementation Requirements for Transformer Prognostics

PHM Implementation Requirements	Requirement Interpretation
The degradation process is stochastic and degradation equation is available	Repeatability (Stochastic)
	Robustness (High)
The degradation of the transformer is not linear and noise is non-gaussian	Data (Non-Linear)
The predictive model should be able to accommodate uncertainties in a probabilistic manner	Uncertainty Representation (Probability Distribution)
The prediction horizon should be long	Prediction Horizon (Long)

The look-up tables for the prognostic technique selection metrics were used to score the techniques that are considered in this thesis. Table 3.11 shows the evaluation of techniques that utilises look up tables to score each technique for the selection metrics based on the PHM implementation requirements and the inherent features of the techniques. The formal evaluation process shows that PF ranks highest which is the approach that was adopted for the RUL estimation of the transformer. Thus, validating the formal evaluation and selection process for prognostic techniques.

Table 3.11 - Ranking of Prognostic Techniques for Transformers based on PHM Implementation Requirements and Inherent Features of the Techniques

Selection Metrics	**LR**	**BLR**	**ARIMA**	**SVR**	**RVM**	**GPR**	**KF**	**EKF**	**UKF**	**PF**
Repeatability	0	1	1	0	1	1	0	1	0	1
Data	0	0	1	0	1	1	0	1	1	1
Uncertainty Representation	0	1	0	0	1	1	1	1	1	1
Robustness	0	0.5	0	0.5	0.5	1	0.5	0.5	0.5	1
Prediction Horizon	1	1	0	1	1	0.5	0	0	0	1
Total Score	1	3.5	2	1.5	4.5	4.5	1.5	3.5	2.5	**5**

3.4.2. Circuit Breaker Prognostics

Circuit breakers play valuable role in protecting the circuit from short circuits and overloads [140]. Failure precursor variables such as SF_6 density, I^2T, or arc timing are used to measure degradation of circuit breakers. For prognostics, LR has been used to estimate the number of days when the SF_6 density within a breaker would reach a critical level known as lockout [132]. The design requirements for PHM [132] implementation that are interpreted into prognostics selection metrics are shown in Table 3.12:

Table 3.12 - PHM Implementation Requirements for Circuit Breaker Prognostics

PHM Implementation Requirements	Requirement Interpretation
The degradation parameter SF6 shows simple linear relationship and is relatively stable	Data (Linear)
	Robustness (Low)
	Implementation Complexity (Low)
The predictive model should be able to accommodate uncertainties using confidence intervals	Uncertainty Representation (Confidence Intervals)
The prediction horizon should be long	Prediction Horizon (Long)

The look-up tables for the prognostic technique selection metrics were used to score the techniques that are considered in this thesis. Table 3.13 shows the evaluation of techniques that utilises look up tables to score each technique for the selection metrics based on the PHM implementation requirements and the inherent features of the techniques. The formal evaluation process shows that LR ranks highest which is the approach that was adopted for the estimation of number of days when the SF_6 density within a breaker would reach lockout stage. Thus, validating the formal evaluation and selection process for prognostic techniques.

Table 3.13 – Ranking of Prognostic Techniques for Circuit Breakers based on PHM Implementation Requirements and Inherent Features of the Techniques

Selection Metrics	**LR**	**BLR**	**ARIMA**	**SVR**	**RVM**	**GPR**	**KF**	**EKF**	**UKF**	**PF**
Data	1	1	0	1	0	0	1	0	0	0
Robustness	1	0.5	1	0.5	0.5	0	0.5	0.5	0.5	0
Implementation Complexity	1	1	1	0.5	1	0.5	1	0.5	0.5	0.5
Uncertainty Representation	1	0	1	1	0	0	0	0	0	0
Prediction Horizon	1	1	0	1	1	0.5	0	0	0	1
Total Score	**5**	3.5	3	4	2.5	1	2.5	1	1	1.5

3.5. Implementation of Formal Evaluation Process for Nuclear Prognostics

In this section, formal evaluation and selection of prognostic technique process is implemented for the application of steam turbines. In this research, prognostics is implemented to predict the RUL of steam turbine based on the failure progression due to the thermal expansion of the casing of a steam turbine (See Section 4.5.4). From the analysis of vibration data, a case study for the implementation of prognostics is extracted (See Section 4.5). This analysis was presented to maintenance engineers in the industry and based on the following discussion on prognostics implementation the design requirements were produced. Table 3.14 shows the interpretation of the design requirements into prognostics selection metrics.

Table 3.14 - PHM Implementation Requirements for Steam Turbine Prognostics

<table>
<tr><th>PHM Implementation Requirements</th><th>Requirement Interpretation</th></tr>
<tr><td>The degradation parameter shows relatively linear relationship</td><td>Data
(Linear)</td></tr>
<tr><td>Technique should be able to accommodate uncertainties</td><td>Robustness
(Low)</td></tr>
<tr><td rowspan="2">Technique should be implemented with existing toolkits and should have mathematical explicability</td><td>Implementation Complexity
(Low)</td></tr>
<tr><td>Explicability
(High)</td></tr>
<tr><td>The estimated RUL should be fully determined by parameters and input values</td><td>Repeatability
(Deterministic)</td></tr>
<tr><td>The predictive model should be able to accommodate uncertainties in a probabilistic manner</td><td>Uncertainty Representation
(Probability Distribution)</td></tr>
<tr><td>The prediction horizon should be long</td><td>Prediction Horizon
(Long)</td></tr>
<tr><td>Technique should be able to produce conservative results</td><td>Accuracy
(High)</td></tr>
<tr><td>The time taken to estimate future failure progression, progression of parameters, and the RUL should be low</td><td>Run Time
(Low)</td></tr>
</table>

The look-up tables for the prognostic technique selection metrics were used to score the techniques that are considered in this thesis. Table 3.15 shows the evaluation of techniques that utilises look up tables to score each selection metric for the techniques based on the PHM implementation requirements and the inherent features of the techniques.

Table 3.15 - Ranking of Prognostic Techniques for Steam Turbine based on PHM Implementation Requirements and Inherent Features of the Techniques

Selection Metrics	LR	BLR	ARIMA	SVR	RVM	GPR	KF	EKF	UKF	PF
Repeatability	1	0	0	1	0	0	1	0	1	0
Data	1	1	0	1	0	0	1	0	0	0
Explicability	1	1	1	1	0.5	0.5	0.5	0.5	0.5	0.5
Uncertainty Representation	0	1	0	0	1	1	1	1	1	1
Implementation Complexity	1	1	1	0.5	1	0.5	1	0.5	0.5	0.5
Run Time	1	1	0.5	1	0.5	0.5	0.5	0	0.5	0
Accuracy	0	0.5	0	0.5	0.5	1	0.5	0.5	0.5	1
Robustness	0	0.5	0	0.5	0.5	1	0.5	0.5	0.5	1
Prediction Horizon	1	1	0	1	1	0.5	0	0	0	1
Total Score	6	**7**	2.5	**6.5**	5	5	6	3	4.5	5

The formal evaluation process shows that the two techniques that rank highest are BLR and SVR. In this research, BLR and SVR are selected as probabilistic and non-probabilistic prognostic techniques for the implementation of prognostics.

The selection metrics that are utilised in the formal evaluation and selection process provides the basic criteria for selecting a prognostic technique. Practitioners can adapt the evaluation and selection process for their requirements by ignoring the metrics that are not important for their implementation or by adding more selection metrics with their look-up tables to further expand the selection criteria. Any additional technique can also be assessed by analysing the inherent features of the technique or assessing its applicability in literature by weighting the technique based on look-up tables of selection metrics which combines the PHM implementation requirements and the inherent features of the technique. Therefore, this enables the practitioners to make an informed decision for the selection of appropriate prognostic technique.

3.6. Summary

This chapter presents a review of the background and theory behind the mathematical techniques that are widely applied in prognostics literature. These techniques were formally assessed against the prognostics selection metrics using look-up tables. The look-up tables combine possible PHM implementation requirements and the inherent features of a technique to formally apply a weighting to a selection metric for a prognostic technique in order to assess their feasibility for prognostics implementation. Two prognostic applications in the field of power systems are evaluated in order to show the applicability and validity of the formal evaluation and selection process. After the validation, the evaluation process was implemented to select two prognostic techniques for nuclear prognostics. The evaluation process ranked BLR and SVR highest. Therefore, BLR and SVR were selected for prognostics implementation.

CHAPTER 4: STEAM TURBINE CONDITION MONITORING

4.1. Introduction

In this chapter, background information is presented on the steam turbine within a nuclear power station for readers unfamiliar with the terminology, practices, and technology utilised therein. Firstly, an overview of nuclear power plant steam turbine will be presented with a description of its subsystems and components. In addition, an introduction to the associated steam turbine instrumentation is presented with the type of measurements that are recorded for a condition-based maintenance analysis. This chapter also presents a problem that is associated with the steam turbine under observation. The preliminary analysis of the data that is collected to assess the health state of the steam turbine is presented. This preliminary analysis allowed extraction of the feature signal (case study) which was later used for prognostics implementation.

4.2. Steam Turbine

4.2.1. General Overview

A Steam turbine is an important part of a nuclear power plant. It extracts and converts the energy content of steam into useful mechanical work. This process must be executed with maximum efficiency and reliability at minimum cost with minimum supervision and starting time. These objectives conflict with each other and the final outcome will be an acceptable compromise between them [141]. Almost without exception, modern large steam turbines are of the axial-flow type [142] as shown in Figure 4.1.

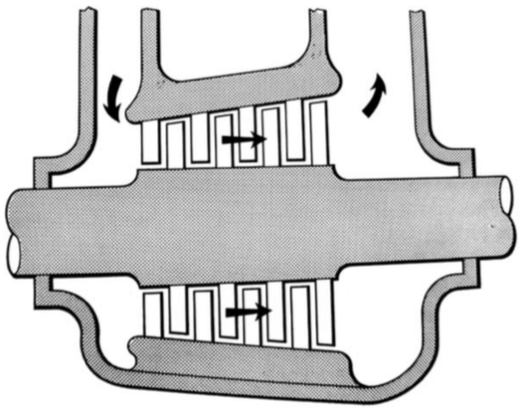


Figure 4.1 - Axial-Flow Turbine [141]

The steam approaches a group of stages at one end, flows axially through the radially-mounted blading and exhausts at the other end of the group stages. Figure 4.2 shows single-flow turbine which has the simplest configuration of blading.

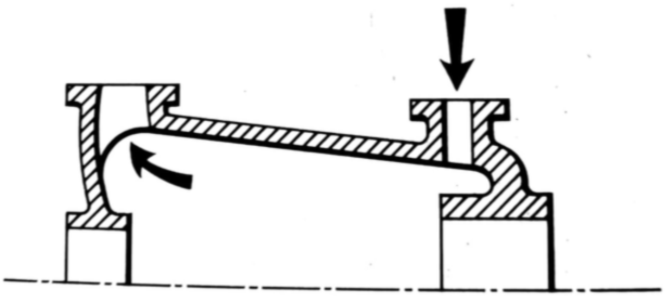


Figure 4.2 - Single-Flow Turbine [141]

Group of stages within a turbine cylinder may be arranged for flow in opposite axial directions. For instance, in double-flow turbine as shown in Figure 4.3 group of stages are arranged so that the steam is admitted at the center of the cylinder and is divided to flow in opposite axial directions towards the ends of the rotor.

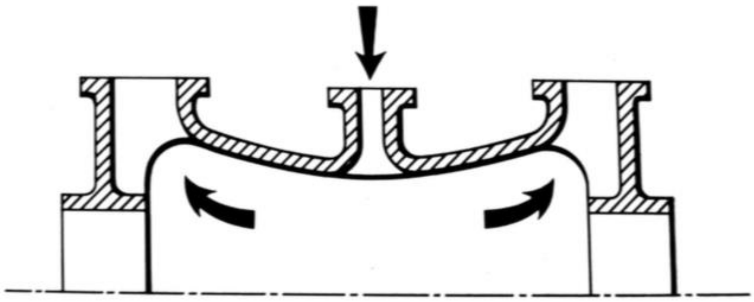


Figure 4.3 - Double-Flow Turbine [141]

For turbines of large output, it is normal to have several double-flow LP cylinders operating in parallel. The double-flow arrangement reduces the axial thrust caused by the steam forces on the moving blades to zero and avoids excessively long blades which would be incurred by a single-flow arrangement [143]. Another type of arrangement which only reduces the axial thrust on the moving blades is the reverse-flow turbine. In this type of arrangement, the steam flows in one direction through one group of stages and is then inducted internally or externally to flow through a second group of stages in the opposite axial direction [142]. Figure 4.4 shows reverse-flow arrangement

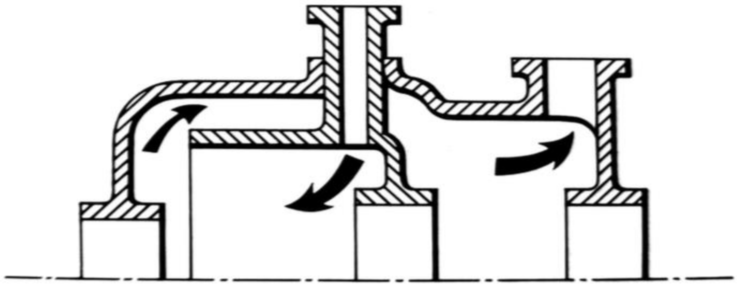


Figure 4.4 - Reverse-Flow Turbine [141]

Large machines use multi-cylinder design [143] as shown in Figure 4.5. The number of cylinders in turbine arrangements depends on terminal conditions and design considerations. A nuclear station would have one High Pressure (HP) turbine, one Intermediate Pressure (IP) turbine, and three Low Pressure (LP) turbines, rotating at 3000 rpm for a 50Hz grid frequency [142]. The IP and LP turbines would probably be double-flow. The turbine with a number of cylinders on a single shaft is described as a tandem compound machine.

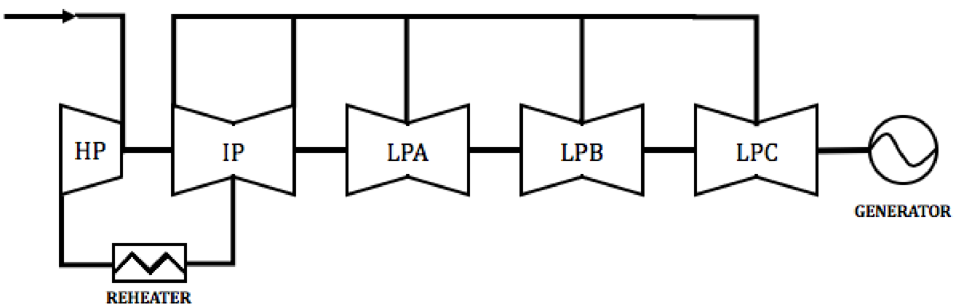


Figure 4.5 - A Multi-Cylinder Turbine Arrangement

The other main type is cross compound machine in which turbine cylinders are mounted on two separate parallel shafts driving two separate generators [144] as shown in Figure 4.6. The steam connections and the auxiliary systems are arranged as for a single generating unit.

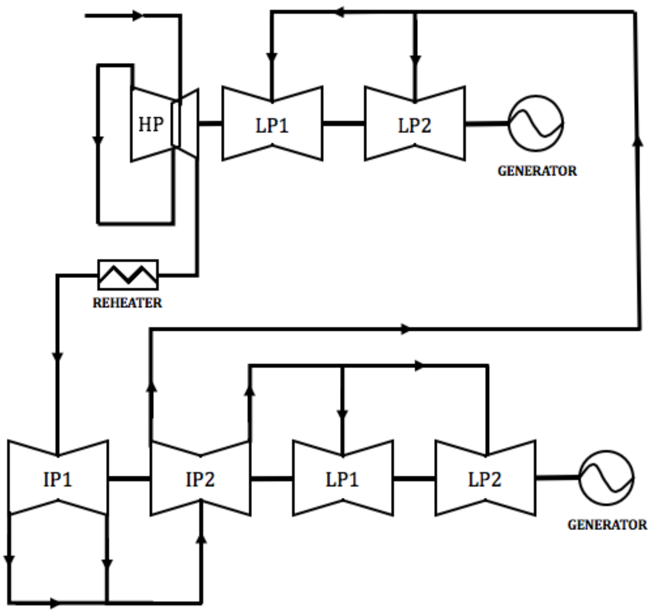


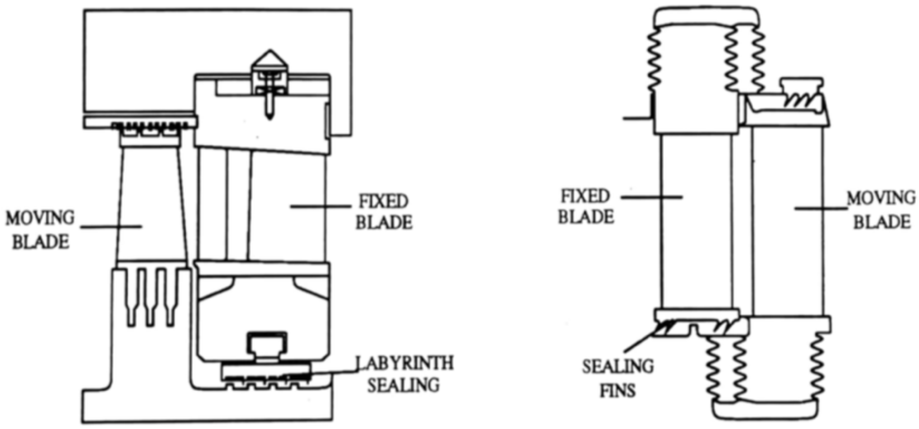
Figure 4.6 - A Cross-Compound Turbine Arrangement

4.2.2. Turbine Components

4.2.2.1. Turbine Blades

The moving turbine blades convert the kinetic energy of the steam that has been accelerated in a nozzle or fixed blades into mechanical work on the turbine shaft. The impact of the steam on the blades produces a change in direction of motion of the steam which gives rise to a change in momentum and therefore to a force. The turbines can be classified as an impulse or reaction type based on the way by which the transfer of energy occurs in moving blades [145].

In the impulse stage, the majority of the heat drop occurs in the stationary blading and the driving force on the stage arises from the change in momentum of the steam across the moving blades. Whereas in the reaction stage arrangement, steam approaches the moving blades with a velocity that is low and substantially axial in direction. Consequently, the driving force applied to the moving blades arises almost entirely from the reaction force of the steam as it accelerates through the moving blades. The impulse and the reaction stage arrangements are shown in Figure 4.7



a) Section Through an Impulse Stage

b) Section Through a Reaction Stage

Figure 4.7 - Impulse and Reaction Turbine Blading [141]

4.2.2.2. Turbine Casing

A turbine cylinder is essentially a pressure vessel with its weight supported at each end on the horizontal centerline. It is designed to withstand hoop stresses in the transverse plane, and to be very stiff in the longitudinal direction in order to maintain accurate clearances between the stationary and rotating parts of the turbine.

The design is complicated by the need for internal access, all casings being split along their horizontal centerline, allowing the rotor to be inserted as a complete assembly. Substantial flanges and bolting are required to withstand the pressure forces at the horizontal joints. The relatively massive flanges respond more slowly to temperature changes than the rest of the casing, resulting in different rates of expansion and the setting up of temperature stresses and distortion, although these are minimised by the application of flange warming steam. Further stress complexities are set up by the gland housing and steam entry and exit passages [144].

HP and IP casings are of cast construction and are circular in cross-section to minimise non-membrane stresses. Flanges, bolting, steam penetrations and other features are as far as possible symmetrically arranged to reduce thermal asymmetry and hence distortion. LP casings may be fabricated or a combination of castings and fabrications [145]. Figure 4.8, 4.9, and 4.10 show HP, IP and LP casing of double-shell design.

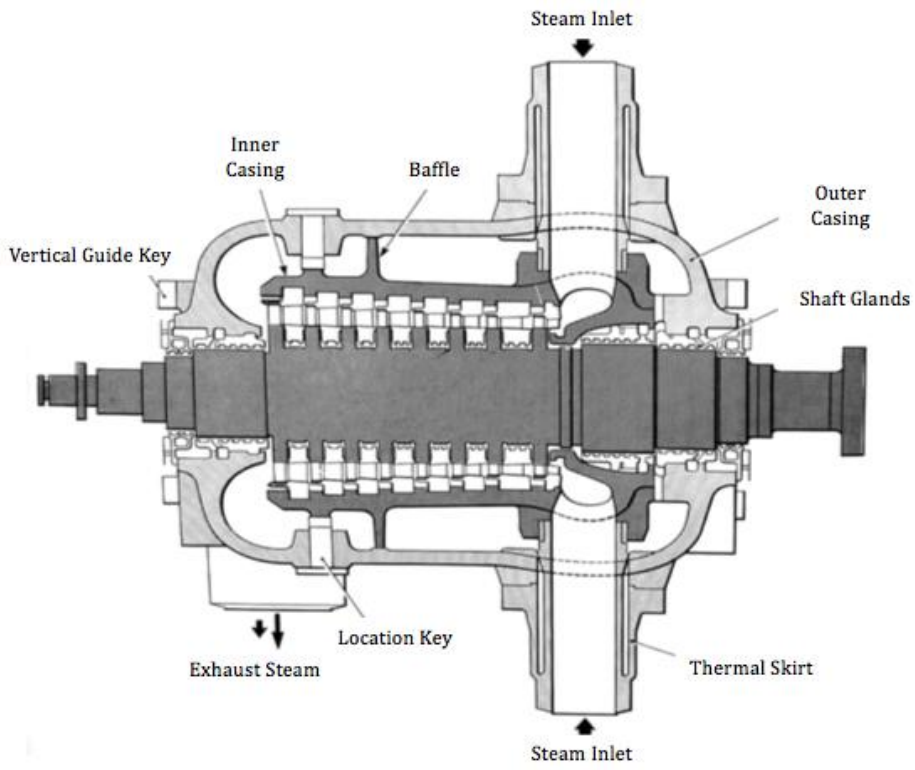


Figure 4.8 - Axial Section of an HP Turbine Cylinder [141]

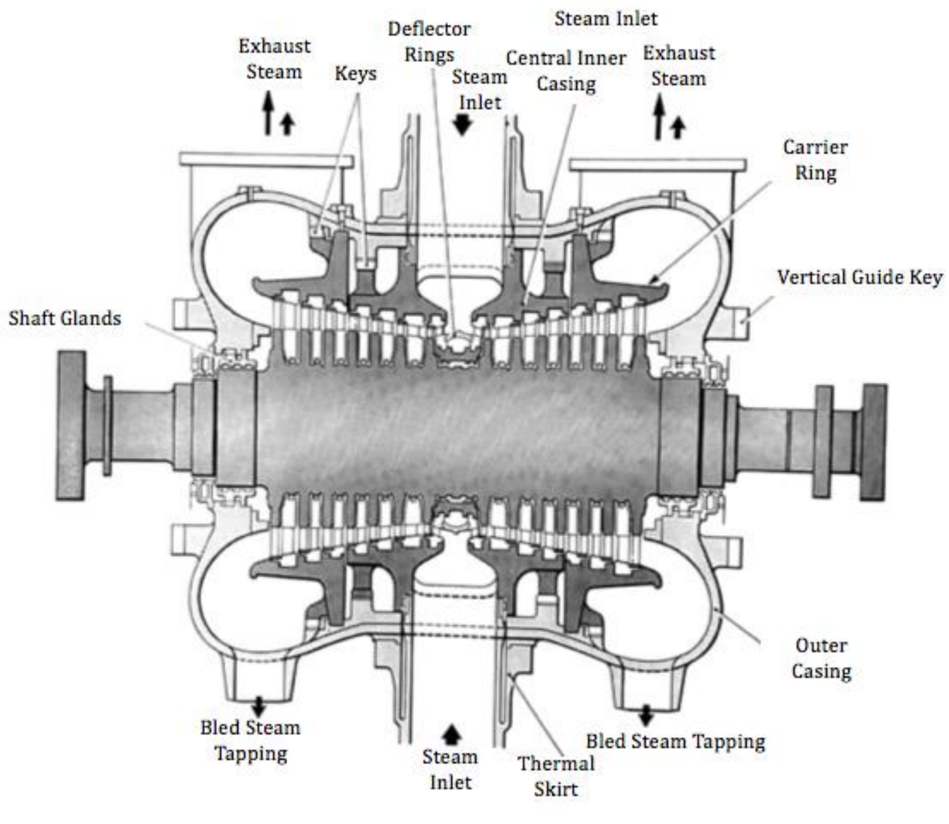


Figure 4.9 - Axial Section of an IP Turbine Cylinder [141]

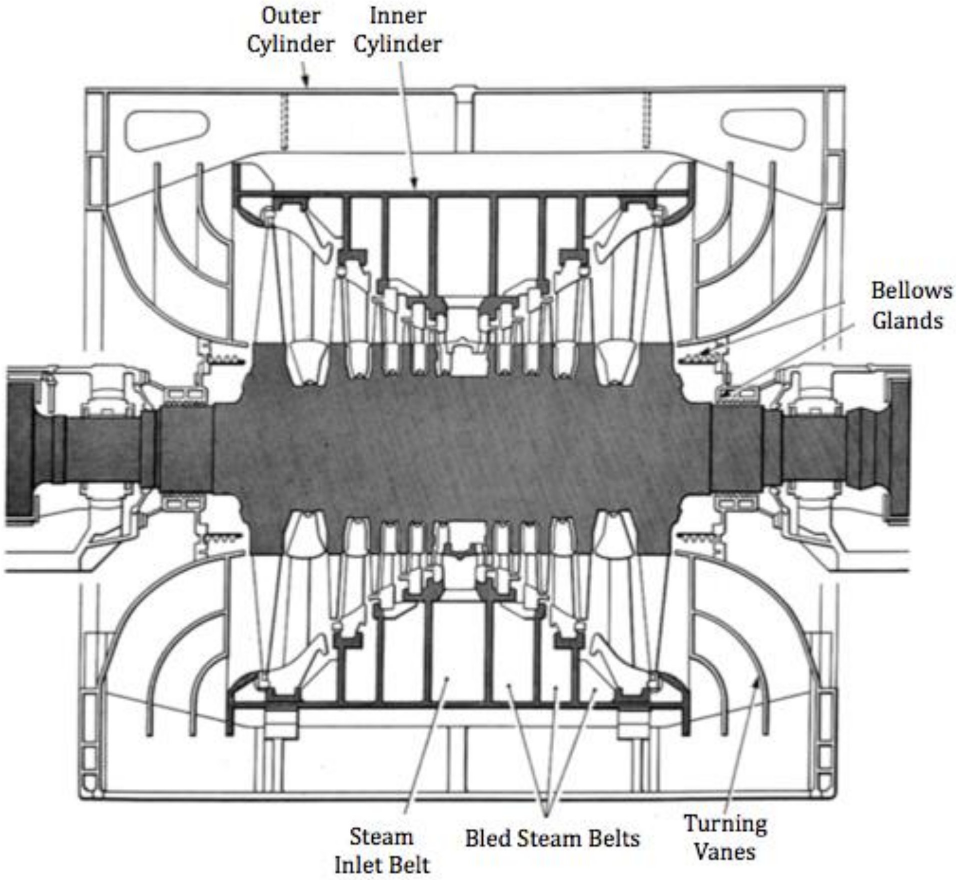


Figure 4.10 - Axial Section of an LP Cylinder [141]

To achieve maximum efficiency in a steam turbine, only small clearances are permitted between fixed and moving parts. These clearances must be maintained under all operating conditions, so the inner and outer casings must be supported in such a way as to maintain concentricity with the rotor as they expand and contract [142].

The temperature change is greatest in the HP and IP cylinders. Therefore, axial expansion occurs mainly in HP and IP cylinders. The casings are supported to allow axial expansion and yet maintain the axial clearances between fixed and moving blades which may only be a few millimeters. Maintaining both concentricity and correct axial expansion leads to a complicated system of sliding supports and keys.

4.2.2.3. Turbine Rotor

Turbine rotor is the moving component of the steam turbine that carries turbine blades on its shaft. The moving blades penetrates between the rows of fixed blades because of the steam that is directed at a right angle for entry into the moving blades. The shafts of the rotors are carried on bearings and are linked together and to the electrical generator. The linking of rotors is achieved by solid couplings.

The turbine rotor is balanced both statically and dynamically. The main aim of balancing is to reduce the amplitude of vibration to negligible level. The rotor must also be properly aligned in order to achieve satisfactory dynamic behaviour of the running shaft line. A long shaft naturally bends under its own weight to form a catenary, but nevertheless revolves around its curved centreline during rotation [145]. The alignment is arranged so that the shaft system has minimum bending moments at the shaft couplings. Figure 4.11 shows a typical shaft catenary for a large turbine.

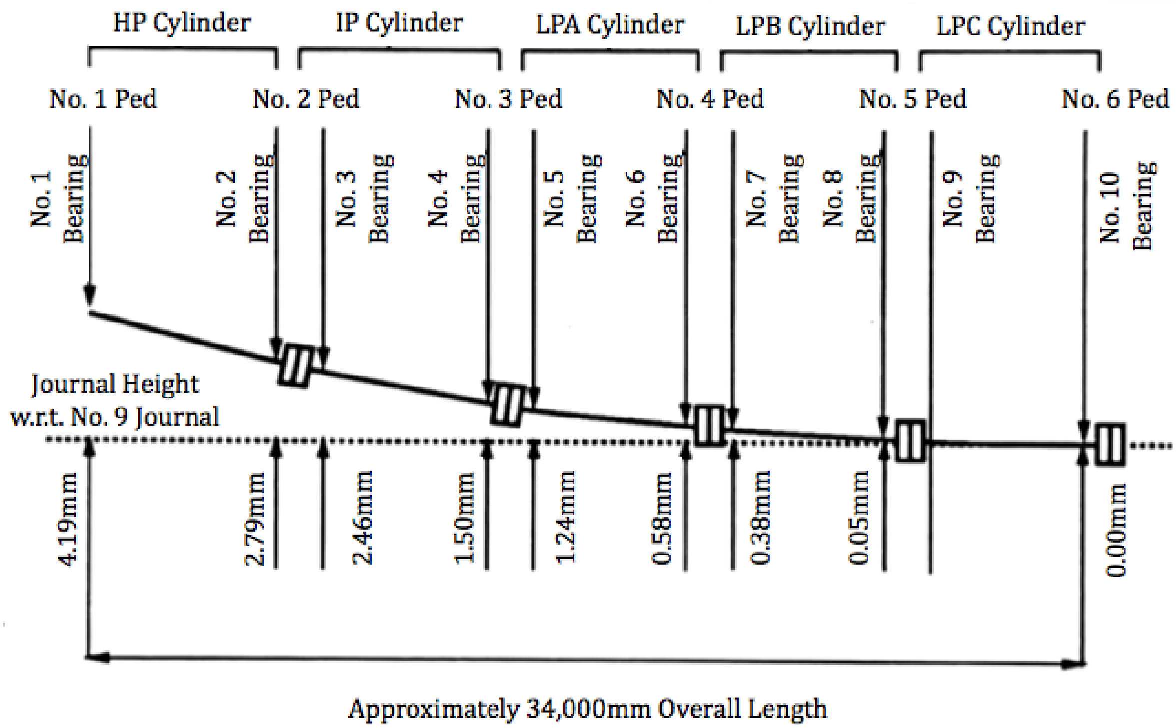


Figure 4.11 - Typical Shaft Catenary for a Large Steam Turbine

Allowance must also be made for differential expansion between the rotors and the casings during thermal transients. Both must be free to expand without upsetting the alignment, while allowing the rotors to expand more quickly and to a greater degree than the casing.

4.2.2.4. Couplings

The couplings are used to link the shafts of multi-cylinder large turbine essentially to transmit torque. The couplings also provide the means to allow relative angular misalignment, transmit axial thrust, and ensure axial location or allow relative axial movement. The main types of couplings include flexible, semi-flexible, and rigid. For large multi-cylinder steam turbines, it is common practice to use rigid couplings. Figure 4.12 shows the cross-section of a rigid coupling.

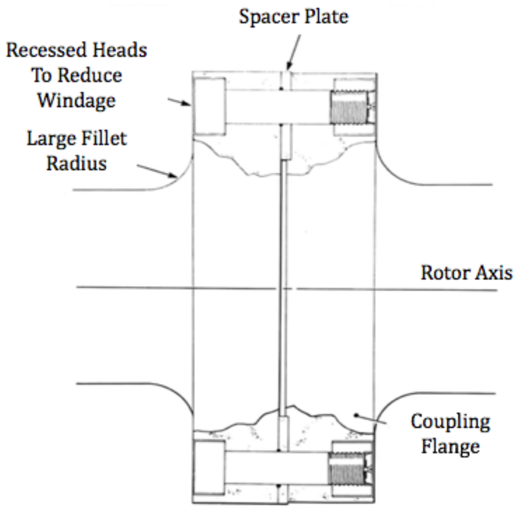


Figure 4.12 - Rigid Monobloc Coupling [142]

4.2.2.5. Journal Bearings

The purpose of a turbine bearing is to retain the rotor system in its correct radial position, relative to the cylinders. In addition, the turbine bearing must provide a low friction support which will withstand the static and dynamic loads of shaft rotation, together with the frictional and conducted heat, and to remain free from maintenance except at major outages.

Two bearings are normally support each section of the turbine shaft, although, with solid couplings, some designs only use one bearing between cylinders in order to save length and bearing losses. Plain white-metalled journal bearings are invariably used because of their high loading capacity, reliability, and absence of wear due to hydro-dynamically generated films of lubricating oil [141]. A main rotor bearing showing steel-back white metal liner is illustrated in Figure 4.13

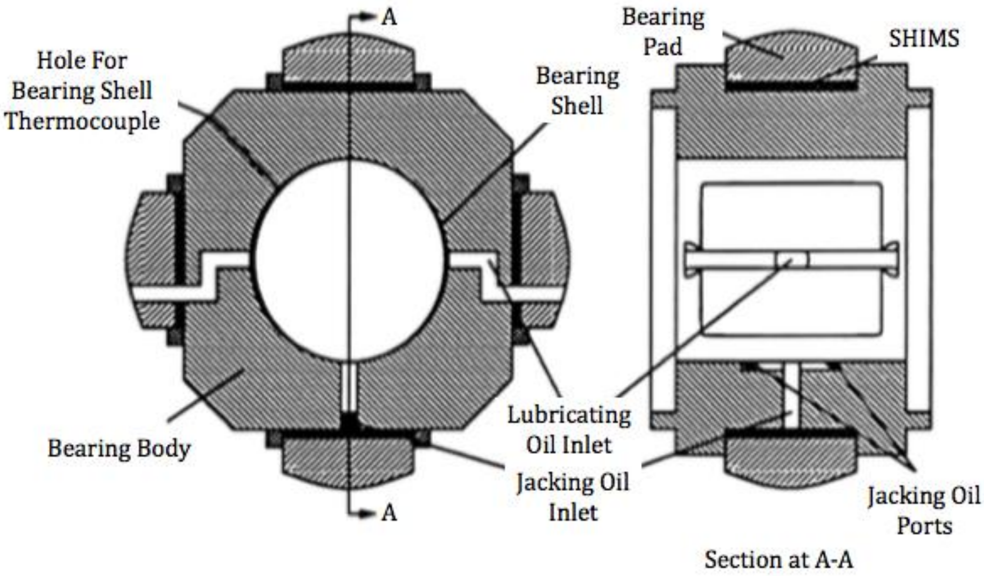


Figure 4.13 - Main Rotor Bearing [142]

Instrumentation specific to the performance of the bearing normally comprises white-metal temperature, and oil inlet pressure and temperature. Provision is also made at the bearing housing to monitor vibration modes. Jacking oil pressure is monitored locally at each bearing.

4.2.2.6. Thrust Bearing

The purpose of the turbine thrust bearing is to provide axial location for the turbine rotors relative to the cylinders. To achieve this, it must be able to withstand the unbalance thrusts due to blade reaction and steam pressure acting on unbalanced areas. It must be free from maintenance, except at major outages [146]. Since it is universal practice to use solid couplings between rotors, only one thrust bearing is required in each complete shaft line. It is normally located close to the areas where blade/cylinder clearances are minimum and operating temperatures are highest and is split on the horizontal split centerline for ease of assembly and maintenance [144]. Figure 4.14 shows tilting thrust pad bearing

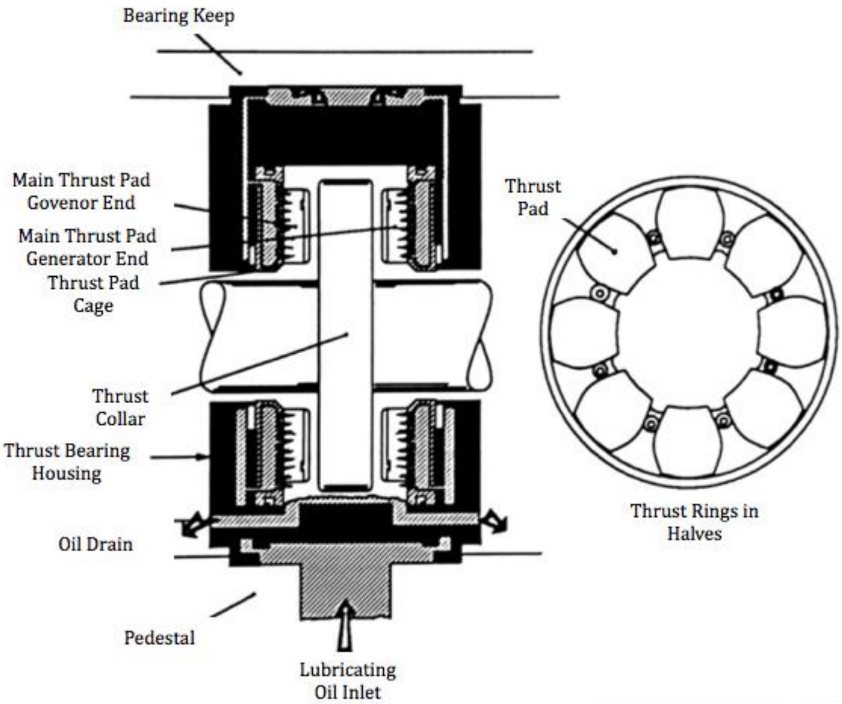


Figure 4.14 - Tilting Pad Thrust Bearing [142]

4.2.2.7. Pedestals

The main purpose of the bearing pedestals is to support the turbine rotor, via the journal bearings, in a fixed relationship to the cylinders so that gland clearances are maintained in all phases of operation. Mounted within (or on) the enclosure are all necessary instrumentation connections (e.g. bearing temperature, differential expansion pick-ups), together with eccentricity and vibration transducers. A manometric level system is attached to the pedestals adjacent to each bearing to detect misalignment due to support structure settlement [142].

Particular care is taken to ventilate around the pedestals, keeping them cool so that any vertical thermal expansion effects, which might disturb the overall vertical alignment of the turbine, are minimised. In addition, those pedestals adjacent to the high temperature components of the turbine are frequently protected by thermal radiation shields, with provision for air circulation in the space between the shield and the pedestal structure, also to minimise thermal expansion effects.

4.3. Plant State and Operating Conditions

The operating conditions of the plant have a considerable bearing on the type and likelihood of fault situations arising. The information about the operational states plays an important role in finding the root-causes of faults identified by analysis of dynamic behaviour [147]. The eight operational states in the general order in which they are experienced are as follows: Stationary; Shut Down, Start Up; Critical Speed; Load Transient; Thermal Transient; Steady State; Run Down.

4.3.1. Stationary

The plant is considered to be in stationary state when the shafting is at rest. However, the plant may be in a wide range of conditions such as jacking oil system in or out of service, main lubricating oil system in or out of service, thermal condition of the plant anywhere between fully cold to fully heat-soaked. In addition, the plant, in its broadest term (i.e. turbine-generator, steam raising plant or auxiliaries) could be undergoing maintenance work.

4.3.2. Shut Down

The plant is in shutdown state when the shafting is on electric turning gear (ETG) and the machinery is cold or cooling down following a period of generation. The conditions for plant shut-down or start-up apply whenever the plant is either taken down or brought back into service.

4.3.3. Start Up

Startup is the operational state of the machine when a set of activities that are needed to take the plant from the conditions of Shut Down through to the actual synchronisation of the machine’s speed with Grid frequency and the closing of the circuit breaker. Startup is the most critical time for a turbine-generator, with many potentially hazardous conditions. A high proportion of the hazards directly relate to the thermal state of the plant at the time of actually putting steam to the machine, referred to as steam-to-set (STS) [147].

4.3.4. Critical Speed

Critical speed indicates that the rotating speed of the machine is relatively close to the resonant frequency of the machine. During critical speed, high vibrations are observed and they can build up to a dangerous level. The critical speed is either above or below running speed, depending on rotor construction. If below, care must be exercised during run-up to ensure that the critical is passed as quickly as possible.

4.3.5. Load Transient

Change of load imply steam pressure and temperature changes in the turbine, and additionally, then imply that the excitation current of the generator rotor will also be changed. Load transient in its broadest sense has an impact on generation. When machine is in hot or cold state, load conditions apply in order to avoid thermal stressing and the rise of excitation current.

4.3.6. Thermal Transient

The thermal transients in this category are those which occur when the unit is generating, but not those directly attributable to the power generated. They relate to the operation of auxiliary systems.

4.3.7. Steady State

Steady state is the normal operation of plant at a steady load and with constant thermal conditions. Steady state is also referred as online state. The Online state is the ideal state in which short-term and long-term trends can be examined.

4.3.8. Run Down

Run down usually indicates the shutdown of the machine which can be due to intentional trip or unintentional trip. The intentional trips are conducted to carry out tests on the machine and after the tests machine is resynchronised with the grid. However, unintentional trips may represent faulty conditions and machine is only returned to the service after the problem has been diagnosed and corrected.

4.4. Steam Turbine Instrumentation

The main purpose of the steam turbine instrumentation is to provide reliable information to operator in order to achieve high plant efficiency. The correct interpretation of the information provided allows the plant to be run-up and loaded in the minimum time consistent with safe operation. Optimum conditions for a given installation are determined by careful analysis of the data obtained during commissioning [148]. Deviation of a reading from the normal range established during commissioning provides advance warning of problems so that corrective action can be taken in time. A diagram of typical turbine supervisory instrumentation installation is shown in Figure 4.15

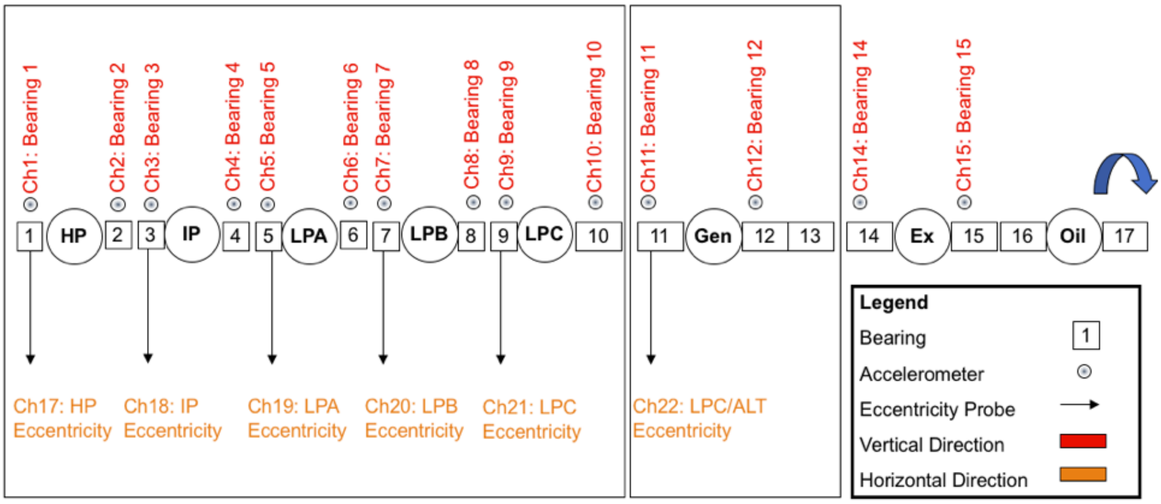


Figure 4.15 - Typical Steam Turbine Instrumentation Arrangement

There are five main types of supervisory measurements that are taken in steam turbines [143] [148]. These measurements include: vibration; eccentricity; phase and speed; rotor and casing movement and expansion; temperature.

4.4.1. Vibration Measurements

In the measurement of vibration, a transducer converts the mechanical vibratory motion of the plant into another form of energy, usually voltage, which is directly proportional to displacement, velocity or acceleration. The moving coil velocity transducer is commonly used to measure vibrations. There is usually one transducer for a bearing and the vibration measurements are taken in vertical direction as shown in Figure 4.16.

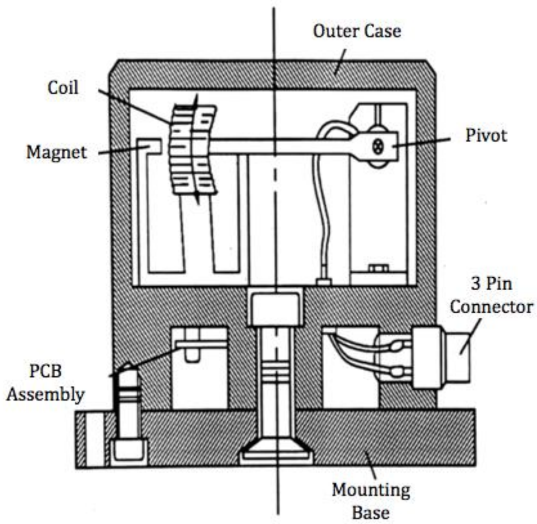


Figure 4.16 - Section Through a Velocity Transducer [142]

4.4.2. Eccentricity Measurements

Eccentricity occurs when the center of rotation is at an offset from the geometric centerline of the shaft. For practical reasons the measurement is made on the shaft within the bearing pedestal. The change in radial airgap within the cylinder is inferred from this measurement. To measure shaft eccentricity, a non-contacting proximity probes, operating on the eddy current principle are used in horizontal direction. The eccentricity measurement is the most sensitive source of changes in dynamic behaviour and can be taken at the sustainable turning speed.

4.4.3. Phase and Speed Measurement

Phase measurements provide further insight into machine diagnostics. It is further used for orbital analysis, rotor balancing, and measuring speed. It is best practice to measure phase using eddy current probe at two quite separate reference points.

4.4.4. Rotor and Casing Movement and Expansion Measurements

The movement and expansion of individual casings is measured in order to ensure that the alignment between pedestals remains within acceptable limits. Rotor clearances are also maintained within the acceptable limits by measuring the movement and expansion of the rotor.

4.4.5. Temperature Measurements

Supervisory temperature measurements comprise casing temperatures and steam to metal temperature differences and thermal gradients. These measurements are provided by means of thermocouples.

4.5. Steam Turbine Maintenance Approach

The measurements captured using steam turbine instrumentation allow the implementation of CBM strategy as they provide the current state of an equipment. Thus, enabling the operator to perform predictive and pro-active maintenance actions based on the observed health of an equipment. CBM strategy involves using real-time system monitoring and data processing. Another capability that may form part of a CBM system is an ability to provide an estimate of the RUL of the system or component being monitored. This type of functionality is known as prognostics, as opposed to diagnostics which is used to assess the current condition of a monitored system.

A CBM approach promises a range of improvements over existing approaches, with a potential reduction in overall maintenance costs being one of the primary drivers for developing such approaches. The cost associated with each of the various maintenance approaches is depicted in Figure 1.1. A corrective maintenance approach has a relatively low maintenance cost (minimal preventative actions), but high-performance costs associated with the high cost of operational failures. In contrast, preventative maintenance generally has a low operating cost, associated with reduced instances of in-service failures, but often uses very conservative estimates regarding the probability of component failures and so has a high maintenance cost, associated with the removal of components before they have reached the end of their useful lives. It would seem, therefore, that the most cost-efficient approach is to undertake maintenance when there is objective evidence of need, i.e. condition-based maintenance.

The development of CBM approaches has been enabled by developments and advancements in sensor technologies, data collection, storage and processing capabilities, and continuous improvements in algorithms and data analysis techniques. CBM systems for steam turbines are founded upon the ability to infer equipment condition using data collected from the steam turbine instrumentation. It incorporates both diagnostic and prognostic capabilities. The distinguishing factor between diagnostic and prognostic capabilities is the nature of the analysis. Diagnostics involves posterior event analysis (i.e. identifying the occurrence of an event which has already happened), while prognostics is concerned with prior event analysis (i.e. predicting the future behaviour of the system).

4.6. Problem Definition

The general arrangement for handling thermal expansion in a steam turbine is shown in Figure 4.17. The outer casing palms of the HP cylinder lean on the transversal keys attached to the bearing pedestals. The transversal keys guide the thermal expansion of the casing. The bottom of the bearing pedestals is attached to the longitudinal keys allowing the bearing pedestal to slide on the foundation frame when the metal temperature of the turbine varies during the start-up, runup and rundown operating conditions [149].

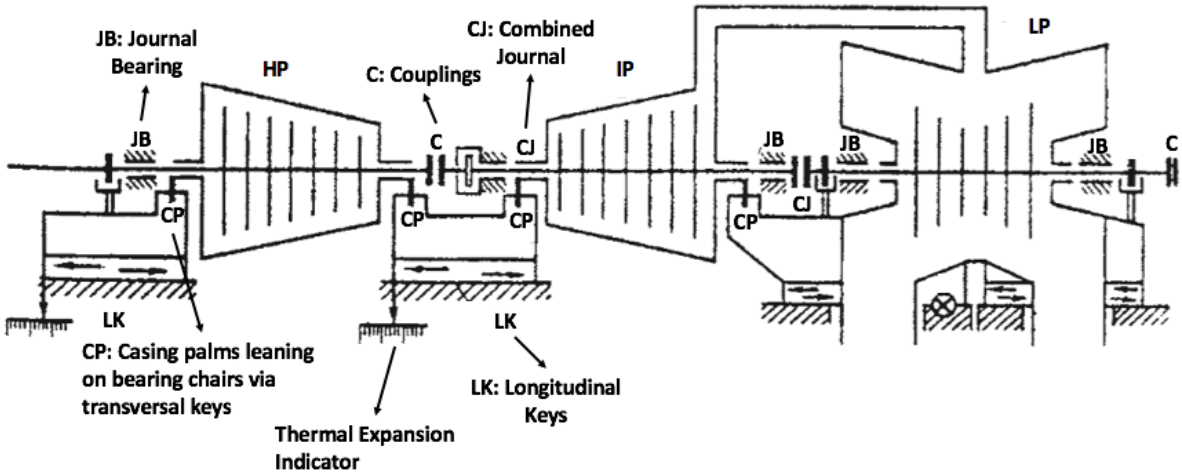


Figure 4.17 - General Steam Turbine Arrangement for Thermal Expansion [149]

The entire weight of the steam turbine rests on the bearing pedestals, as a result of which substantial frictional forces are produced which hinder the axial movement of the bearing pedestal along the foundation frame. This can be manifested in an increased displacement of the HP shaft, and increased level of vibrations within the bearings. HP gap measurements also indicate the level of clearances between the turbine blading and the casing. The fault is slow and progressive, in that without intervention the level of displacement increases over time which can result in distortion of casing, increased vibration, damage to the turbine bearings and couplings etc. However, if the turbine is taken offline or stopped and the casing cools sufficiently, the displacement may reduce as well.

This fault was observed within one turbine, fully analysed by the engineers, and corrective action taken by changing the interface between the pedestal and foundation from injected grease (which was inserted at first as a remedial solution to reduce friction) to a self-lubricating graphite-impregnated material.

4.7. Preliminary Data Analysis and Data Transformation

4.7.1. Data

Data used in this work was obtained using the PlantProtech™ Analyser in proprietary format. A parser program was written in C++ to convert the data from proprietary format into MATLAB readable format. Within this research, data mining was used to discover trends and features within the data that was collected from an operational nuclear steam turbine in the UK. The obtained data is used for the development of degradation-based prognostics to predict the remaining useful life of the steam turbine using degradation parameters that are specific to the steam turbine operating in specific conditions and an environment.

The data contained 6685 files. Fields of data records varied from 1 to 4032 in these files. Typically, a single file contains 144 fields of data for a single day when conditions are stable operationally (i.e. online). However, the sampling frequency of the data varies depending on the operational status of the machine. AC, DC and Digital channels were used to record the data. There are 22 AC channels, which were used to record bearing velocity and shaft displacements at the different stages of the turbine. The number of DC channels varied from 16 to 172. However, the main DC channel parameter that was used for analysis is DC Channel 1 (Generated Power (MW)) as it indicated the supervisory operational status of the machine. Whereas, other DC Channels were deemed irrelevant for data analysis and were discarded after discussions with industrial experts. The file also contained data from 8 Digital channels.

The overall summary of the data extracted from a single file is shown in Table 4.1.

Table 4.1 - Overall Summary of Data File

AC Channel 1-22	DC Channel 1 – 16/172	Digital Channel 1 - 8	Rotor Speed	Elapsed Time	FFT Data

The data was then segregated based on operational states. The operational states are discussed in Section 4.3. For data analysis, online data was selected as this was the largest dataset and it is anticipated that when operating in online mode, the machinery response should be fairly consistent and any unusual behaviour and degradation should be easier to identify.

4.7.2. Preliminary Data Analysis

Mean values for each file were calculated to allow this large volume of data to be summarised. In other words, single file was represented by one value, the mean value of that parameter. For instance, there were 501406 measurements recorded for each parameter and by calculating the mean these measurements can be summarised by 6420 mean values. This allowed the full dataset to be analysed at a coarse resolution, but will allow the major trends in the data to be identified.

The initial analysis of the data involved assessing the affect of mean power on the mean vibration levels. It is essential that the operational routines are correctly identified so that higher vibration levels during these operational routines are not mistaken for machinery faults. Figure 4.17 shows the online profile of the mean power

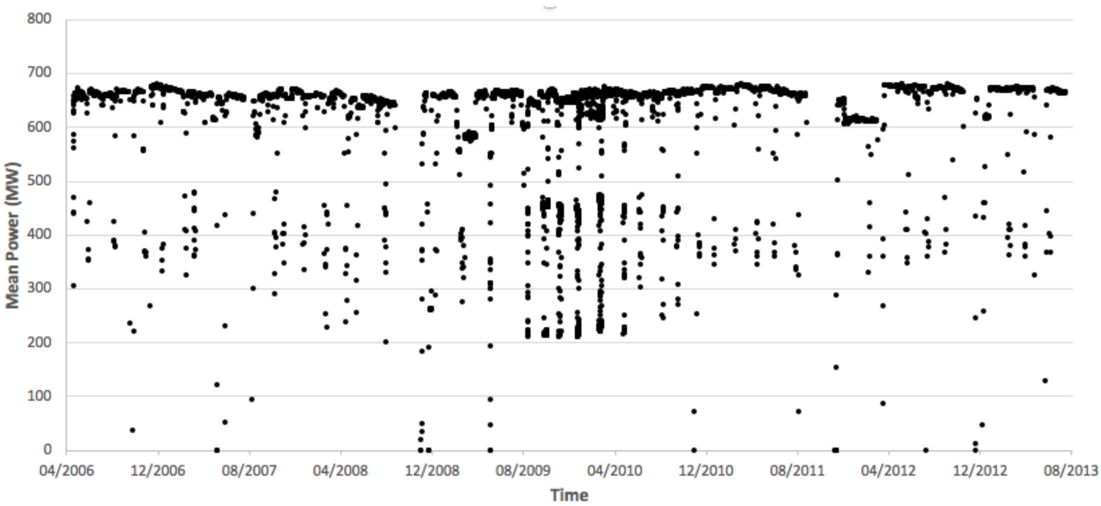


Figure 4.18 - Mean Online Power

From Figure 4.18, it can be seen that mean power is relatively steady. The maximum mean power generated is 680MW at 3000rpm approximately, and the minimum power generated is 0MW. In the majority of cases mean power lies within the band of 635MW – 680MW. It is also observed that power fluctuates to approximately 30% and 70% of relatively steady power, which can be seen in the histogram of the mean power shown in Figure 4.19

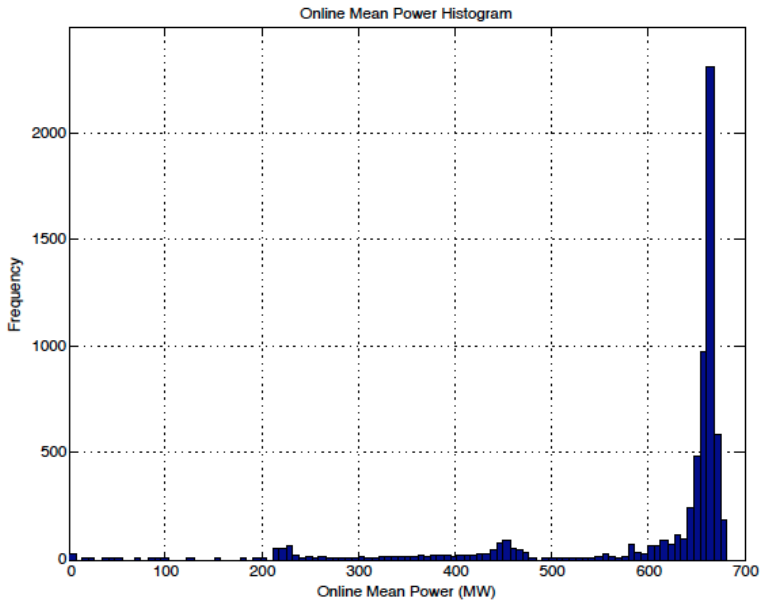


Figure 4.19 - Mean Online Power Histogram

The peaks at 230MW and 460MW have been identified as being due to refuelling events. Two such events are shown in Figure 4.20 and Figure 4.21

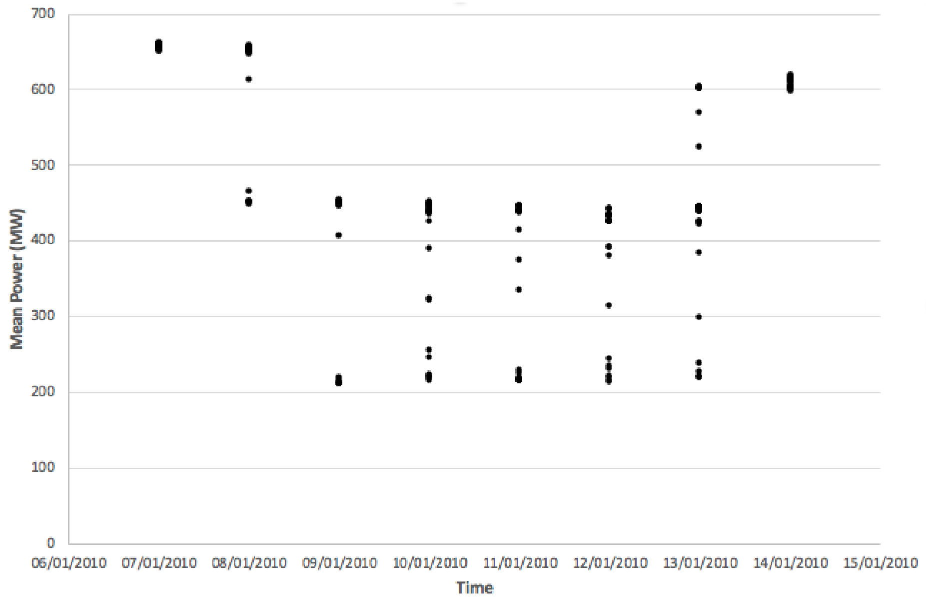


Figure 4.20 - Refuelling Event 1

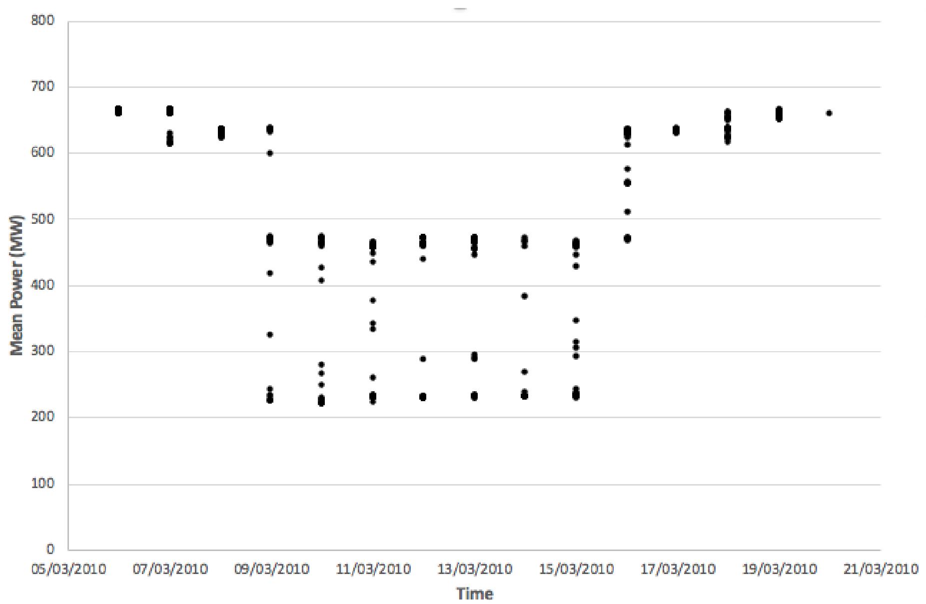


Figure 4.21 - Refuelling Event 2

These refuelling events are considered normal, as they are part of the operational routine. The data relating to refuelling events was removed from the set for initial analysis, as changes in power were clearly seen to influence vibration and displacement data. For example, Figure 4.22 shows mean online bearing 1 vibration and it can be seen that bearing vibration fluctuates with changes in power. This makes it difficult to identify any pattern visually by considering this full set of data across all power levels.

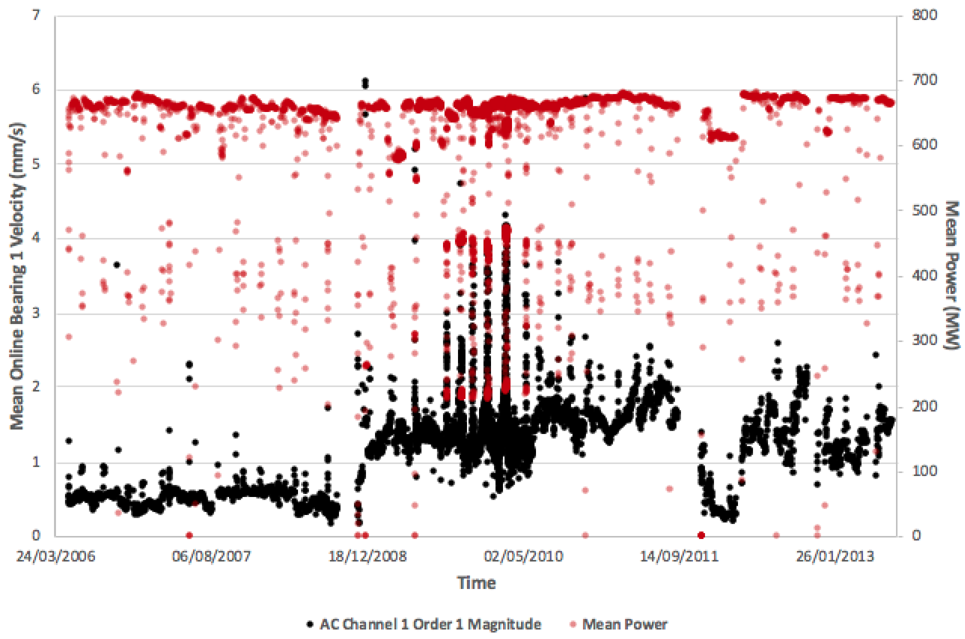


Figure 4.22 - Mean Online Bearing 1 Vibration vs Mean Online Power

However, due to large variation in mean power, it was believed that data should be subdivided further in order to identify any patterns. A new data set called Full Power Dataset was created, based on the histogram of mean online power (Power ≥ 560MW) as shown in Figure 4.23.

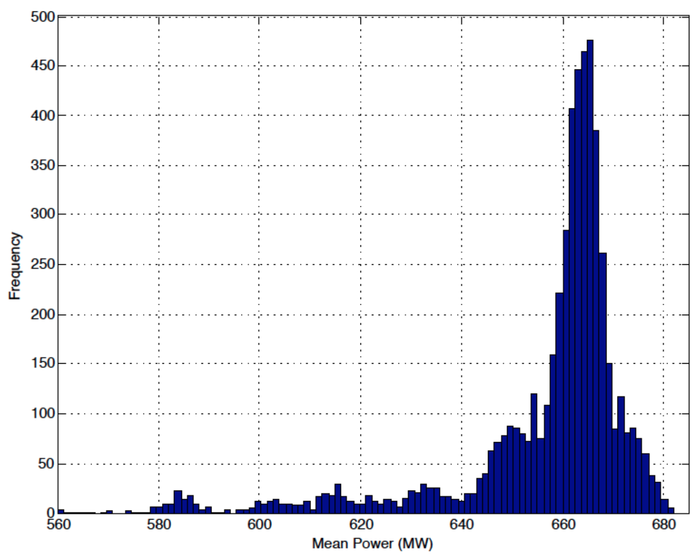


Figure 4.23 - Histogram of Mean Online Power ≥ 560MW

From Figure 4.22, it can be seen that most of the data is within the range of 637MW – 681MW (±4% of 667MW). Therefore, this range is used to create Full Power Dataset. It is anticipated that the machinery response should be fairly consistent and any operational changes and deviations due a fault should be easier to identify. Figure 4.24 shows mean online full power

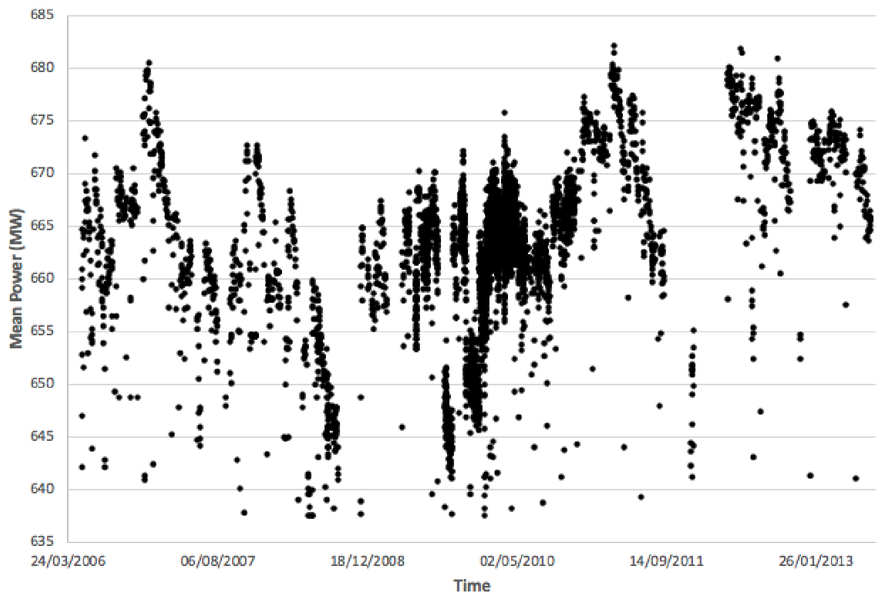


Figure 4.24 - Mean Online Full Power

The full power dataset was used to create visualisations of vibrations and displacements. The analysis of vibration and displacement trends clearly showed patterns in the HP displacement of a pedestal in the HP turbine stage. Figure 4.25 shows full power mean online HP displacement

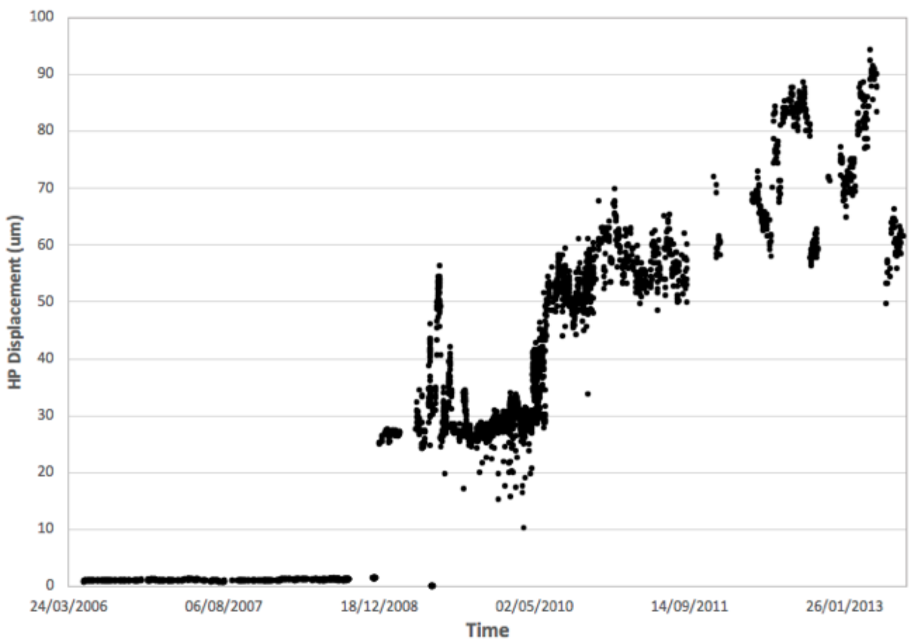


Figure 4.25 - Full Power Mean Online HP Displacement

4.7.3. Change Point Analysis

Change point analysis is a technique used to identify points in which data parameters change notably over time [150]. This can be used to define step changes in time series data or detect subtle changes in data missed by visual inspection. Change point analysis also allows different modes of operation to be found within the data.

Change point analysis can be performed through calculating the cumulative sum of differences (CUMSUM) of a data parameter from its mean value [150]. This is shown in Equation 4.1 where C_i is the CUMSUM at time step i, C_{i-1} is the CUMSUM at the previous time step, x_i is the data value at time step i and $\bar{x}$ is the mean of the data. Changes in the gradient of C can be used to identify and define change points.

$$C_i = C_{i-1} + (x_i - \bar{x}) \tag{4.1}$$

Figure 4.26 shows CUMSUM plot for detecting multiple change points in HP displacement. Two change points in the CUMSUM plot indicate the change in operational mode and the point in time at which the HP displacement starts to increase.

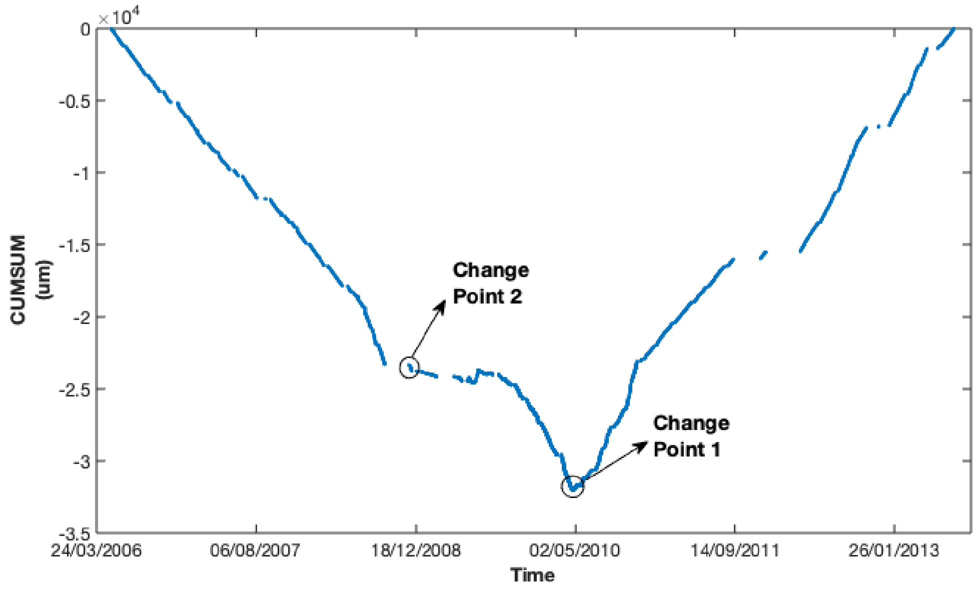


Figure 4.26 - CUMSUM Plot of HP Displacement

This technique identifies change points in iterations. For HP displacement, two iterations were performed based on the observation of the online full power HP displacement data. In the first iteration, the cumulative sum of the difference of the online full power HP displacement data from its mean was calculated, which resulted in the change point 1 as shown in Figure 4.26. This change point is the lowest cumulative sum of the difference between the data points and their mean.

In iteration 2, the lowest cumulative sum of the difference between data points before the change point 1 and their mean is calculated. The lowest cumulative sum in iteration 2 is change point 2.

Change point analysis reveals three patterns in HP displacement over time as shown in Figure 4.27. The patterns are labelled as with region numbers. In region 1, there is very low HP displacement. After this region a step change is observed which is due to a change in operational conditions. In region 2, HP displacement tends to remain relatively steady with fluctuations towards the start. In region 3, a ramp up in HP displacement can be observed.

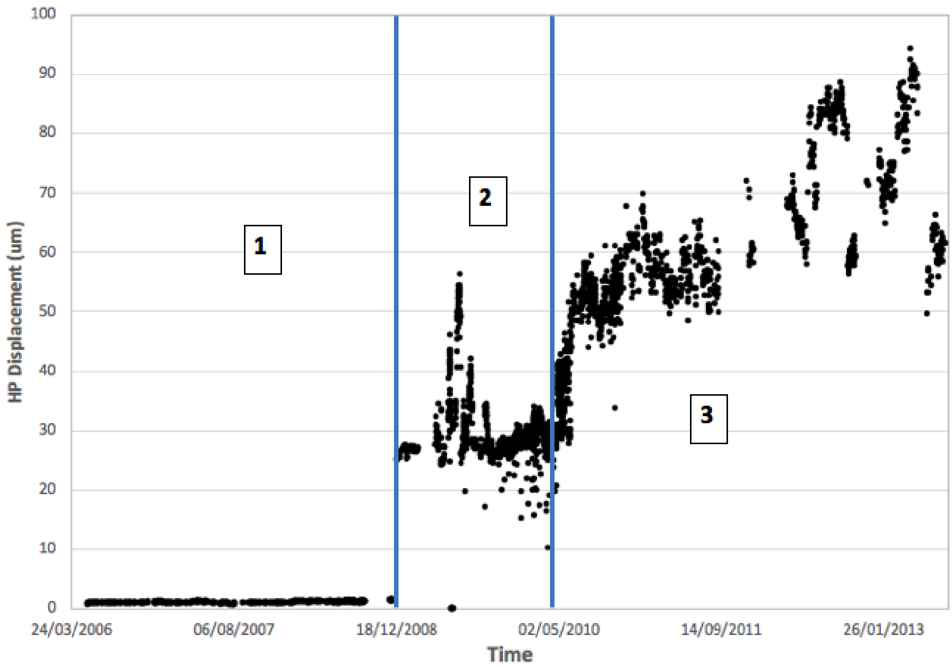


Figure 4.27 - Identified Patterns in HP Displacement and HP Gap through Change Point Analysis

The first change point as shown in Figure 4.26 is used to isolate the online full power HP displacement data of region 3 as shown in Figure 4.27. This dataset forms the HP ramp case study, which is shown in Figure 4.28

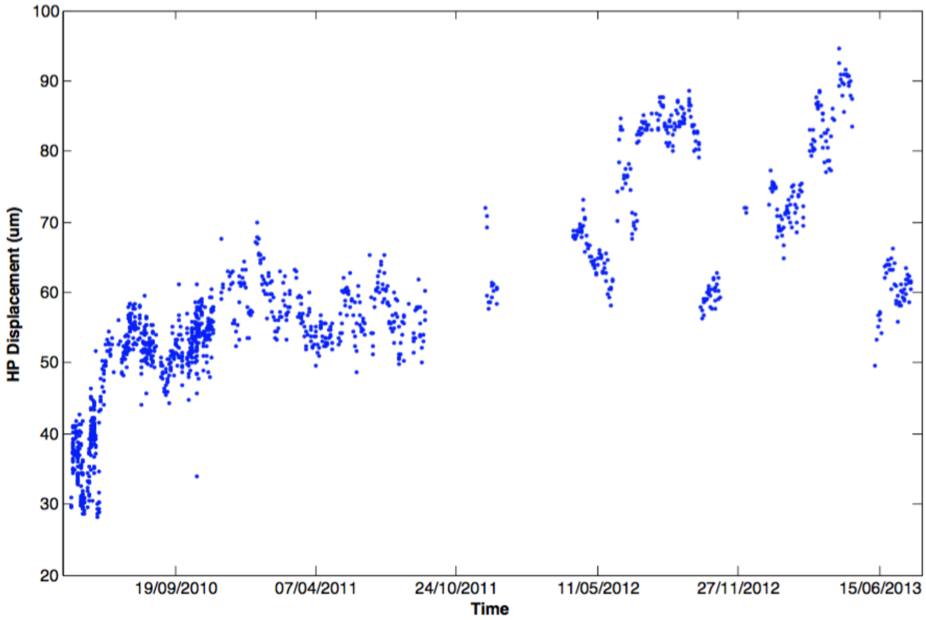


Figure 4.28 - HP Ramp Case Study with gaps

The gaps in the data are due to the removal of the outages/stoppage durations, online data captured below full power, high vibrations experienced during critical speed state and other vibration data captured during the state of run up. The gaps in the data were removed and the x-axis was converted into Time Index from date format 'dd/mm/yyyy' by calculating the cumulative sum of time differences between the data points. Figure 4.29 shows four patterns that were observed in HP Ramp Case Study. The patterns are labelled as the region numbers. In region 1, HP displacement starts with the step and then tends to increase steadily. After this region, HP displacement ramps very sharply. To control this sharp increase in HP displacement, maintenance is performed which resets the HP displacement as shown at the start of region 3. In region 3, HP displacement increases sharply again and another maintenance is carried out to rectify the problem (See Section 4.5.4). The HP displacement in region 4 settles.

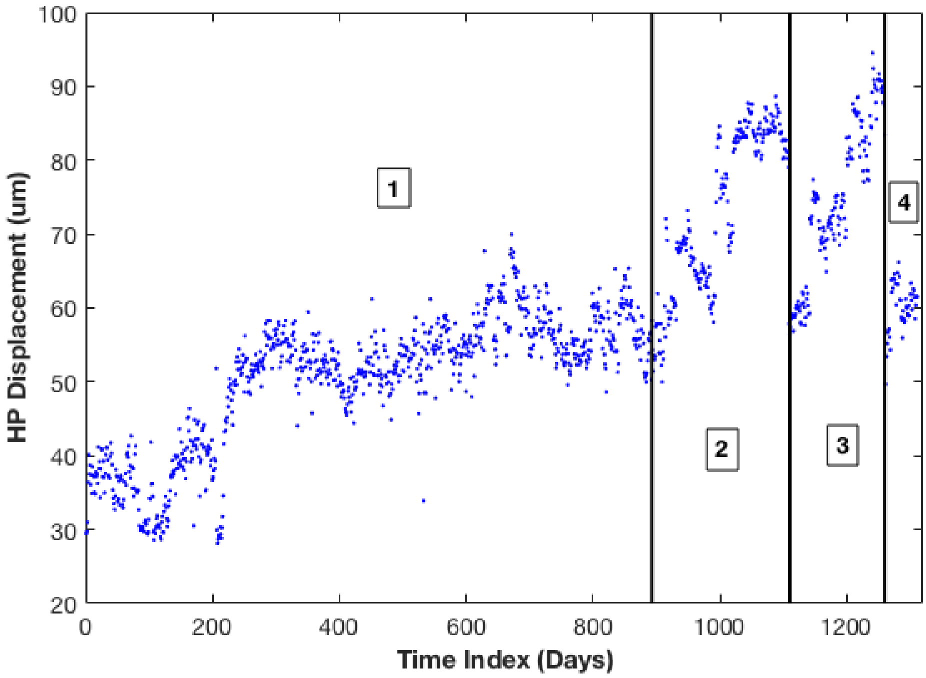


Figure 4.29 - HP Ramp Case Study with Labelled Regions

4.8. Synthetic Data Generation

The synthetic data provides a powerful method to validate the performance of a given prognostics algorithm because the characteristics of the synthetic data closely mimics the real case study. To achieve such resemblance, a three-step process is followed for generating the synthetic data. In first step, underlying model of the case study data is established by fitting curves to HP displacement data shown in Figure 4.28 . In second step, the variance within the case study data is captured by modelling noise. In third step, the underlying model is combined with the noise model to randomly generate the synthetic data. These steps for generating the synthetic data are explained below

4.8.1. Curve Fitting

The curve fitting models of first order polynomial, second order polynomial, third order polynomial, and exponential models were applied to the HP ramp case study as shown in Figure 4.30 in order to characterise the underlying model of the case study.

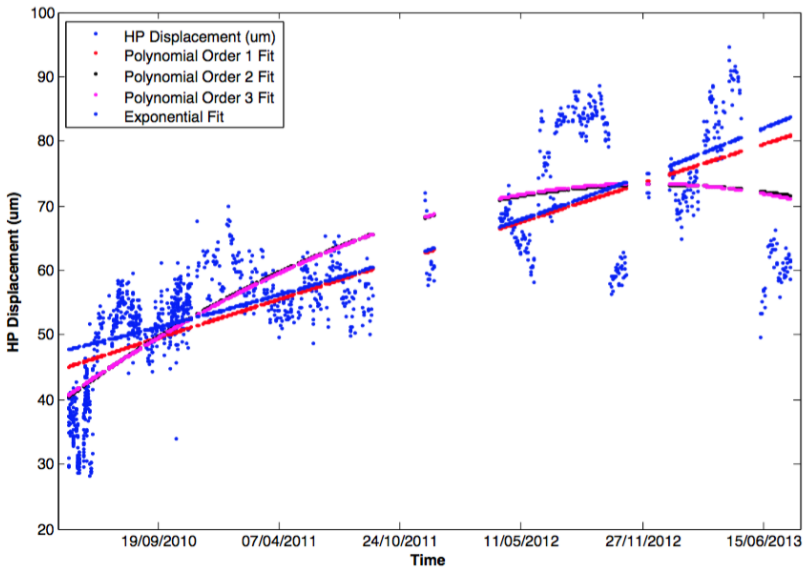


Figure 4.30 - Curve Fitting for Underlying Model Discovery

The R-square errors (measured on the scale of 0-1, where the closer the value to 1, the better the fit of the model) of the candidate models are given in Table 4.2 which shows that the second order polynomial and the third order polynomial perform marginally better than the first order polynomial. However, the first order polynomial was selected as the underlying model for the case study as it provides a balance between goodness of the fit and simplicity of predictive algorithm implementation.

Table 4.2 - R-Squared Values of Curve Fitting Models

Fitting Models	R-squared Error
First order polynomial	0.6392
Second order polynomial	0.7046
Third order polynomial	0.7048
Exponential	0.6097

It is noted that there is room for improvement here, by selecting a more representative degradation model, particularly one accounting for periods of inactivity where no degradation takes place. However, for the purposes of generating a baseline of synthetic data, this first order polynomial fit was deemed adequate.

4.8.2. Noise Modelling

The region 2 of the full power HP displacement as shown in Figure 4.27 is used to model noise as the HP displacement remained relatively stable in region 2. The residuals for the underlying model (Polynomial Order 1) of region 2 were estimated by calculating the difference between the region 2 data points and model data points. These residuals represent noise of the real data signal. The distribution of these residuals is shown in Figure 4.31.

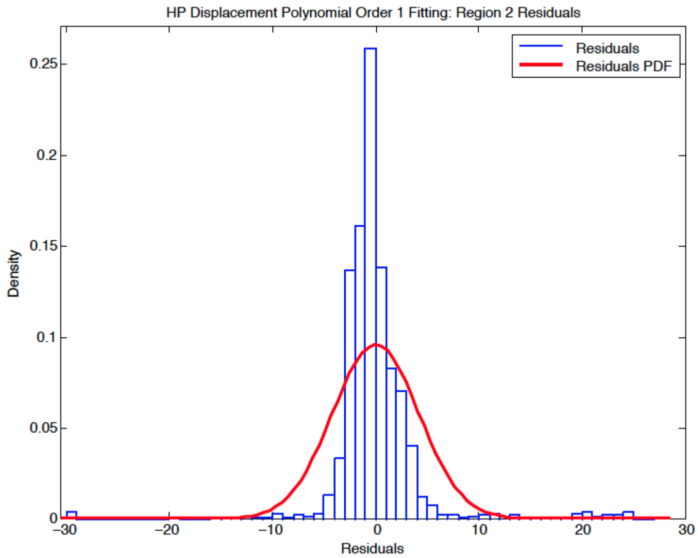


Figure 4.31 - Noise/Residual Distribution

The residuals' distribution was characterised based on its statistical moments and it approximately follows a Gaussian (Normal) distribution.

4.8.3. Synthetic Data Generation

Case study data can simply be generated by combining the underlying model of the case study and the noise model together. By introducing small variation in the polynomial parameters of the underlying model a wider range of data can be generated, while still retaining the underlying characteristic of the degradation. A sample of synthetic case study data is shown in Figure 4.32.

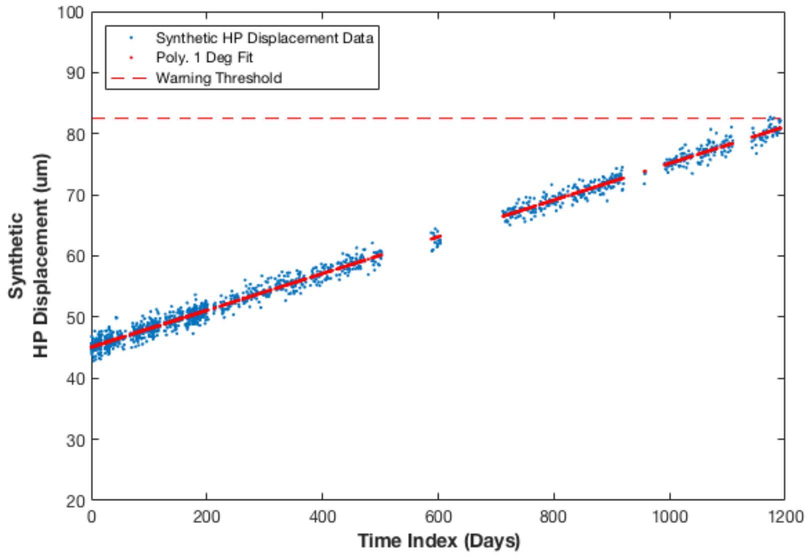


Figure 4.32 - Sample of Synthetic Case Study Data

The gaps in the synthetic data replicate the gaps in the case study data. The comparison of the HP displacement with the generated synthetic data is shown in Figure 4.33.

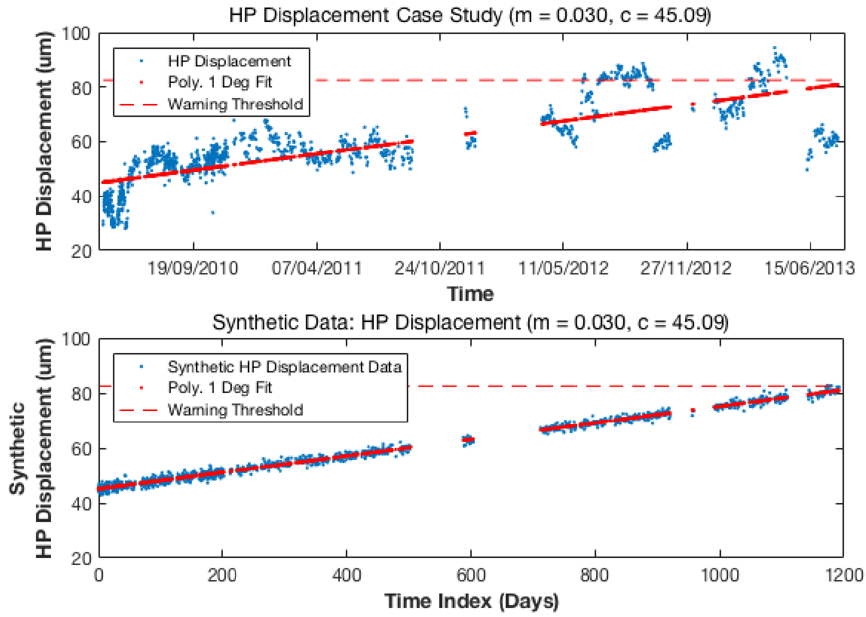


Figure 4.33 - Comparison of HP Displacement Case Study Data and Synthetic Data

The differences between the actual case study and the synthetic data tend to appear later in the data because of the maintenance carried out to replace injected grease to a self-lubricating graphite-impregnated material. Table 4.3 shows the comparison of the parameters of the case study and the generated synthetic data.

Table 4.3 - Parameters of HP Displacement Case Study Data and Synthetic Data

Parameters	Synthetic Data	HP Displacement Case Study
Mean	57.182	57.174
Variance	126.850	196.467
Slope (m)	0.030	0.030
Intercept (c)	45.090	45.090

The mean, slope and the intercept values of both datasets are similar. However, the variance of the datasets is different which is due to different noise models of the datasets. The synthetic data is generated based on the underlying model and the noise model of the region 2 of the HP displacement. As shown in Figure 4.27, the data points in region 2 of the HP displacement are very close to the fit as compared to the data points in region 3. Therefore, it was expected that the variance of the synthetic data will be smaller than the variance of the HP displacement case study. This comparative analysis of the case study with the generated synthetic data shows that synthetic data is relatively similar to the case study. By varying the slope, intercept, and the variance of the noise model, wide range of data scenarios can be generated for the validation of prognostics algorithms. A sample of synthetic case study data that was generated without gaps is shown in Figure 4.34.

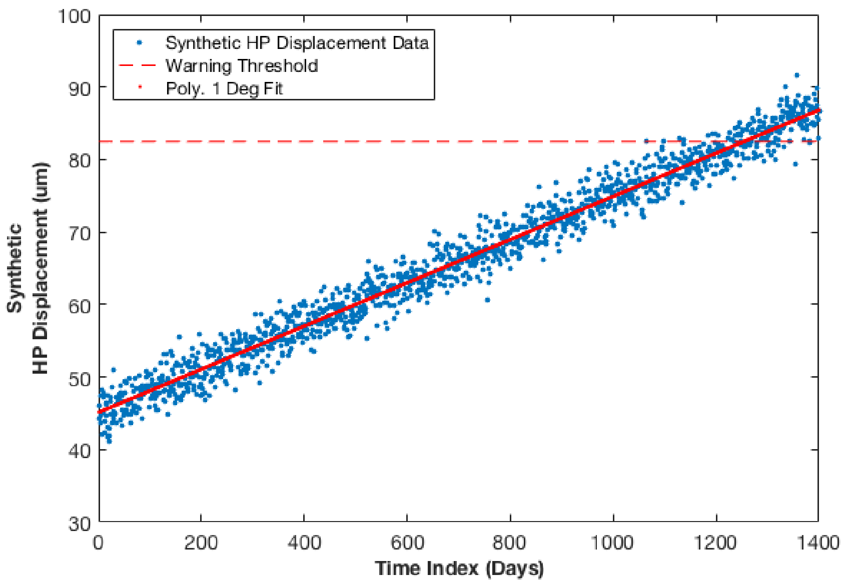


Figure 4.34 - Synthetic Data without Maintenance Intervals

Another sample of synthetic case study data that was generated to accommodate maintenance repairs is shown in Figure 4.35. In this sample of data, maintenance is randomly introduced.

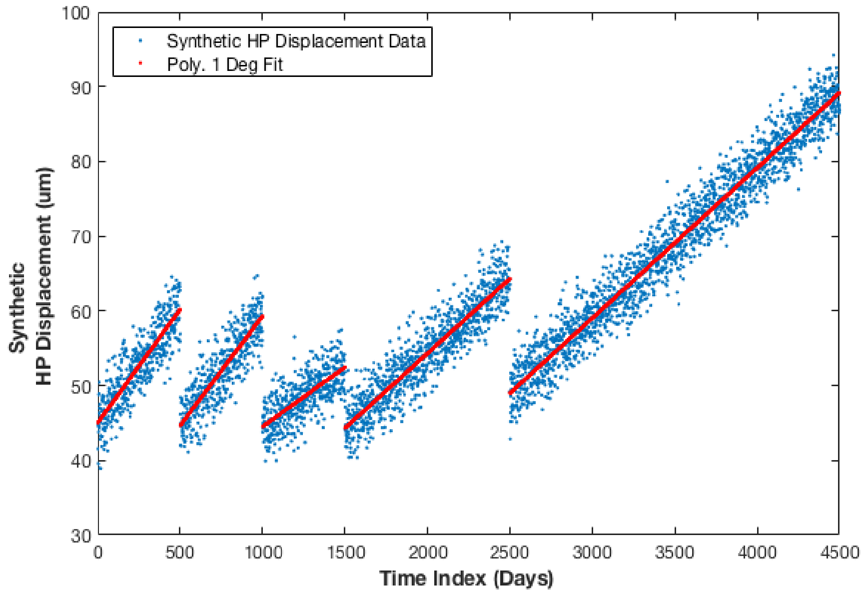


Figure 4.35 - Synthetic Data with Maintenance Intervals

In the synthetic data with maintenance intervals, equipment deterioration is assumed to be continuous. Though, after maintenance machine health do not return to "as good as new" but the changes in machine health are simulated. This data set also simulates different rates of degradation as indicated by the linear fits of the data segments. This synthetic data with maintenance intervals is used to validate the performance of prognostics algorithms that are adapted to accommodate maintenance incorporating effects of maintenance actions.

4.9. Summary

In this chapter, the background information on the steam turbine of a nuclear power plant was presented. An overview of the main components of the steam turbine was discussed, beginning with the description of the major constituent parts. Each part of the steam turbine was presented in such detail that the function of these components was ultimately described. In addition, the reader was also introduced to the associated plant states, operating conditions, and steam turbine instrumentation. This chapter also describes the analysis on the data that was collected using the associated steam turbine instruments. This analysis allowed extraction of the case study datasets which were later used to test the implementation of prognostics technique that were adapted for maintenance intervals. To validate the effective implementation of the prognostic algorithms, synthetic data was generated based on the underlying degradation and noise model.

CHAPTER 5: BAYESIAN LINEAR REGRESSION (BLR) FOR STEAM TURBINE PROGNOSTICS

5.1. Introduction

Prognostics is very important aspect of condition-based maintenance as it provides operator and maintenance personal with the decision support for maintenance in order to avoid equipment failure in time and in cost-effective manner. The inherent uncertainties associated with the generation of long-term predictions of equipment health affect the performance of prognostic algorithms. In this chapter, the development of Bayesian Linear Regression (BLR) as a prognostic technique for predicting remaining useful life (RUL) of a nuclear steam turbine is presented. The technique is capable of representing and managing uncertainties that are associated with predicting the future behaviour of degrading equipment. A real-world case study data from an operational nuclear power plant in the UK is used to test the newly developed prognostic algorithm. To further validate the performance, a synthetic case study is also used. The BLR is adapted to accommodate maintenance in order to provide better estimation of RUL by updating the parameters of the algorithm. The adapted algorithm is tested for different post maintenance scenarios using case studies.

5.2. Bayesian Linear Regression for Prognostics

Bayesian Linear Regression (BLR) is a statistical framework of linear regression that utilises Bayesian inference to update prior probability of model parameters into posterior probability by incorporating the evidence provided by the data in the form of the likelihood function. Thus, providing the ability to track model uncertainty. The resulting generalised degradation model can be used to obtain predictive degradation at a given point in time. In comparison to BLR, LR minimises SSR error to estimate model parameters as single estimates.

For prognostics implementation, the BLR framework as shown in Figure 3.1 is extended in order to obtain warning threshold breach time distribution and the remaining useful life (RUL) of degrading equipment. Figure 5.1 shows extension of BLR framework for prognostics implementation

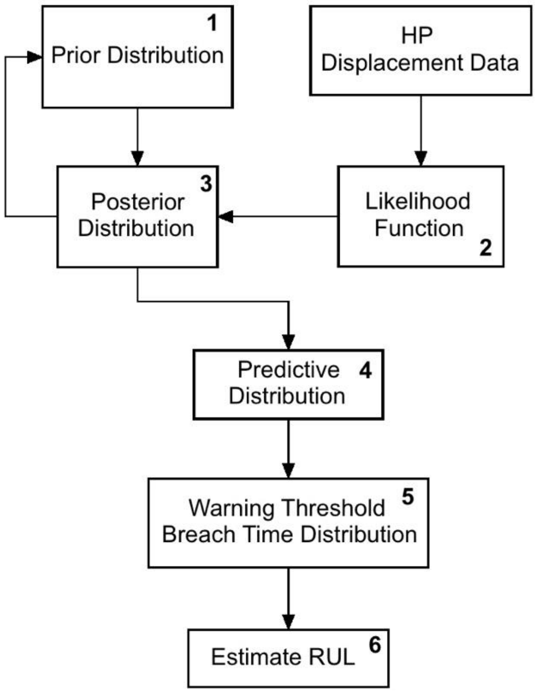


Figure 5.1 - BLR Framework extended for prognostics implementation

The following subsections describe warning threshold breach time distribution and estimation of RUL of degrading equipment.

5.2.1. Warning Threshold Breach Time Distribution

The application of BLR for prognostics places two requirements on the handling of the threshold. As discussed in Chapter 4, the HP displacement is used to form a real-world case study for prognostics. The case study was also used to generate synthetic data for prognostics validation. The intervention threshold is derived from ISO 7919-2:2009 [151], an industry standard which is used to establish operational vibrational limits that take the form of alarms and trips. The limits are established when a new steam turbine is commissioned and in the industry these limits are also referred as acceptance zones. The ISO standard categorises acceptance zones into four categories of zone A, B, C, and D to permit the evaluation of vibration severity and to provide guidelines on possible actions. In this research, zone boundary B/C is used to define a warning threshold at 82.5 μm of displacement. That means that when displacement breaches this threshold, y_{Thresh}, an intervention is required by the plant operator before more serious limits are reached and damage to the machine is occurred.

Within the case study data, the point of threshold breach after consultation with industrial experts has been defined as the mean time of the first 20 data points to breach y_{Thresh}. This was chosen because a single data point may breach the threshold due to transient behaviour, but 20 data points represents a more consistent trend. This mean time of threshold breach is considered the true end-of-life point that the prognostic system should predict.

Secondly, early predictions are preferred over late predictions. In order to reduce the chance of late predictions, a Warning Threshold Breach Time Distribution is obtained by noting all possible predicted threshold breach times t. The predicted threshold breach time t is the predicted end-of-life point when the mean of the predictive distribution y_{new} reaches or exceeds the threshold y_{Thresh}. Together, all values of t give a distribution of predictions.

A final prediction, T, is chosen as the time two standard deviations below the mean of this distribution. If the mean of breach times t was chosen as T, there would be an equal chance of early and late predictions. By selecting an earlier point, late predictions should be less likely.

5.2.2. Estimation of RUL

RUL is the remaining time before the degradation signal crosses the threshold and can be calculated as:

$$RUL = T - x_t \tag{5.1}$$

where T is the warning threshold breach time and x_t is the current time or the time of the prognosis.

5.2.3. BLR Application: HP Displacement Case Study

The HP displacement case study was used to assess the performance of the developed algorithm. Figure 5.2 and Figure 5.3 show RUL estimates when 300 and 400 data points of the HP displacement case study are used respectively. It can be seen that the implemented algorithm estimates the RUL of the steam turbine using the case study data (blue dots) and the warning threshold (red dotted line). The warning threshold (See Section 5.2.1, for detailed interpretation) provides the means for maintenance intervention before serious damage to the machine is occurred.

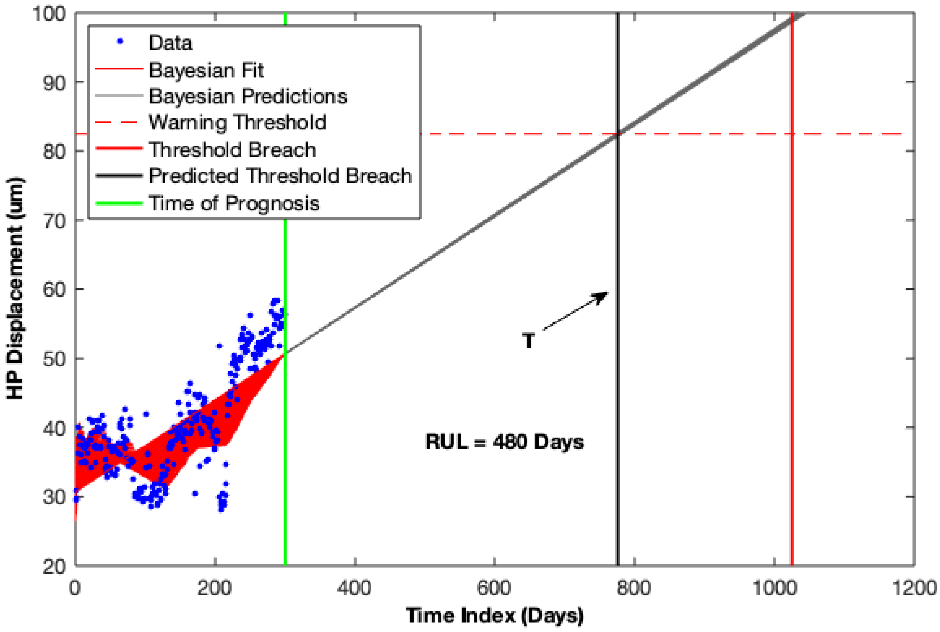


Figure 5.2 - RUL Predictions: 300 Data Points

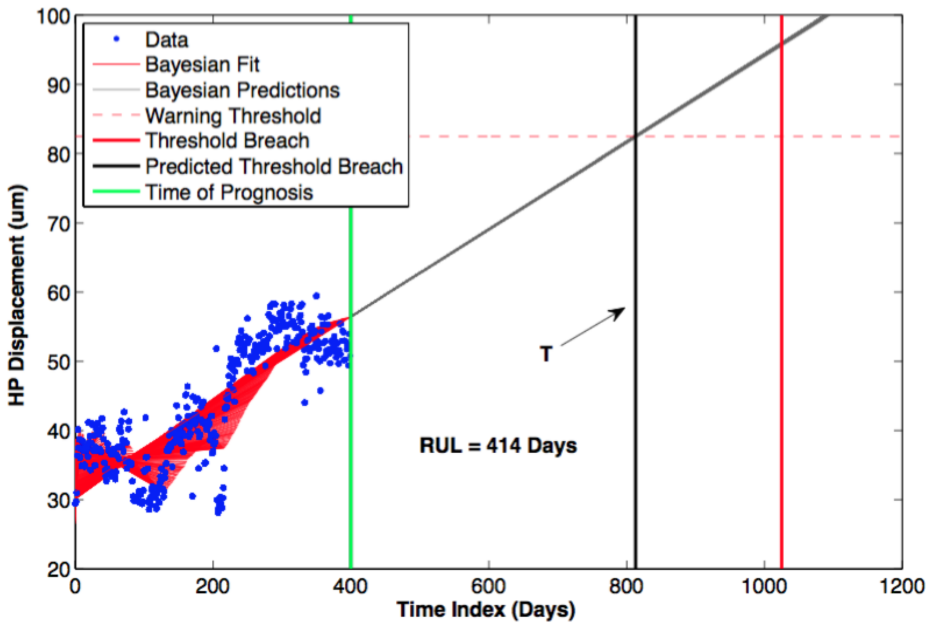


Figure 5.3 - RUL Predictions: 400 Data Points

The distributions of warning threshold breach times t for the batch of 300 and 400 data points are shown in Figure 5.4 and Figure 5.5.

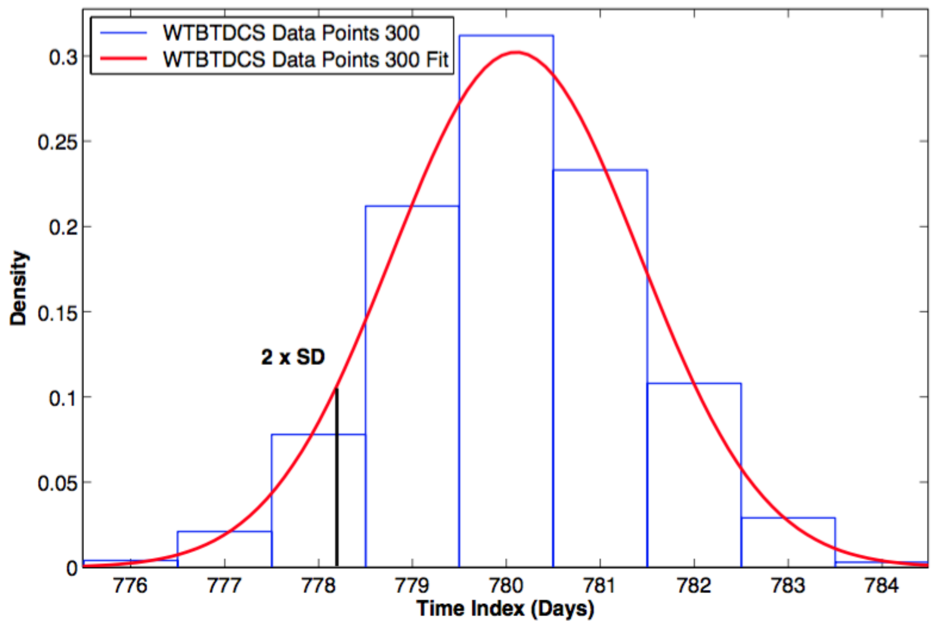


Figure 5.4 - Warning Threshold Breach Time Predictions: 300 Data Points

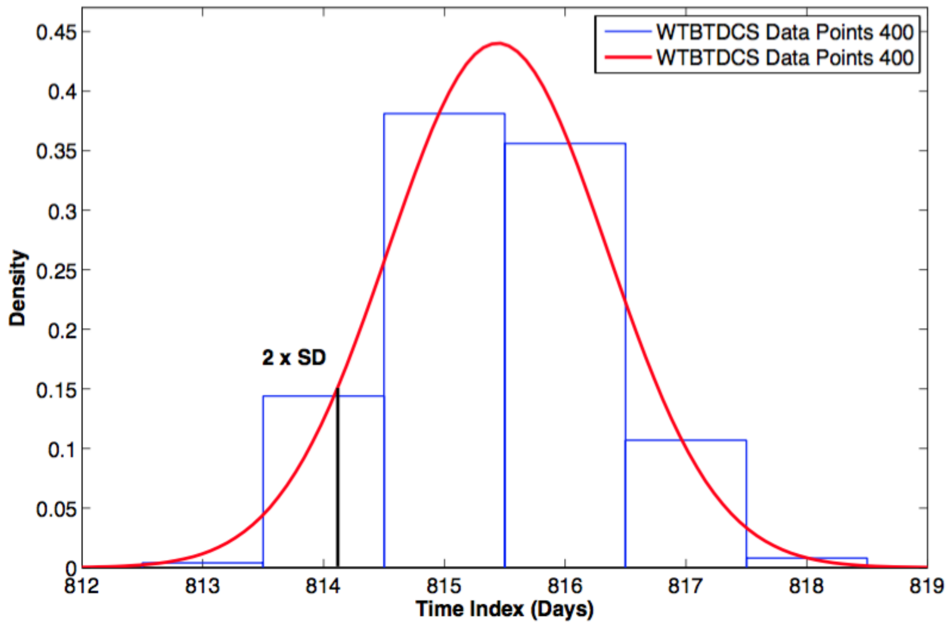


Figure 5.5 - Warning Threshold Breach Time Predictions: 400 Data Pints

As described in Section 5.2.1, a value of two standard deviations from the mean was chosen as the warning threshold breach time T. The case study contains data points that exceed the warning threshold. To evaluate the performance of the algorithm, estimates of true RUL and predicted RUL are compared. True RUL is the difference between the average of the first 20 breach times (i.e. data points breaching the warning threshold) and the time of the prognosis (i.e. data points used for prognostic algorithm). Whereas, the predicted RUL is the difference between the average of the first of 20 predicted breach times and the time of prognosis. The comparison of true RUL and predicted RUL is given in Table 5.1.

Table 5.1 - Early Predictions: Comparison of True RUL and Predicted RUL

Set of Data Points	True RUL (Days)	Predicted RUL (Days)	Prediction (Early or Late)
300	726	480	250 Early
350	676	396	280 Early
400	626	414	212 Early
450	576	502	74 Early

The results show that when 300, 350, 400 and 450 data points of the HP displacement case study are fed into the BLR framework, early prediction of warning threshold breach is observed which is due to increase in HP displacement data just before the time of prognosis (represented as solid green lines in Figure 5.2 and Figure 5.3). It should also be noted that due to the slow and progressive nature of the fault, large values of RUL predictions are observed.

As mentioned above, the BLR algorithm can provide predictions of time remaining until displacement breaches the warning threshold. However, there are two crucial aspects to consider further.

First, the errors in Table 5.1 are generally large. If the error is over 200 days, there is a significant amount of remaining life that may be lost through early scheduling of maintenance. While early predictions are preferred, overall accuracy is also important.

Secondly, and more critically, the performance of the algorithm tends to vary with different amounts of input data. For instance, when batches of 500 and 900 data points are used, the predictions are late as shown in Figure 5.6 and Figure 5.7.

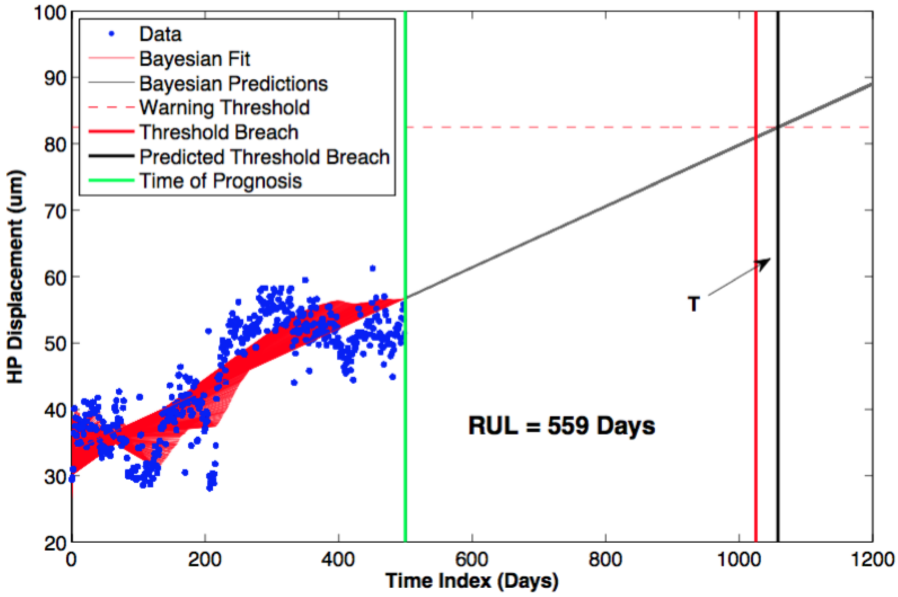


Figure 5.6 - Late RUL Predictions: 500 Data Points

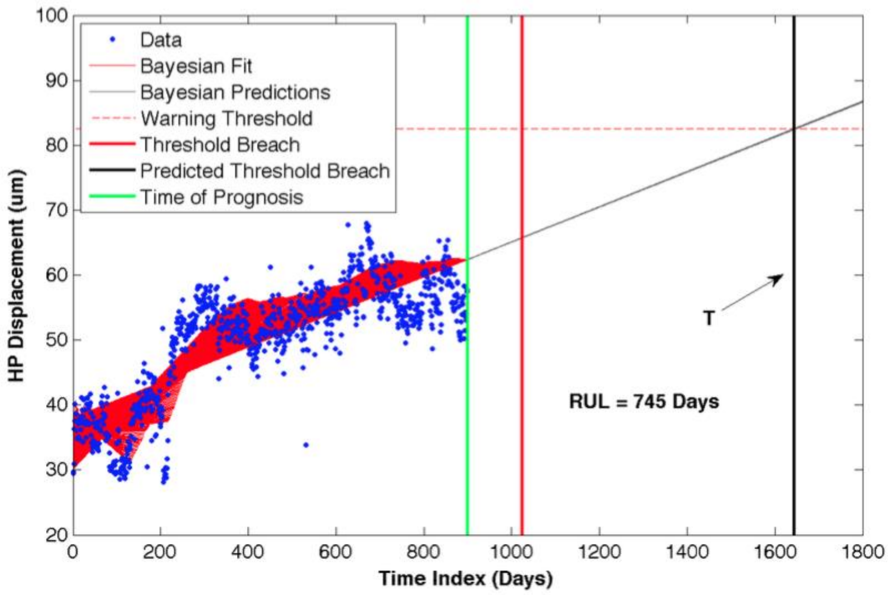


Figure 5.7 - Late RUL Predictions: 900 Data Points

The comparison of true RUL and predicted RUL is given in Table 5.2.

Table 5.2 - Late Predictions: Comparison of True RUL and Predicted RUL

Set of Data Points	True RUL (Days)	Predicted RUL (Days)	Prediction (Early or Late)
250	776	941	165 Late
500	526	559	33 Late
750	276	575	299 Late
900	126	745	619 Late

The results show that the technique does generate late predictions. When it may be expected that performance improves with more data, in fact the predictions become later and less accurate when derived from more data. Reasons for this performance were considered in detail. The original case study data was re-examined alongside the BLR performance. It is clear that the technique is performing correctly, as the predicted linear trend updates as new data is added. However, while the case study exhibits an overall linear trend, the short-term behaviour captures some additional process. The technique is affected by the outliers (i.e. data points that are significantly away from mean), resulting in skewing the distributions. However, as more data becomes available the effect of outliers tend to diminish. The BLR predictions are also highly dependent on the trend of the data at the prediction time x_t, and the technique has difficulty in separating the long term and short-term behaviour.

As mentioned in Section 4.5 of Chapter 4, the raw data was transformed into the Full Power dataset by removing the refuelling data, outages/stoppage durations, online data captured below full power, and other vibration data captured during the state of run up which will almost certainly affect the degradation. The turbine will have the chance to cool down and therefore, a temporary reduction in vibration levels would be seen. In addition, the fault was recognised during the case study time period and maintenance actions were taken. These maintenance actions resulted in reducing the vibration levels. While BLR is able to make predictions when this fault type occurs, specifics of the application domain mean that an alternative data set such as synthetic data must be considered in order to validate the performance of BLR. The results also show that in order to enhance the performance and efficacy of BLR application, post-maintenance effects must also be incorporated.

5.2.4. BLR Application: Synthetic Case Study

To validate the performance of BLR under constant degrading conditions, synthetic case study data as shown in Figure 4.34 was used. In this synthetic data set, constant degradation of steam turbine is assumed and the steam turbine does not undergo any maintenance before it reaches the warning threshold. Figure 5.8 and Figure 5.9 show RUL estimates when 250 and 500 data points of the synthetic HP displacement case study are used respectively. It can be seen that the BLR estimates RUL using the synthetic data and the warning threshold.

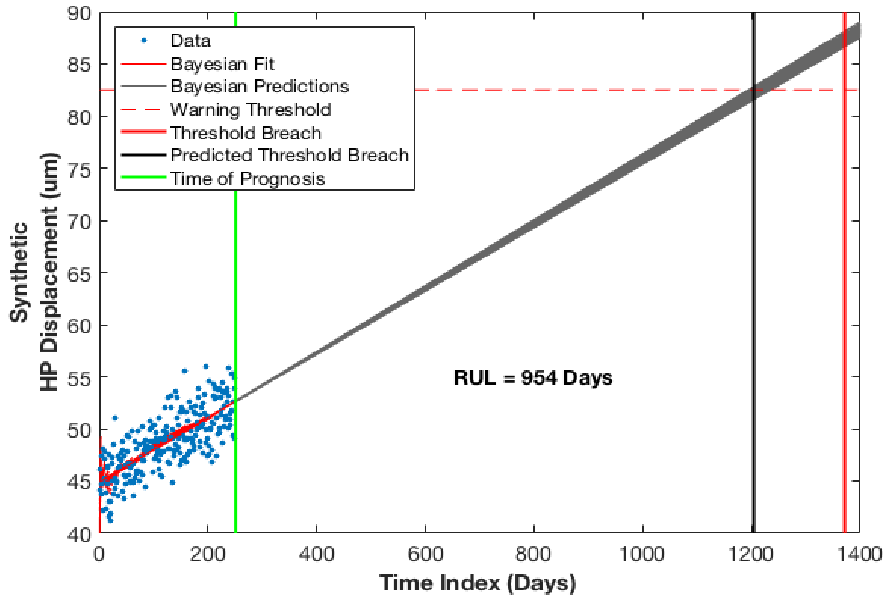


Figure 5.8 - RUL Predictions: 250 Synthetic Data Points

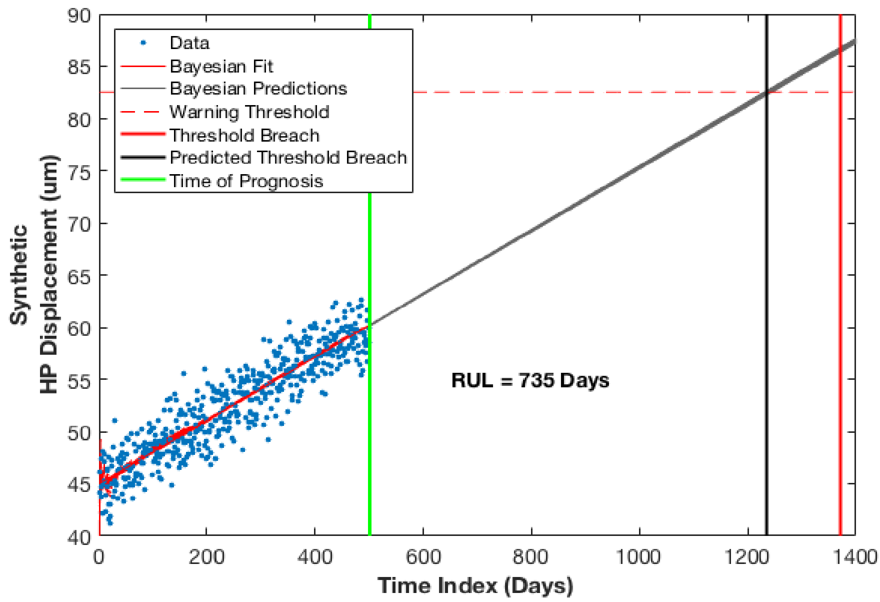


Figure 5.9 - RUL Predictions: 500 Synthetic Data Points

The performance of the BLR under constant degrading conditions is recorded in Table 5.3

Table 5.3 - Synthetic Data Performance Assessment

Set of Data Points	True RUL (Days)	Predicted RUL (Days)	Prediction (Early or Late)
250	1121	954	167 Early
350	1021	857	164 Early
500	871	735	136 Early
750	621	499	122 Early

The results show that the technique is performing correctly, as the predicted linear trend updates as new data is added. This indicates that BLR can consistently produce only early predictions. However, it is important to note that for synthetic data constant degradation is assumed and operating conditions are excluded. In practice, the varying operating conditions of the turbine effect the rate of degradation. This shows that the technique is still required to be reliable enough to be used in the context when the operations of a machinery is non-linear. In other words, prognostics should be able to accommodate multiple operating conditions. Designing algorithms that incorporate operating conditions is therefore a next step to increase prognostics efficacy and enhance performance.

5.3. Adapting BLR to Incorporate Maintenance

Maintenance aims to bring machinery into a state where it is safe and reliable to operate while recovering health of the machine. Welz et. al. [152] categorised maintenance actions into two types: replacement, a maintenance action which restores a system to good as a new condition, and repair, a maintenance action restoring a system to working condition but removes less degradation than replacement. Both types of maintenance actions aim to improve the health of a machinery. However, they introduce deviations in degradation model thus affecting the performance of prognostics. Therefore, prognostic algorithms must incorporate post maintenance effects into prognostics. Figure 5.10 shows adapted BLR framework for accommodating post maintenance effects

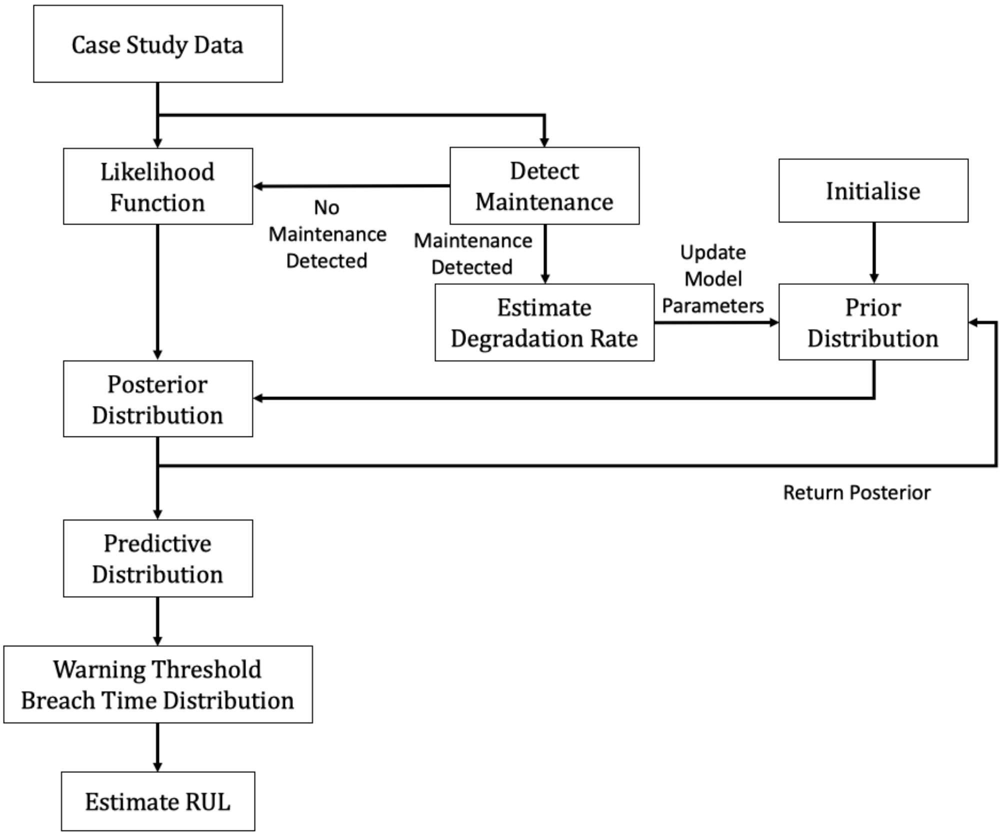


Figure 5.10 - Adapted BLR Framework

As shown in Figure 5.10, the adapted BLR accommodates post maintenance effects by detecting maintenance window, estimating degradation rate and updating model parameters. The following subsections describe detecting maintenance, estimation of degradation rate and model parameter update.

5.3.1. Detect Fault and Maintenance Events

The change point analysis is used to detect fault and maintenance events within the data. The fault and maintenance events are the lowest cumulative sum of the difference between the data points and their mean (See Section 4.5.3, for estimation of change points). As shown in Figure 5.10, the change points are calculated for the data points continuously and in parallel to the BLR algorithm. If cumulative sum of the difference between the data points and their mean is the lowest, the degradation rate is estimated. However, if cumulative sum is not lowest, predictive distribution is estimated.

5.3.2. Estimate Degradation Rate

The degradation rate is estimated to detect changes in model that occur due to post-maintenance effects which may lead to changes in degradation rate. As a result of which, degradation model is also affected. To estimate the degradation rate, first ten data points are used to estimate the slope of current degradation path. If the slope of degradation path is different from the slope of pre-maintenance event degradation path, new model is estimated. However, if the slope of the degradation path is the same as the slope of pre-maintenance event data, the intercept of the model for post-maintenance event data is updated in order to incorporate maintenance event into prognostics.

5.3.3. Adapted-BLR Application: HP Displacement Case Study

The HP displacement case study data shown in Figure 4.29 is used to test the implementation of the Adapted-BLR. The fault manifested as increased levels of vibrations is labelled as region 2 in Figure 4.29. To control increased levels of vibrations, maintenance was performed to inject grease as a remedial solution to reduce friction. As a result, vibration levels drop which is detected by the algorithm as maintenance event. However, as shown in labelled region 3 of Figure 4.29 vibration levels tend to increase again. Figure 5.11 shows RUL estimate when 75 HP displacement data points of the labelled region 3 of Figure 4.28 are used while retaining the degradation model of the HP displacement data of labelled region 2. It can be seen that Adapted-BLR estimates the future health of the steam turbine using the warning distribution which is obtained based on the predicted values exceeding the warning threshold.

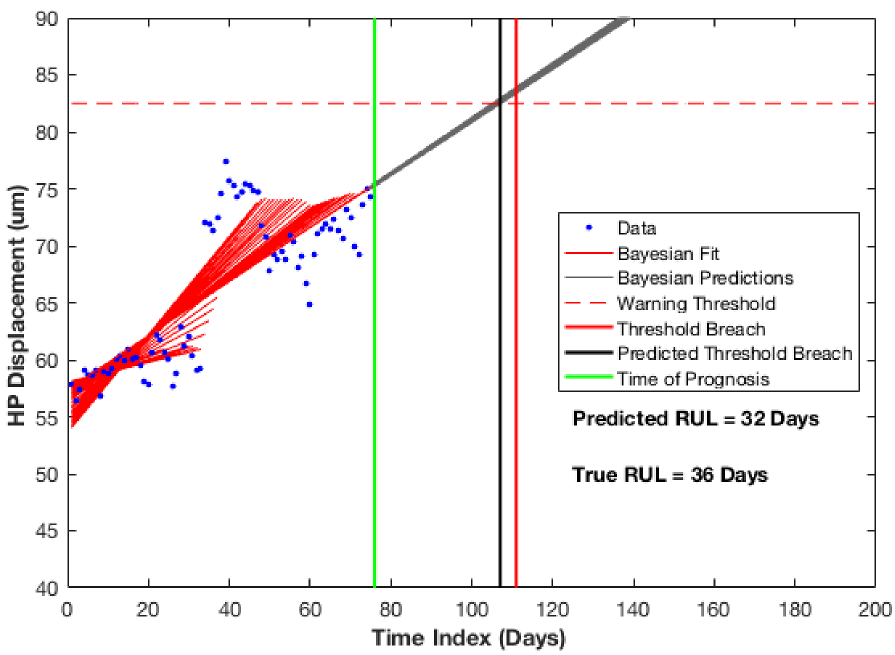


Figure 5.11 – Adapted-BLR RUL Predictions: 75 Data Points

Figure 5.12 and Figure 5.13 show performance comparisons of Adapted-BLR and BLR when the rate of degradation (i.e. slope) of post-maintenance data labelled as region 3 in

Figure 4.29 is similar to the rate of degradation pre-maintenance data which is labelled as region 2 in Figure 4.29. The Adapted-BLR retains rate of degradation (i.e. slope) of pre-maintenance data to inform prior distribution. As shown in Figure 5.12, the retention of rate of degradation results in better performance of model parameters as they tend to remain relatively close to the ground truths (i.e. slope and intercept of post-maintenance data). For the estimation of expected ground truth, linear regression has been used based on consultation with industrial peers. The model parameters of BLR take time to converge to Adapted-BLR model parameters and remain relatively close to the ground truth.

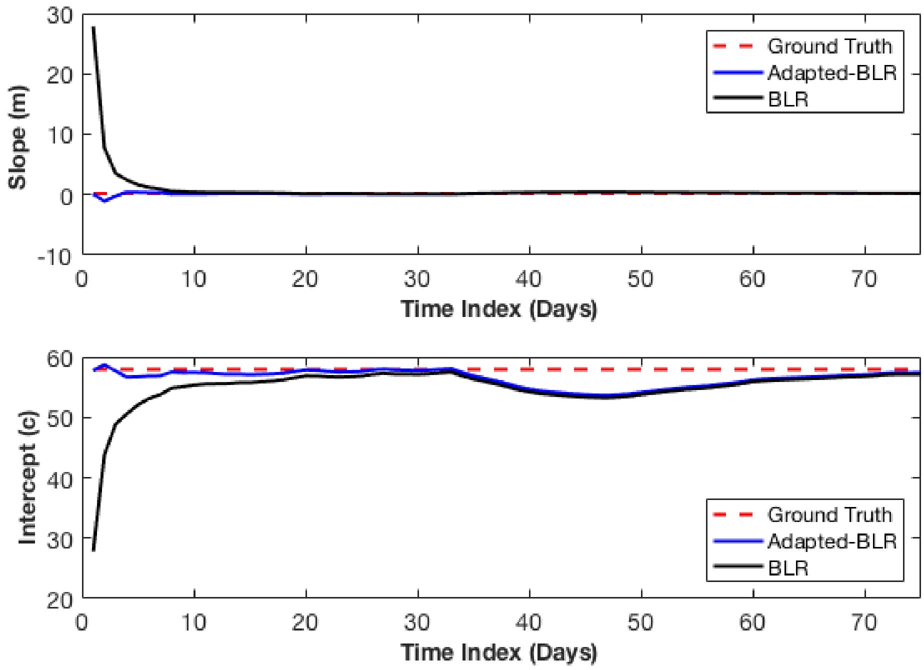


Figure 5.12 - Comparison of Adapted-BLR and BLR Parameters

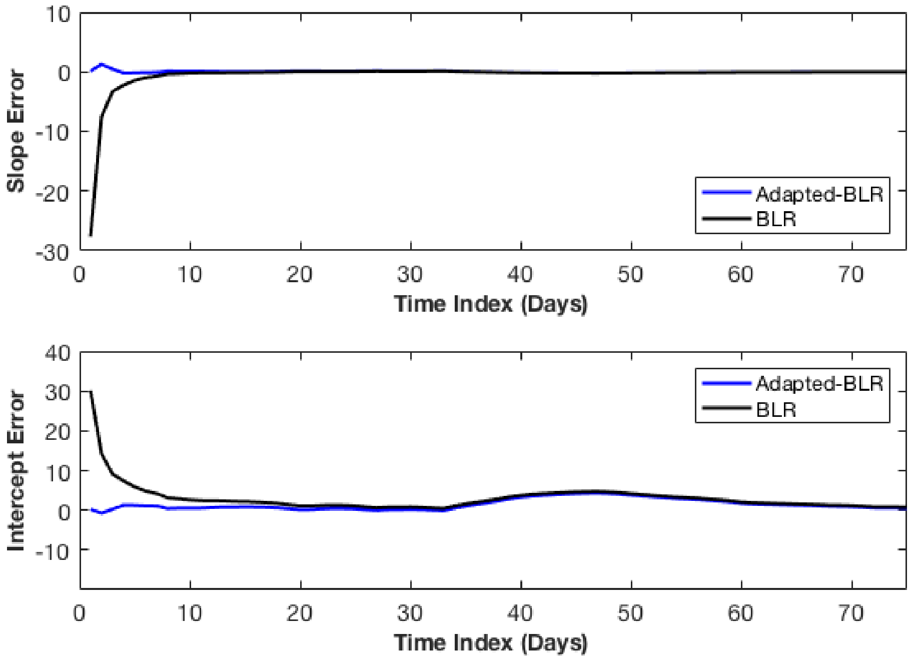


Figure 5.13 - Parameter Error Comparison of Adapted-BLR and BLR

The comparison of RUL estimates produced by the BLR and the Adapted-BLR is shown in Table 5.4

Table 5.4 - RUL comparison of BLR and Adapted-BLR when degradation rate is similar to the degradation rate of pre-maintenance data

Set of Data Points	BLR (RUL: Days)	Adapted-BLR (RUL: Days)	Gain (Days)
5	14	42	28
10	48	60	12
15	58	65	7
20	78	80	2
75	32	32	0

The results show that the Adapted-BLR is able to produce better RUL estimates with greater certainty using fewer data points. The retention of degradation model results in prognostic gain (i.e. the number of days for which maintenance can be deferred to avoid loss of RUL through early scheduling of maintenance) as the model parameters tend to remain relatively closer to the ground truth. As more data points become available, the performance of both algorithms tends to converge.

The Adapted-BLR also shows superior performance when the rate of degradation of post-maintenance data (i.e. data labelled as region 4 in Figure 4.28) is different from pre-maintenance data (i.e. data labelled as region 3 in Figure 4.28). The retention of degradation rate of pre-maintenance data allows Adapted-BLR to estimate RUL with greater certainty with less data. Figure 5.14 and Figure 5.15 show performance comparisons of Adapted-BLR and BLR when the rate of degradation of post-maintenance data is different from the rate of degradation of pre-maintenance data.

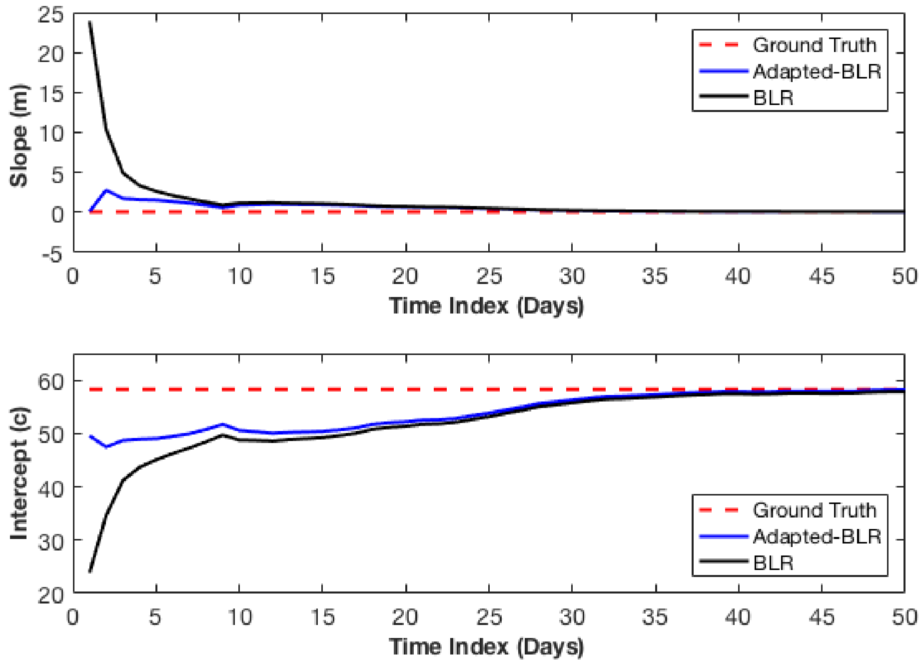


Figure 5.14 – Performance Comparison of Adapted-BLR and BLR Model Parameters when rate of degradation is different from the rate of degradation of pre-maintenance data

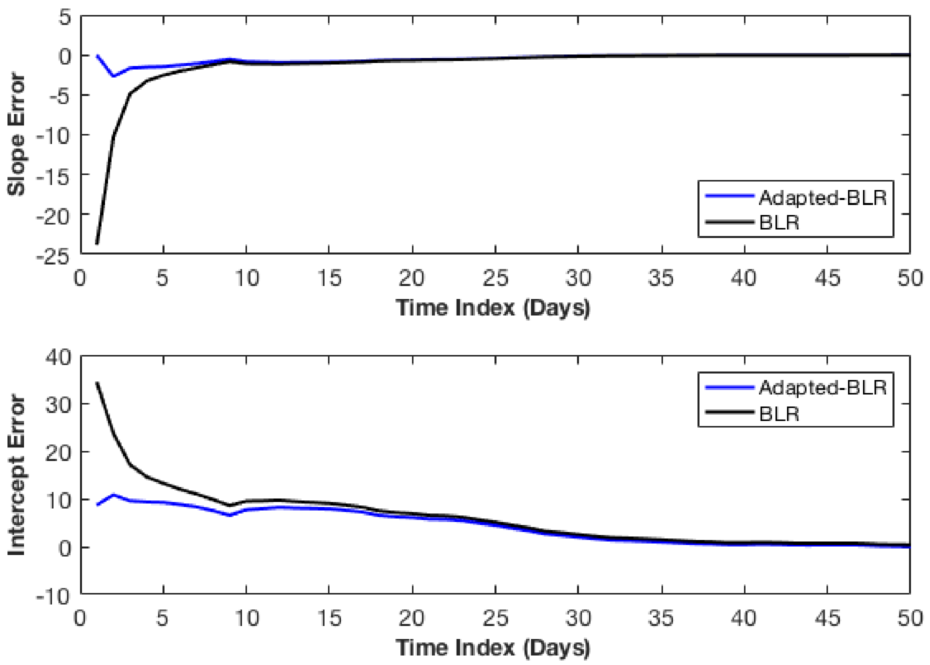


Figure 5.15 – Parameter Error Comparison of Adapted-BLR and BLR Model Parameters when rate of degradation is different from the rate of degradation of pre-maintenance data

Table 5.5 shows the comparison of RUL estimates produced by the BLR and the Adapted-BLR when the degradation rate of the post-maintenance data is different from the degradation rate of the pre-maintenance data

Table 5.5 - RUL comparison of BLR and Adapted-BLR when degradation rate is different from the degradation rate of pre-maintenance data

Set of Data Points	BLR (RUL: Days)	Adapted-BLR (RUL: Days)	Gain (Days)
5	10	17	7
10	19	24	5
15	16	18	2
20	23	24	1
50	255	255	0

It can be seen from the comparison that the retention of rate of degradation allows Adapted-BLR to produce better RUL estimates with fewer data points as the model parameters of the Adapted-BLR remain relatively closer to the ground truth as shown in Figure 5.14. Thus, producing RUL estimates with greater certainty compared to BLR. The Adapted-BLR produces RUL estimates with prognostic gain which tends to decrease over time as the performance of both algorithms converges. The prognostic gain can help practitioners avoid the loss of RUL through early scheduling of maintenance.

It must also be noted that though retaining degradation rate of pre-maintenance data results in better performance. However, Adapted-BLR also produces late predictions due to inherent difficulty in separating the long term and short-term behaviour. The changes in operational settings also allow turbine to cool down and therefore, a temporary reduction in vibration levels would be seen. Therefore, synthetic case study data with maintenance events must be considered in order to validate the performance of Adapted-BLR.

5.3.4. Adapted-BLR Application: Synthetic Case Study

To validate the performance of Adapted-BLR, synthetic case study data as shown in Figure 4.35 was generated. Synthetic case study data simulates equipment deterioration at constant rate. Post-maintenance effects (i.e. change in rate of degradation after maintenance as indicated by the linear fits of the data segments) are also simulated. Figure 5.16 to Figure 5.19 show performance comparison of model parameters of Adapted-BLR and BLR. The rate of degradation of pre-maintenance data is retained and is used to inform prior distribution of Adapted-BLR.

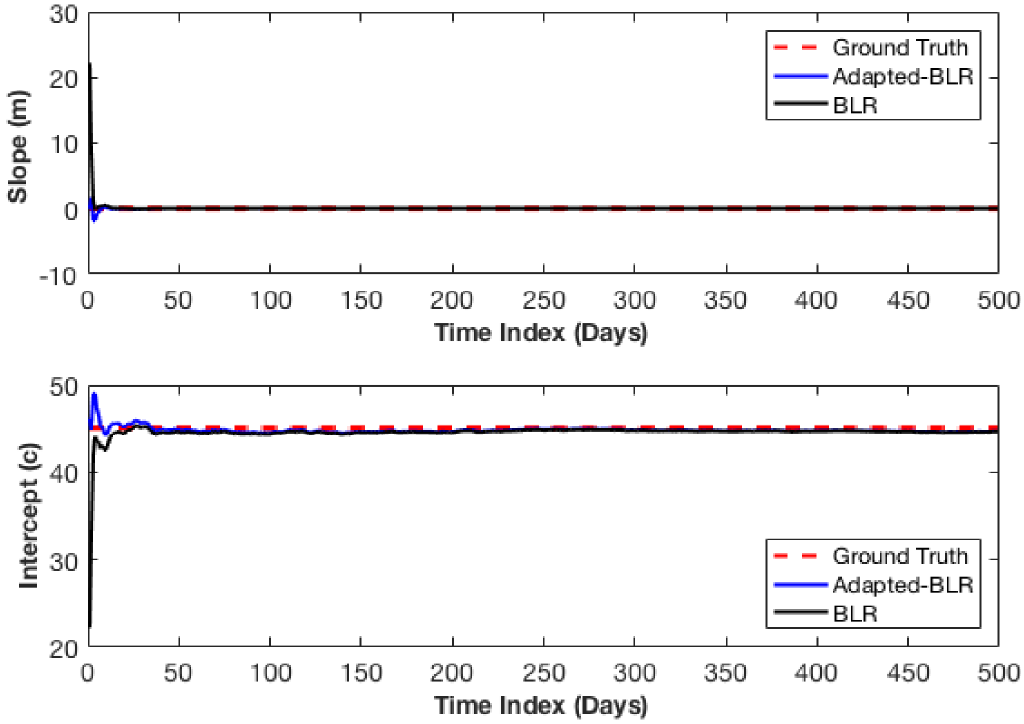


Figure 5.16 - Performance comparison of Adapted-BLR and BLR when rate of degradation is retained for Adapted-BLR and is similar to the rate of degradation of pre-maintenance data

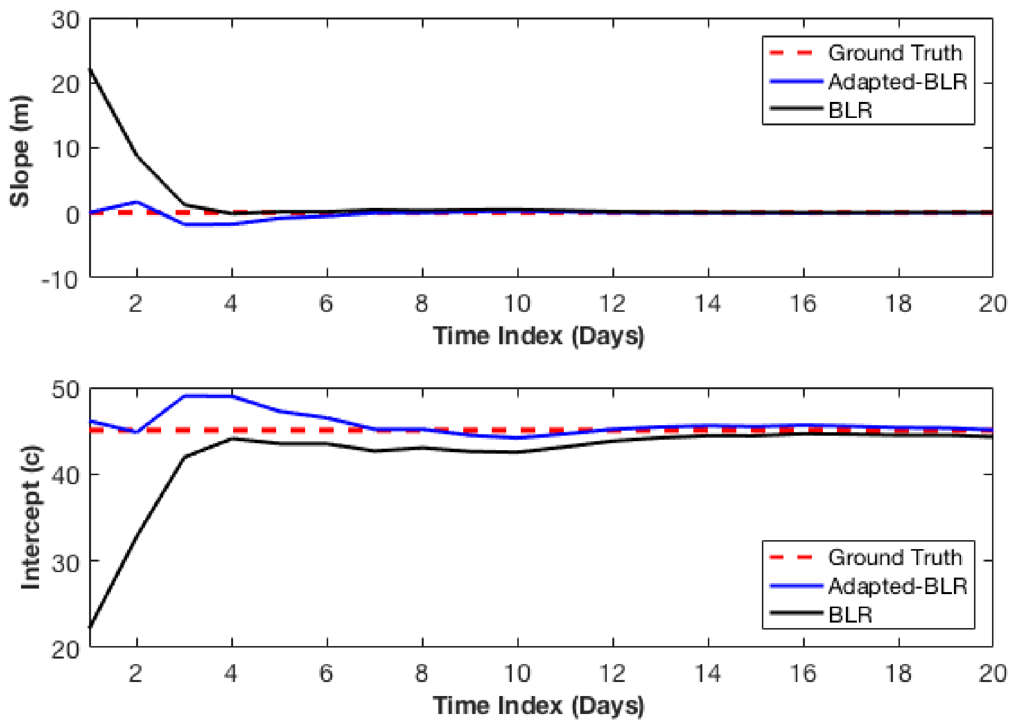


Figure 5.17 – Zoomed version of performance comparison of Adapted-BLR and BLR as shown in Figure 5.16

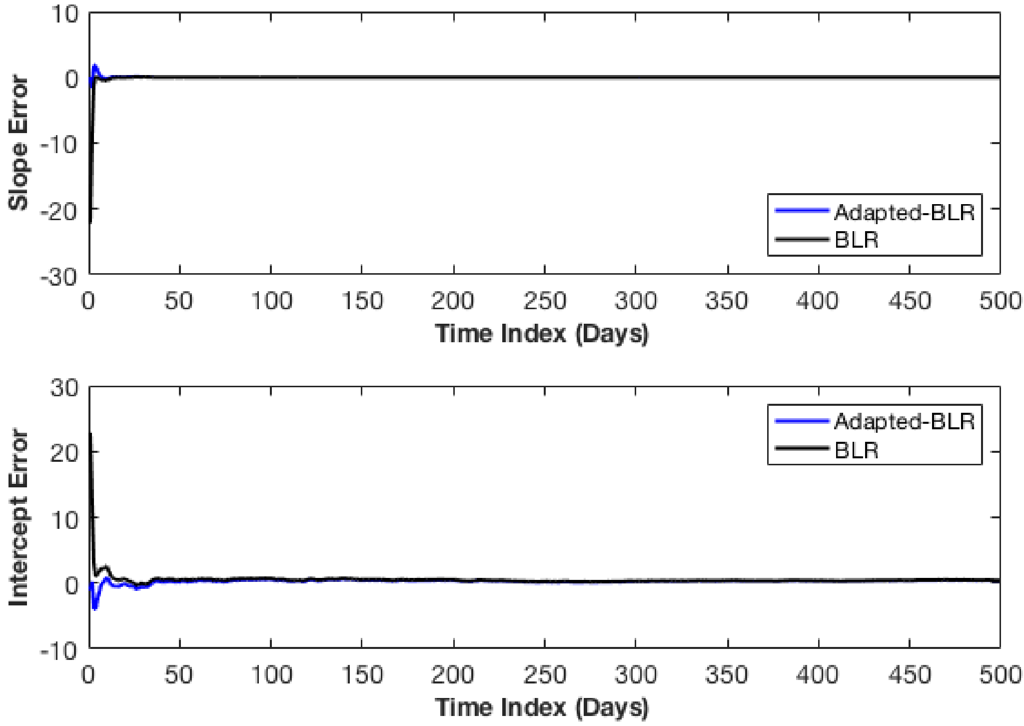


Figure 5.18 - Parameter Error Comparison of Adapted-BLR and BLR when rate of degradation is retained for Adapted-BLR and similar to the rate of degradation of pre-maintenance data

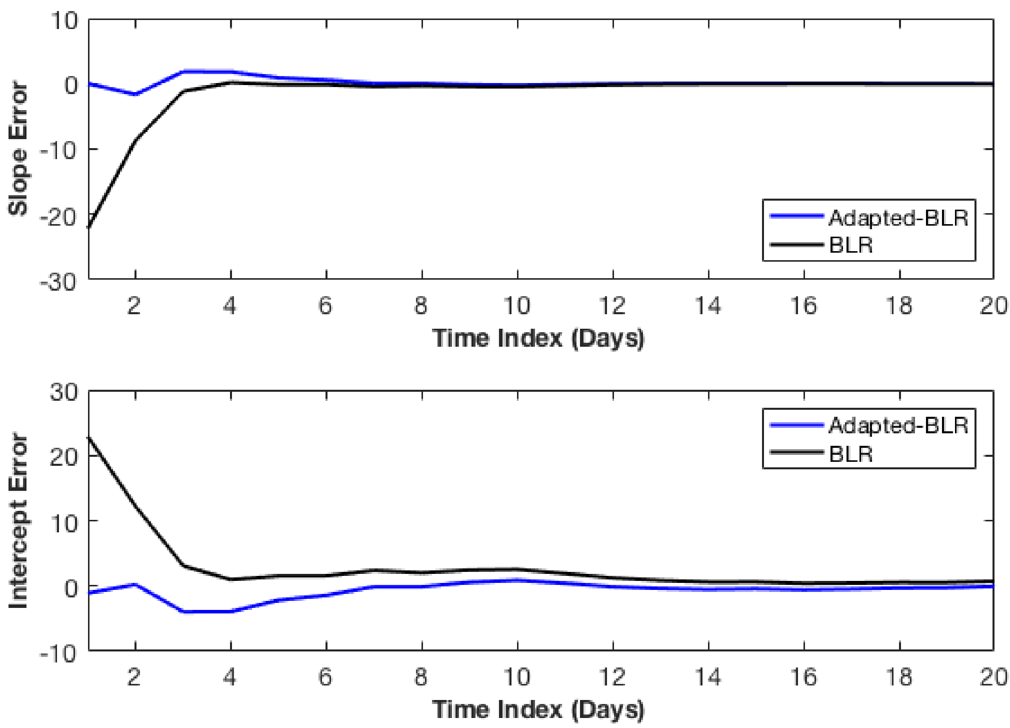


Figure 5.19 – Zoomed version of Parameter Error Comparison of Adapted-BLR and BLR as shown in Figure 5.18

Table 5.6 shows comparison of RUL produced using the BLR and the Adapted-BLR for the synthetic data set

Table 5.6 - RUL comparison of the BLR and the Adapted-BLR when degradation rates of pre-maintenance and post-maintenance data sets are similar

Set of Data Points	BLR (RUL: Days)	Adapted-BLR (RUL: Days)	Gain (Days)
3	5	16	11
5	26	28	2
10	63	87	24
15	334	335	1
500	785	785	0

It can be seen from the comparison that the Adapted-BLR tends to produce RUL with prognostic gain. As shown in Figure 5.16 and Figure 5.17, the model parameter values tend to remain closer to the ground truth values compared to the model parameter values of the BLR. Due to informed priors, the practitioners are able to produce RUL predictions at the earlier stages when Adapted-BLR is used to estimate RUL. Therefore, helping the maintenance engineers avoid loss of RUL.

Synthetic data also validates the superior performance of Adapted-BLR for RUL estimations when the rate of degradation of pre-maintenance data is retained and different from the rate of degradation of post-maintenance data. It can be seen in Figure 5.20 and Figure 5.21 that model parameters of Adapted-BLR converge at much faster rate compared to BLR.

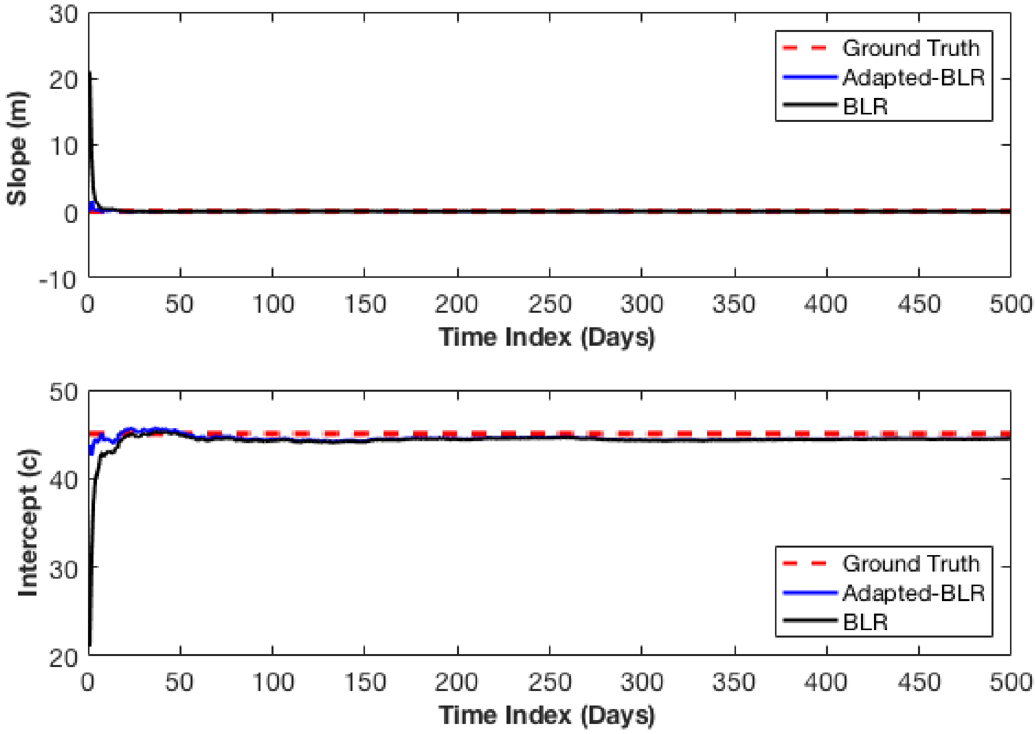


Figure 5.20 - Performance comparison of Adapted-BLR and BLR when rate of degradation is different from the rate of degradation of pre-maintenance data

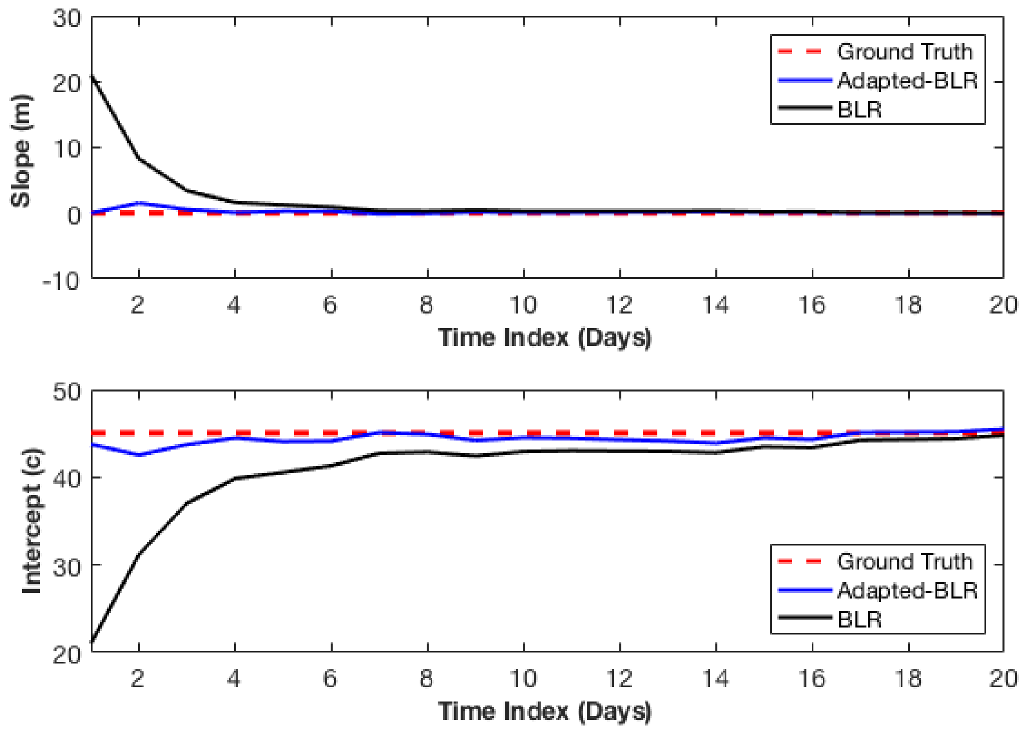


Figure 5.21 - Zoomed version of performance comparison of Adapted-BLR and BLR as shown in Figure 5.20

The model parameter error of Adapted-BLR is also very low when compared to BLR as shown in Figure 5.22 and Figure 5.23.

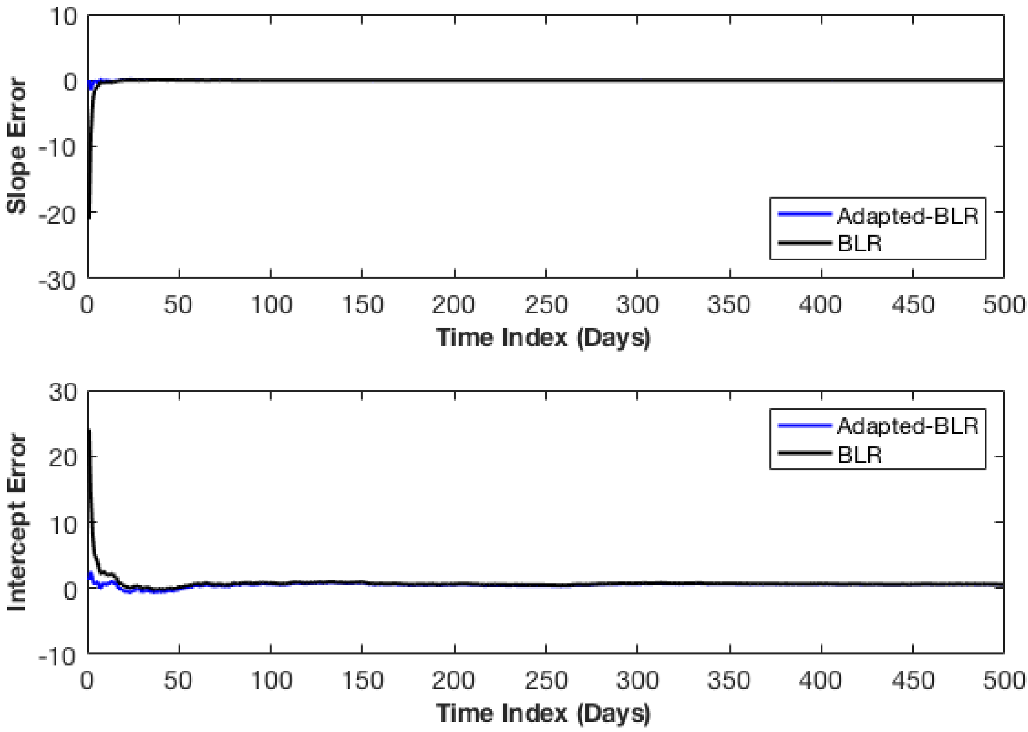


Figure 5.22 - Parameter Error Comparison of Adapted-BLR and BLR when rate of degradation is different from the rate of degradation of pre-maintenance data

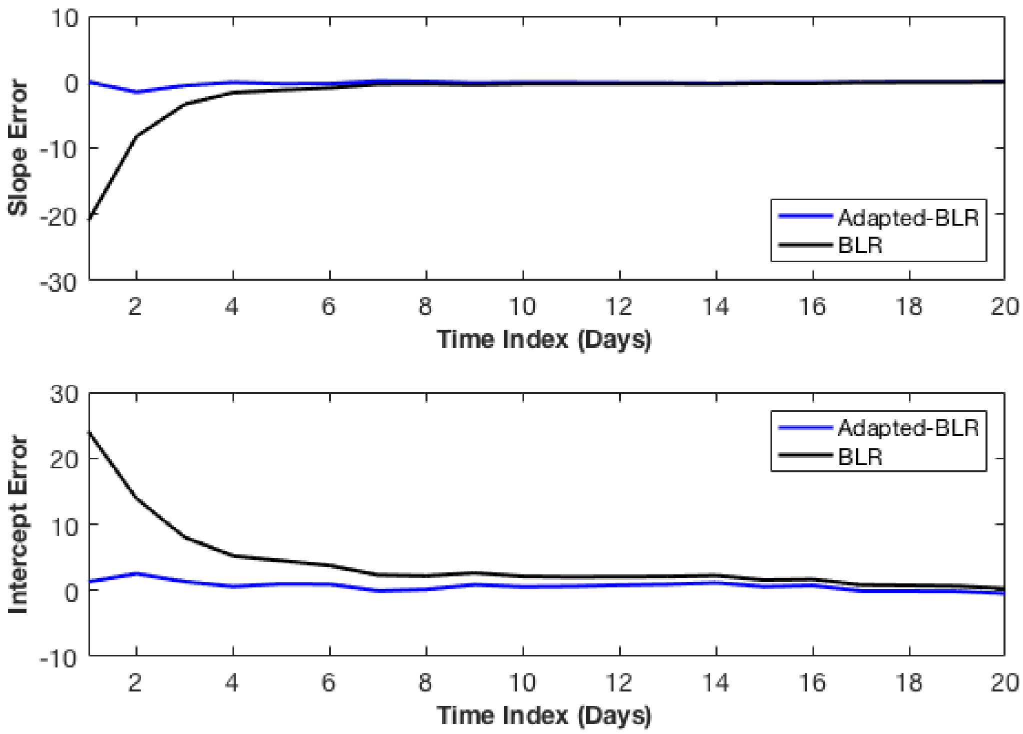


Figure 5.23 - Zoomed version of Parameter Error Comparison of Adapted-BLR and BLR when rate of degradation is different from the rate of degradation of pre-maintenance data

Table 5.7 shows RUL comparison of the BLR and the Adapted-BLR for the post-maintenance synthetic data which has rate of degradation compared to the pre-maintenance data

Table 5.7 - RUL comparison of Adapted-BLR and BLR when rate of degradation is different from the rate of degradation of pre-maintenance data

Set of Data Points	BLR (RUL: Days)	Adapted-BLR (RUL: Days)	Gain (Days)
3	11	41	30
5	48	67	19
10	150	162	12
15	246	249	3
500	1855	1855	0

The validation results using synthetic data show that the technique is performing correctly. The Adapted-BLR can consistently produce reliable RUL predictions with prognostic gain even with fewer data points. The implementation of the technique also showed that technique is capable of producing only early predictions with uncertainty representation for longer prediction horizon. The uncertainty that is associated with the predictions tends to increase with longer prediction horizons. It must be noted that though under constant degradation conditions Adapted-BLR produces consistent results. However, in practice, the varying operating conditions of the turbine effect the rate of degradation. The variance within the data due to different operating conditions impacts the overall performance of the algorithm. Therefore, uncertainty in predictions is higher due to non-linear operational modes. To further enhance the performance of the algorithm in terms of reliability, robustness, and accuracy, the prognostic algorithm must also accommodate operational events within the data that result in deviation from the expected degradation path.

5.4. Summary

In this chapter, BLR is presented as a prognostic technique for predicting RUL of a nuclear steam turbine. The technique is capable of representing and managing uncertainties that are associated with predicting the future behaviour of degrading equipment. A real-world case study data from an operational nuclear power plant in the UK was used to evaluate the performance of the algorithm. The results show varying performance due the inability of the technique to distinguish between short-term and long-term behaviours. The operating conditions of the plant also affect the performance of the algorithm.

Therefore, for further validation, a synthetic case study is used. The results of synthetic case study data show that the technique is working correctly under constant degradation conditions. This chapter also presents the improvements that are made to enhance the performance and efficacy of BLR. The Adapted-BLR is capable of producing more reliable RUL predictions by retaining the degradation rate of the pre-maintenance data. The model parameters of the Adapted-BLR tend to converge to ground truth at much faster rate while maintaining low error rate when compared to BLR. The Adapted-BLR also results in prognostic gain, thus, helping the maintenance engineers avoid loss of RUL through early scheduling of maintenance.

CHAPTER 6: SUPPORT VECTOR REGRESSION (SVR) FOR STEAM TURBINE PROGNOSTICS

6.1. Introduction

In this chapter, the development of Support Vector Regression (SVR) as a non-probabilistic prognostic technique for predicting remaining useful life (RUL) of a nuclear steam turbine is presented. To test the newly developed algorithm, a real-world case study data from an operational nuclear power plant in the UK is used. A synthetic case study is also used to further validate the performance of the algorithm. The SVR is adapted to accommodate maintenance and estimate RUL by utilising synthetic data that is generated based on the model retained prior to maintenance. The adapted algorithm is tested for different post maintenance scenarios using case studies for wider applicability and performance validation.

6.2. Support Vector Regression for Prognostics

Support Vector Regression (SVR) maps non-linear data into higher dimensional feature space and solves a linear regression problem in this feature space. Compared to LR which minimises SSR errors to estimate model parameters, SVR provides analytical framework based on support vectors to determine the decision boundary, hyperplanes, and model parameters. The resulting decision boundary can be extrapolated at any point in time to predict degradation and estimate RUL. For prognostics implementation, the SVR framework as shown in Figure 6.1 is developed in MATLAB in order to estimate the remaining useful life (RUL) of the degrading equipment.

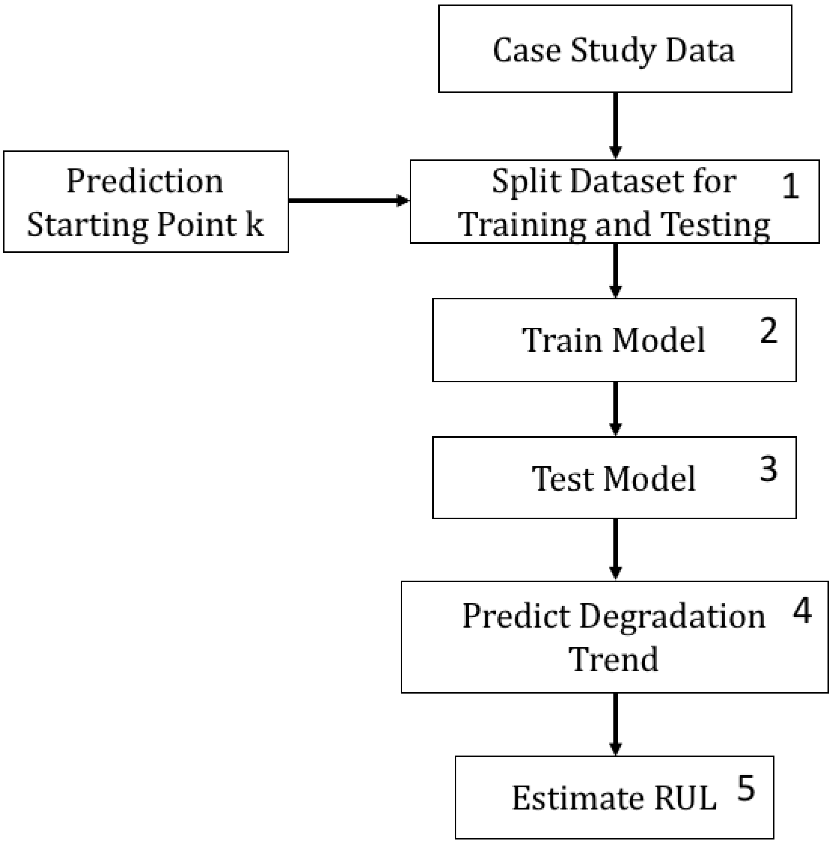


Figure 6.1 - SVR Framework

There are five parts in the SVR framework. In the first part of the algorithm, based on the recommendation of reliability engineering experts, 70/30 ratio is used to split data into training and testing data sets. To create training and testing data sets random sampling method is used. In the second part of the algorithm, model is trained using the training dataset. To generalise the model, the k-fold cross validation method is used which splits the training data into k-folds/data subsets (default value of 10 is used). Models are trained using k-1 folds and the remaining folds are used to validate models. The average of prediction accuracies of models is estimated to finalise the model. To tune the hyperparameters C (the penalty factor which determines the trade-off between flatness of function $f(x)$ and the number of deviations larger than ε) and ε (epsilon which represents prediction precision or error margin), the random grid search [153] method is implemented. The random grid search method uses random combination of hyperparameters and selects hyperparameters that best fits the model based on model accuracy. In the third part, the tuned model is tested to assess the accuracy of the algorithm and obtain the model parameters (i.e. intercept and slope). These model parameters are used in the fourth part of the algorithm to predict degradation signal y at a given future point in time. In the last part of the algorithm, RUL is estimated by subtracting the current time or the time of prognosis from the time when degradation trend exceeds the warning threshold limit (See Equation 5.1). The detailed description of warning threshold (i.e. 82.5um displacement) is provided in Chapter 5 Section 5.2.1.

6.2.1. SVR Application: HP Displacement Case Study

The HP displacement case study was used to assess the performance of the developed algorithm. Figure 6.2 and Figure 6.3 show RUL estimates when 300 and 400 data points of the HP displacement case study are used respectively. It can be seen that the implemented algorithm estimates the future health of the steam turbine using the case study data (blue dots).

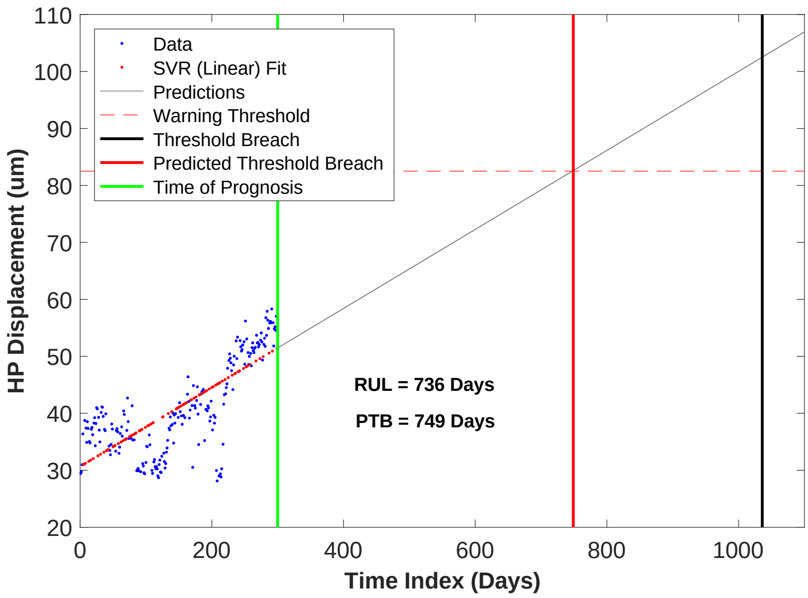


Figure 6.2 - RUL Predictions using SVR: 300 Data Points

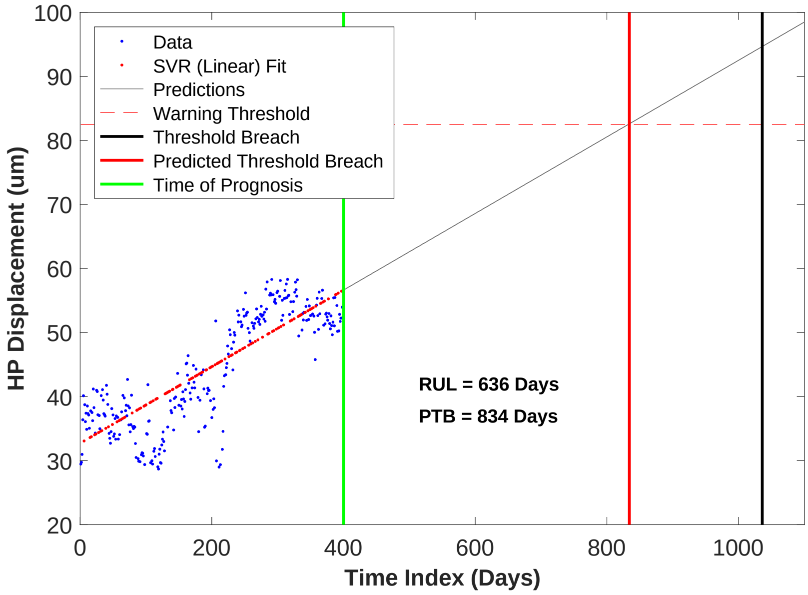


Figure 6.3 - RUL Prediction using SVR: 400 Data Points

The comparison of true RUL and predicted RUL is given in Table 6.1.

Table 6.1 - Early Predictions: Comparison of True RUL and Predicted RUL

Set of Data Points	True RUL (Days)	Predicted RUL (Days)	Prediction (Early or Late)
300	736	449	287 Early
350	686	425	261 Early
400	636	434	202 Early
450	586	497	89 Early

The results show that when 300, 350, 400 and 450 data points of the HP displacement case study are fed into the BLR framework, early prediction of warning threshold breach is observed which is due to increase in HP displacement data just before the time of prognosis (represented as solid green lines in Figure 6.2 and Figure 6.3). It should also be noted that due to the slow and progressive nature of the fault, large values of RUL predictions are also observed.

The SVR algorithm can provide predictions of time remaining until displacement breaches the warning threshold. However, as discussed in Chapter 5, there are two crucial aspects to consider further for the development of the algorithm.

First, large remaining useful life predictions will result in loss of significant amount of remaining life through early scheduling of maintenance. While early predictions are preferred, overall accuracy is also important.

Secondly, and more critically, the performance of the algorithm also tends to vary with different amounts of input data. For instance, when batches of 500 and 900 data points are used, the predictions are late as shown in Figure 6.4 and Figure 6.5.

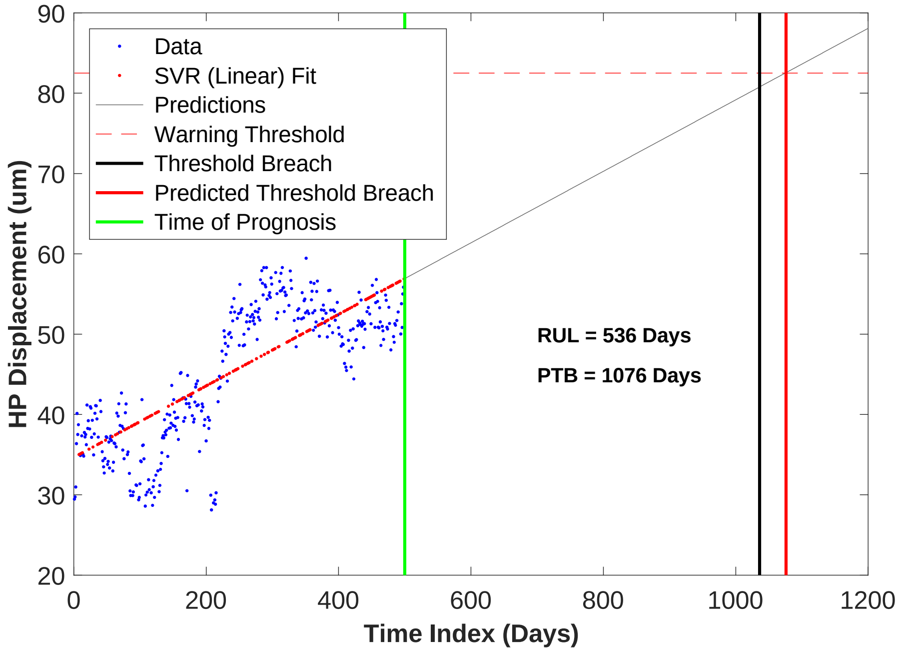


Figure 6.4 - Late RUL Predictions using SVR: 500 Data Points

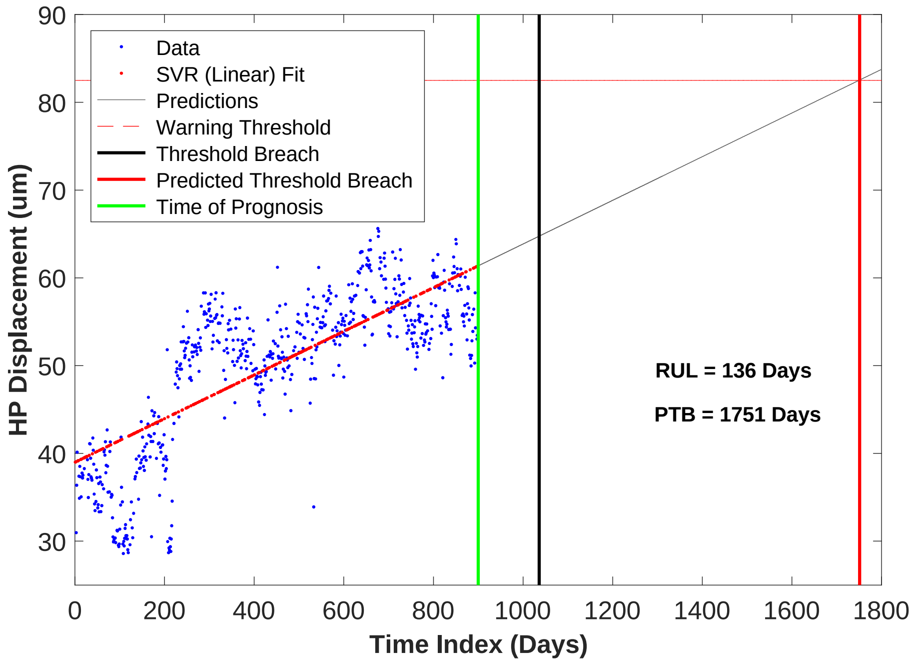


Figure 6.5 - Late RUL Predictions using SVR: 900 Data Points

The comparison of true RUL and predicted RUL is given in Table 6.2.

Table 6.2 - Late Predictions: Comparison of True RUL and Predicted RUL

Set of Data Points	True RUL (Days)	Predicted RUL (Days)	Prediction (Early or Late)
250	786	895	109 Late
500	536	576	40 Late
750	286	575	289 Late
900	136	851	715 Late

The results of the SVR as a prognostics algorithm indicate that the technique generates late predictions. With the addition of more data, when it may be expected that performance improves instead the predictions become later and less accurate. Reasons for this performance were considered in detail. The original case study data was re-examined alongside the SVR performance. The technique is performing correctly, as the predicted linear trend updates as new data is added. Outliers are penalised and tend to have marginal impact on the degradation model as the orientation of the degradation trend is estimated using the support vectors (i.e. data points on the hyperplanes). Thus, providing a robust framework for the estimation of degradation trend. However, the short-term behaviour capturing some additional process results in affecting the performance of the SVR despite the fact that the case study exhibits an overall linear trend. The SVR predictions are highly dependent on the trend of the data at the prediction time x_t, and the technique has difficulty in separating the long term and short-term behaviour.

As mentioned in Chapter 4, the case study is a transformed dataset which only includes data points when the power is full and other operating conditions (i.e. refuelling, outages/stoppage durations, online data captured below full power, and other vibration data captured during the state of run up) are not considered and has been excluded. It was anticipated that when operating in online mode, the machinery response would be fairly consistent and any unusual behaviour and degradation would be easier to identify. The fault was recognised during the case study time period and maintenance actions were taken. These maintenance actions resulted in reducing the vibration levels. While SVR is able to make predictions when this fault type occurs, specifics of the application domain mean that an alternative data set such as synthetic data must be considered in order to validate the performance of the SVR. The results also show that in order to enhance the performance and efficacy of the SVR, post-maintenance effects must also be incorporated in order to provide better RUL estimations.

6.2.2. SVR Application: Synthetic Case Study

The synthetic case study as shown in Figure 4.34 was used to validate the performance of SVR under constant degrading conditions. As mentioned in Chapter 4, constant degradation of steam turbine was assumed for this case study. It was also assumed that the steam turbine does not go under any maintenance before it reaches the warning threshold. Figure 6.6 and Figure 6.7 show RUL estimates when 250 and 500 data points of the synthetic HP displacement case study are used respectively. It can be seen that the SVR estimates remaining life of the steam turbine using the synthetic data.

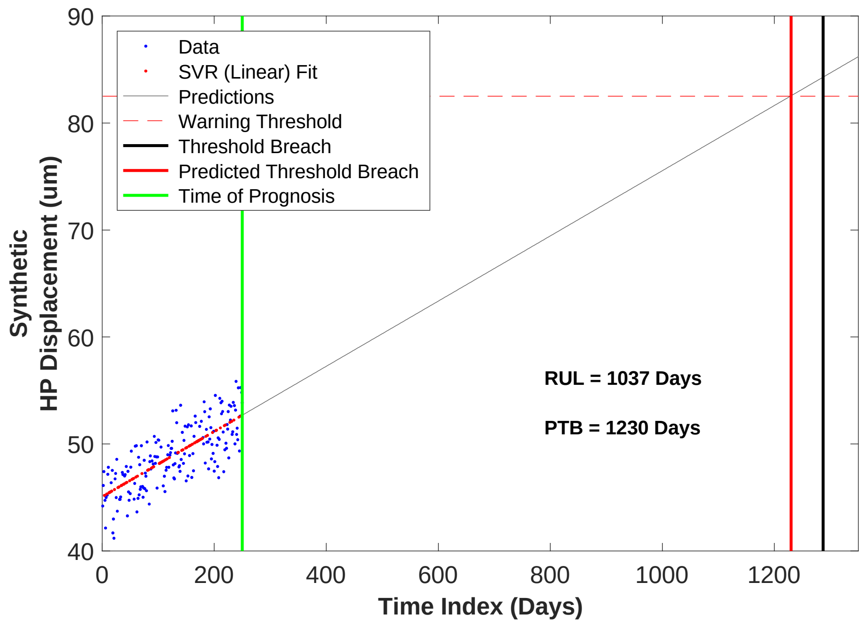


Figure 6.6 - RUL Prediction using SVR: 250 Synthetic Data Points

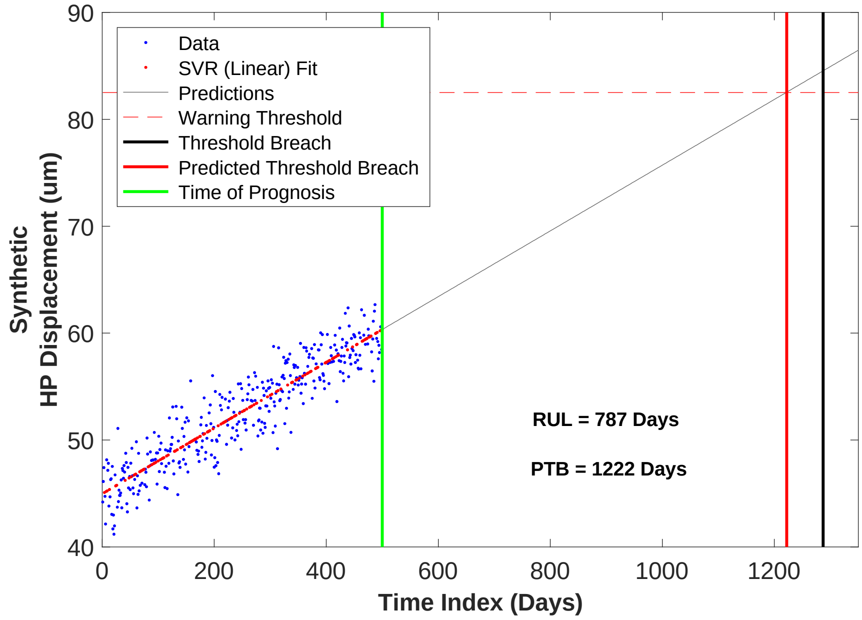


Figure 6.7 - RUL Prediction using SVR: 500 Synthetic Data Points

The performance of the SVR under constant degrading conditions is recorded in Table 6.3

Table 6.3 - Synthetic Data Performance Assessment

Set of Data Points	True RUL (Days)	Predicted RUL (Days)	Prediction (Early or Late)
250	1037	980	57 Early
350	937	845	92 Early
500	787	722	65 Early
750	537	509	28 Early

The results validate the performance of SVR as a prognostics technique. As expected, the predicted linear trend updates as new data is added. This shows that SVR can consistently produce only early predictions. However, it must be noted that constant degradation is assumed for the synthetic case study while excluding operating conditions other than online. In practice, the varying operating conditions of the turbine effect the rate of degradation and is exhibited as additional vibrational magnitude or variation within the vibration. Designing algorithms that are capable of incorporating operating conditions, maintenance affects, etc. is therefore considered the next logical step to increase prognostics efficacy and enhance performance by providing better RUL estimations.

6.3. Adapting SVR to Incorporate Maintenance

The main purpose of maintenance is to bring machinery into a safe and reliable state for operation while improving the health of the machine either by repair or replacement. Both type of maintenance actions tends to introduce deviations in the degradation model, thus, affecting the performance of prognostic algorithms. Therefore, prognostic algorithms must incorporate post maintenance effects into prognostics in order to deal such deviations and provide better RUL estimates. Figure 6.8 shows adapted SVR framework for accommodating post maintenance effects

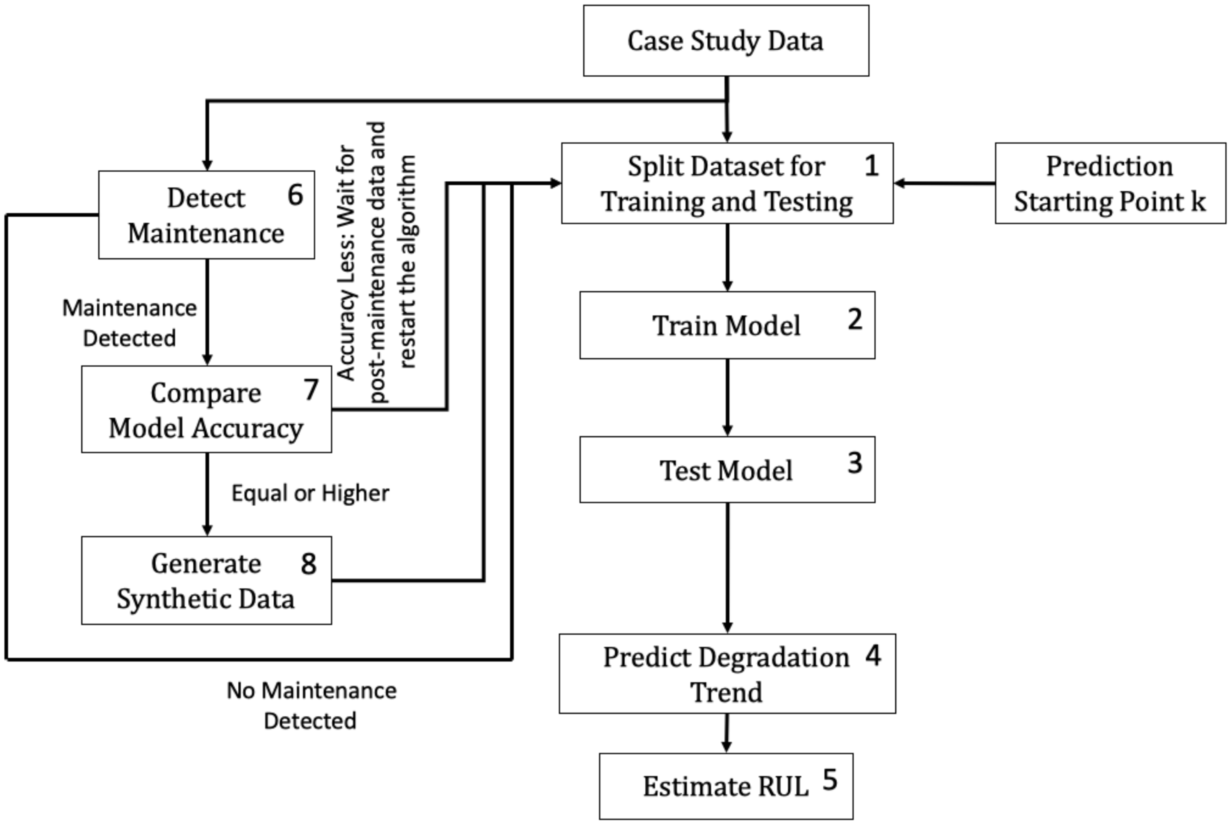


Figure 6.8 - Adapted SVR Framework

As shown in Figure 6.8, the adapted SVR accommodates post maintenance effects by detecting maintenance window, comparing pre-maintenance and post-maintenance model accuracy, and generating synthetic data. The following subsections describe detection of maintenance, comparison of model accuracy and synthetic data generation.

6.3.1. Detect Maintenance Events

The maintenance events within the data are identified using Change Point Analysis. As shown in Figure 6.8, the change points are estimated for the batch of data points that is used for testing and training of the SVR model. If the cumulative sum of the difference between the data points and their mean is the lowest, the point in time is considered as a change point or maintenance event. However, if cumulative sum is not lowest, model parameters at that point in time can be used to predict degradation trend y at a given future point in time.

6.3.2. Compare Model Accuracy

After the maintenance event has been identified, the model for the pre-maintenance data is tested using the post-maintenance data. If the accuracy of the model is higher or equal than the accuracy of the pre-maintenance data, the model parameters of the pre-maintenance data are used to generate historic synthetic data. However, if the accuracy of the model when tested with the post-maintenance data is lower than the accuracy of the pre-maintenance data, the model is considered not suitable for generating historic synthetic data. Therefore, a new model must be built for the post-maintenance data.

6.3.3. Generate Synthetic Data

The historic synesthetic data is generated using the model parameters of the pre-maintenance data. This historic synthetic data is then combined with the post-maintenance data to form a new data set which is then used to retrain the model on the data that contains historic information while fine tuning the hyperparameters for better predicting the degradation trend and remaining useful life.

6.3.4. Adapted-SVR Application: HP Displacement Case Study

The HP displacement case study data shown in Figure 4.28 is used to test the implementation of the Adapted-SVR. The labelled region 2 in Figure 4.29 represents the fault manifested as increased levels of vibrations. Maintenance was performed to control these vibrations by injecting grease as a remedial solution to reduce friction. This resulted in lowering the vibrations levels which is detected as a maintenance event. However, vibration levels tend to increase again as shown in the labelled region 3 of the Figure 4.29. Figure 6.9 shows RUL estimate using adapted SVR framework when 75 HP displacement data points of the labelled region 3 of Figure 4.29 are used. The accuracy of the model when tested with the data in the labelled region 3 was higher than the accuracy of the data in the labelled region 2 of Figure 4.29. Therefore, 200 historic synesthetic data points were generated using the model parameters of the labelled region 2 and are combined with the data in the labelled region 3. It can be seen that Adapted-SVR estimated the future health of the steam turbine.

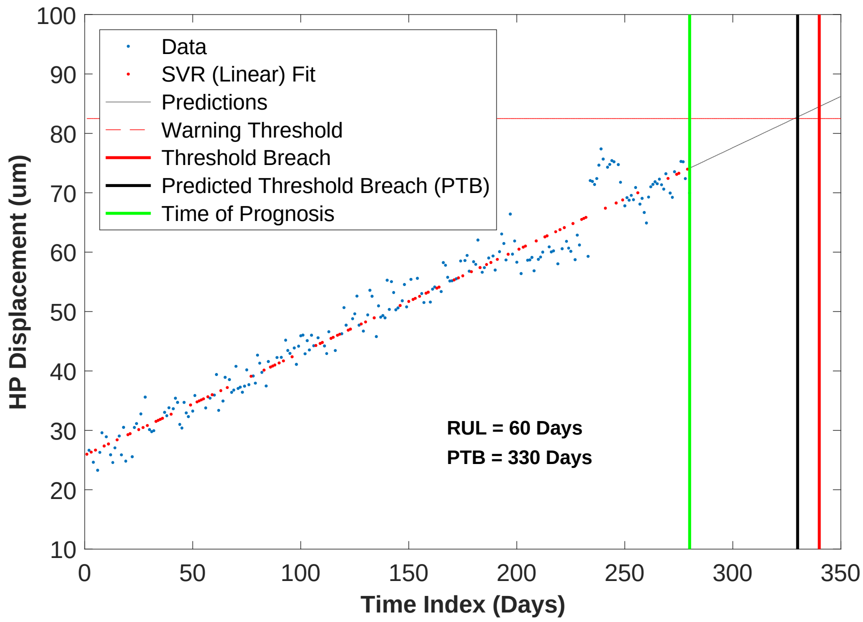


Figure 6.9 - Adapted-SVR RUL Predictions: 75 Data Points

Figure 6.10 shows comparison of Adapted-SVR and SVR parameters. It can be seen that the addition of historic synthetic data, which is generated based on the model parameters prior to maintenance, to the post-maintenance data results in better performance of model parameters as they tend to remain relatively close to the ground truths (i.e. slope and intercept of post-maintenance data) and converge into the ground truths. The utilization of model parameters of the data prior to maintenance allows the retention of historic information which later can be simulated to accommodate maintenance. The performance of model parameters of SVR is also shown in Figure 6.10. The intercept of the SVR model was adjusted by bringing the point of intercept for the post maintenance data to same point as the intercept for the data prior to maintenance. It can be seen that the model parameters do not converge to the ground truths but remain relatively closer.

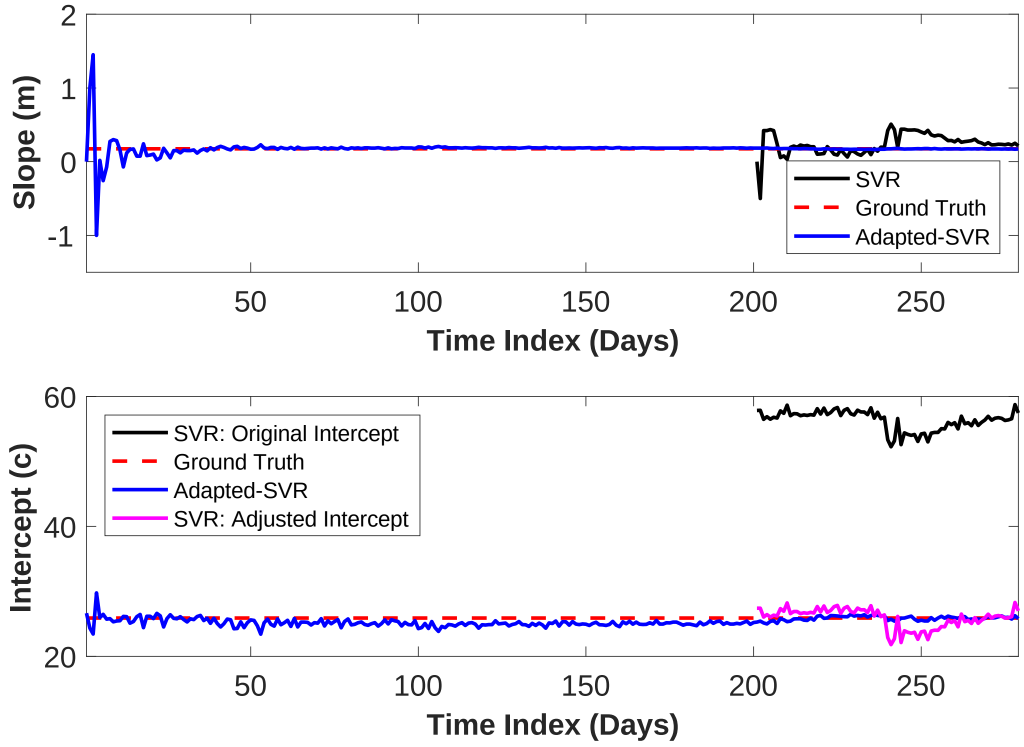


Figure 6.10 - Comparison of Adapted-SVR and SVR Parameters

The model parameter errors of Adapted-SVR is also very low when compared to SVR as shown in Figure 6.11

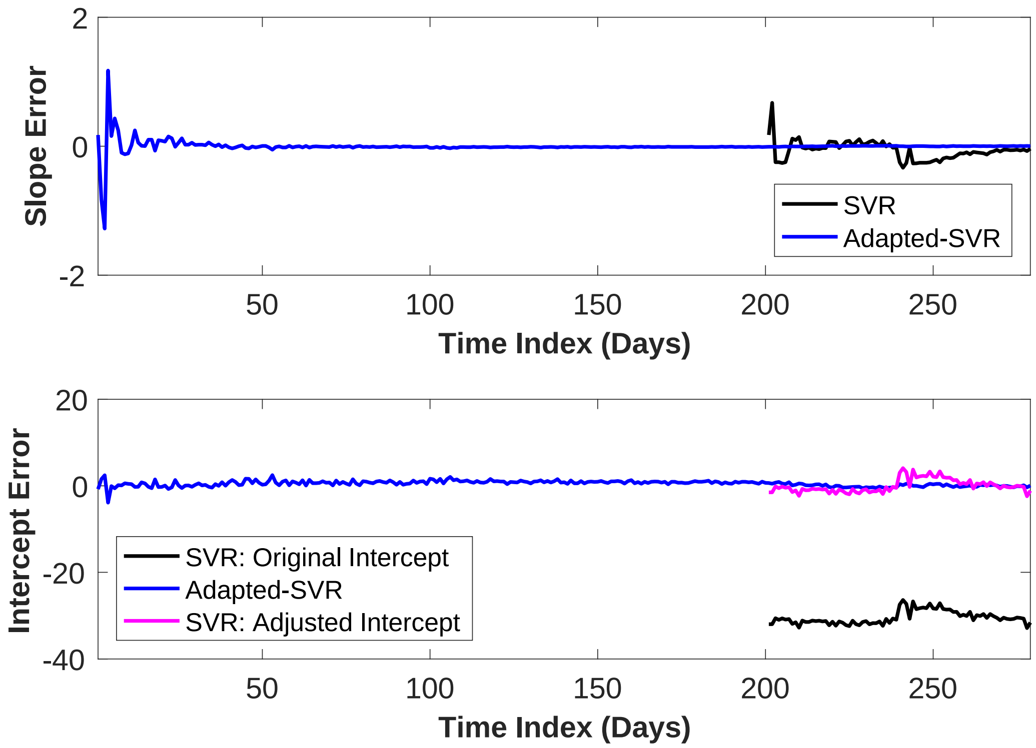


Figure 6.11 - Parameter Error Comparison of Adapted-SVR and SVR

The comparison of RUL estimates produced by the SVR and the Adapted-SVR with prognostic gain is showed in Table 6.4

Table 6.4 - RUL comparison of the Adapted-SVR and the SVR when pre-maintenance model is retained

Set of Data Points	SVR (RUL: Days)	Adapted-SVR (RUL: Days)	Gain (Days)
5	32	49	17
10	54	63	9
15	67	70	3
20	74	77	3
75	59	60	1

The adapted-SVR is capable of estimating RUL with prognostic gain using fewer data points. The model parameters of the Adapted-SVR tend to remain relatively closer to the ground truth as shown in Figure 6.10. The ground truth of model parameters is estimated using linear regression. The Adapted-SVR helps practitioners estimate early RUL predictions while avoiding the loss of RUL through early scheduling of maintenance.

As mentioned above, the adapted-SVR after detecting the maintenance compares the accuracy of the pre-maintenance model for the post-maintenance data with the accuracy of the pre-maintenance data. If the accuracy of the model for the post-maintenance data is lower than the model accuracy of the pre-maintenance data, the adapted-SVR only utilises the post-maintenance data to train and test the model. Figure 6.12 shows the performance of model parameters when maintenance is detected but the accuracy of the model for pre-maintenance data is lower when tested with the post-maintenance data.

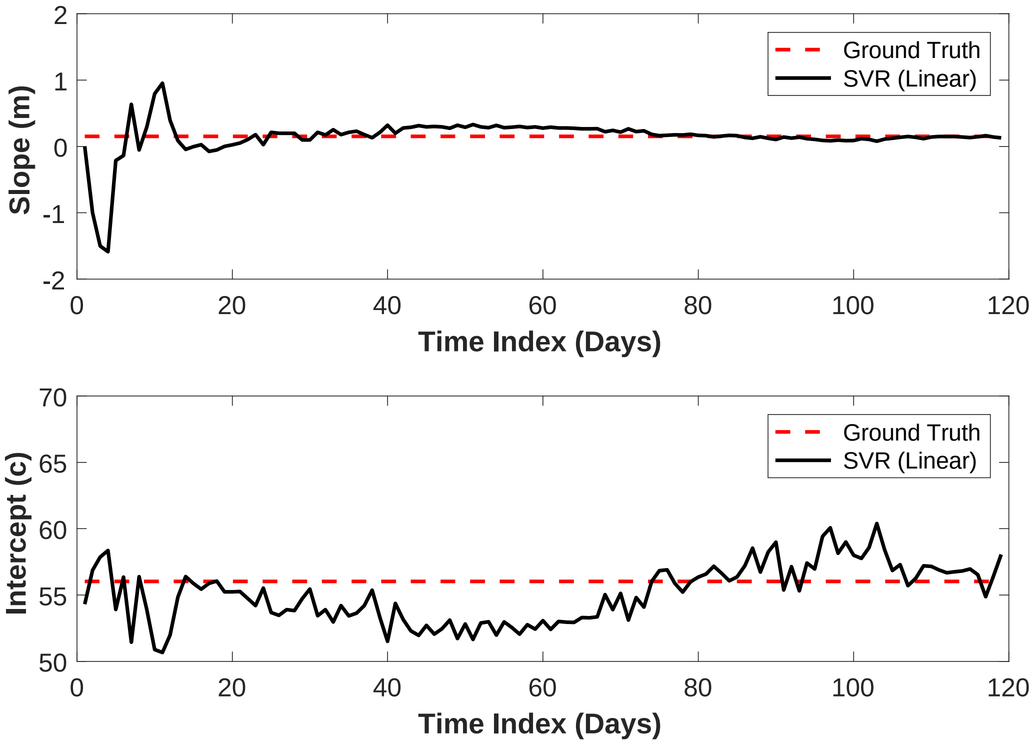


Figure 6.12 - Performance of model parameter of Adapted-SVR when the accuracy of the model for the pre-maintenance data is lower when tested with post-maintenance data

It can be seen from the comparisons that using the model parameters before the maintenance to generate historic synthetic data allows accommodation of maintenance while allowing the adapted-SVR produce better RUL estimates with fewer data points. Thus, producing RUL estimates with greater certainty compared to SVR. It must also be noted that the Adapted-SVR also suffers from the inherent difficulty in separating the long-term and short-term behaviour despite of its better performance. Temporary reductions in vibration levels were seen due to changes in operational settings which allowed the turbine to cool down. Therefore, to validate the performance of Adapted-SVR, a synthetic case study data with maintenance events must be considered.

6.3.5. Adapted-SVR Application: Synthetic Case Study

A synthetic case study data as shown in Figure 4.35 was used to validate the performance of the Adapted-SVR. This case study assumes constant rate of equipment deterioration while simulating post-maintenance effects (i.e. change in rate of degradation after maintenance as indicated by the linear fits of the data segments). Figure 6.13 and Figure 6.14 show performance comparison of the model parameters when model parameters of pre-maintenance data are used to generate historic synthetic data. From the comparison, it can be seen that the model parameters of the Adapted-SVR remain relatively close to the ground truth and converge into the ground truths at much faster rate. For example, the slope of the Adapted-SVR converge into the ground truth in 33 days whereas the SVR takes 51 days to converge. The intercept of the SVR takes same amount of time to achieve same performance as the Adapted-SVR. The performance of model parameters of the Adapted-SVR indicate that the technique is able to produce better RUL estimations with fewer data points and greater certainty compared to SVR.

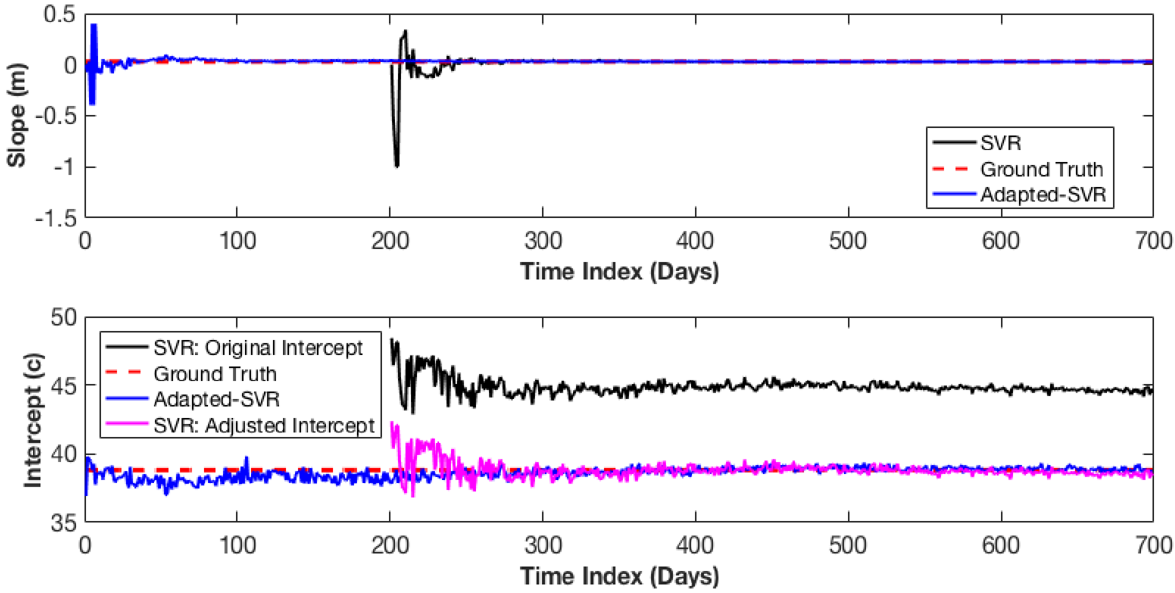


Figure 6.13 - Performance comparison of model parameters of Adapted-SVR and SVR using synthetic data

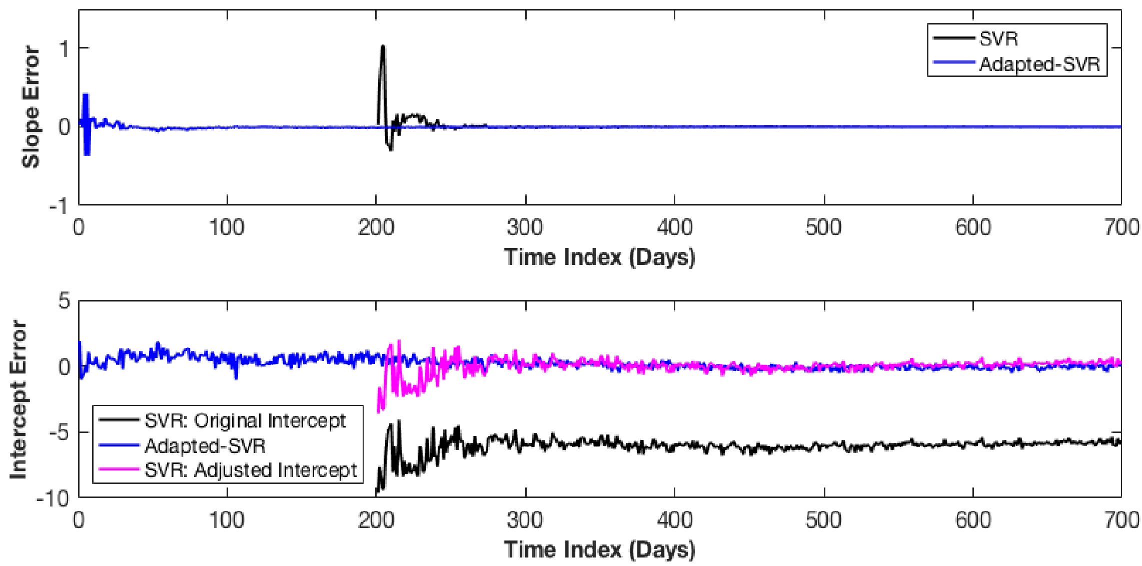


Figure 6.14 - Error comparison of model parameters of Adapted-SVR and SVR using synthetic data

The comparison of RUL estimates produced by the SVR and the Adapted-SVR using synthetic data while retaining the pre-maintenance model is shown in Table 6.5

Table 6.5 - RUL comparison of the SVR and the Adapted-SVR using synthetic data

Set of Data Points	BLR (RUL: Days)	Adapted-BLR (RUL: Days)	Gain (Days)
3	11	28	17
5	26	54	28
10	92	97	5
15	332	339	7
500	786	788	2

The results show that the Adapted-SVR can consistently produce reliable RUL predictions with prognostic gain with fewer data points. The Adapted-SVR was also tested for the scenario when maintenance is detected, however, the accuracy of the post-maintenance data when tested with the model for the pre-maintenance data is lower. Figure 6.15 and Figure 6.16 show the comparison of the model parameters of the Adapted-SVR and SVR. It can be seen from the comparison that the Adapted-SVR trains and tests the model with the post-maintenance data resulting in the performance of model parameters which is similar to the performance of the model parameters of SVR.

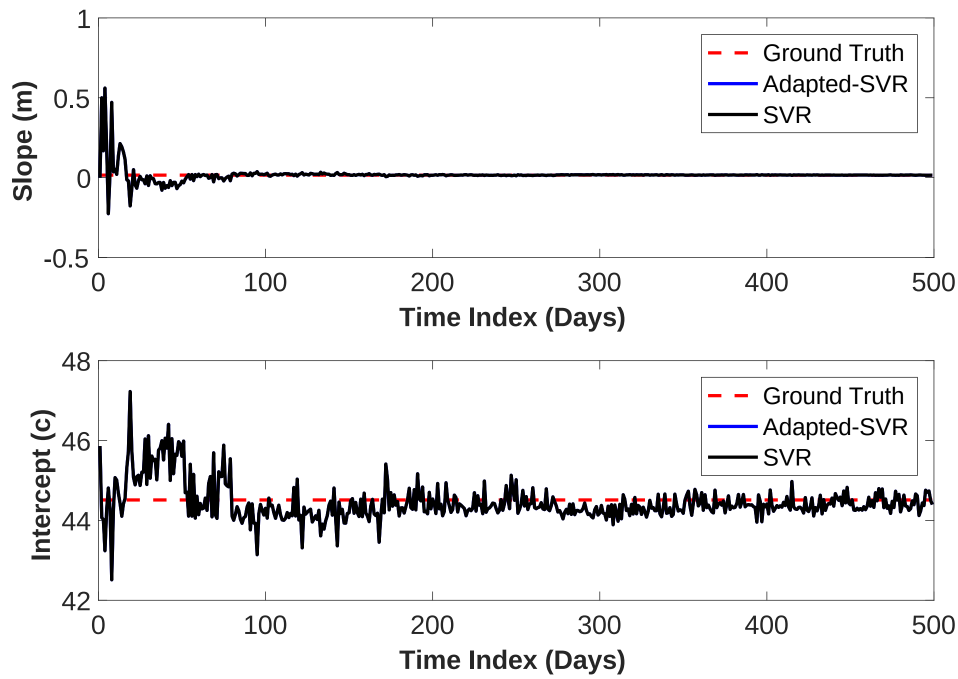


Figure 6.15 - Performance comparison of model parameters of Adapted-SVR and SVR using synthetic data when the accuracy of the model for the pre-maintenance data is lower when tested with post-maintenance data

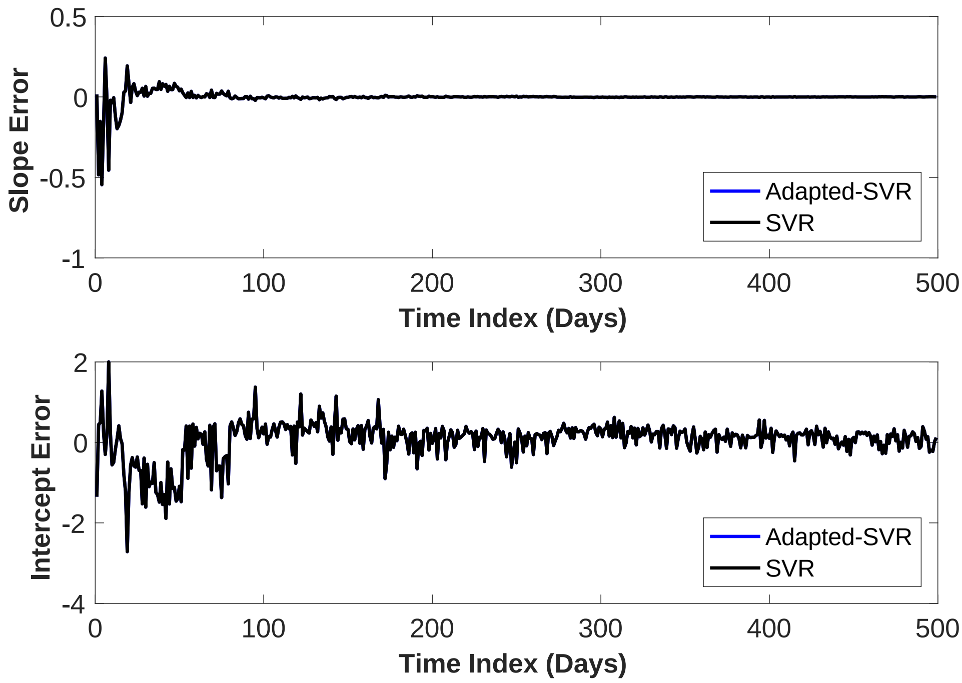


Figure 6.16 - Error comparison of model parameters of Adapted-SVR and SVR using synthetic data when the accuracy of the model for the pre-maintenance data is lower when tested with post-maintenance data

The implementation of Adapted-SVR using synthetic data indicates that the technique is performing correctly and is capable of consistently producing reliable early RUL predictions with fewer data points. However, the technique is incapable of representing the uncertainty that is associated with the model and predictions. The uncertainty in predictions tends to increase over longer prediction horizons. As mentioned earlier, constant degrading conditions were assumed for the synthetic case study. In practice, the varying operating conditions of the turbine effect the rate of degradation, which impacts the overall performance of the algorithm because of higher uncertainty when machine is operating in multiple operational modes.

6.4. Summary

In this chapter, SVR is presented as a prognostic technique for predicting RUL of a nuclear steam turbine. The technique is capable of predicting the future behaviour of degrading equipment. A real-world case study data from an operational nuclear power plant in the UK was used to assess the performance of the algorithm. The results show varying performance due the inability of the technique to distinguish between short-term and long-term behaviours. The operating conditions of the plant also affect the performance of the algorithm. Therefore, for further validation, a synthetic case study is used. The results of synthetic case study data show that the technique is capable of producing early RUL prediction. This chapter also presents the improvements that are made to enhance the performance and efficacy of SVR. The Adapted-SVR is capable of producing more reliable early RUL predictions with fewer data points by retaining pre-maintenance model which is used to generate historic synthetic data. The model parameters of the Adapted-SVR tend to remain relatively closer to the ground truths and converge to ground truths at much faster rate while maintaining low error rate when compared to SVR. The Adapted-SVR also produces prognostic gain, thus, helping maintenance practitioners avoid loss of RUL.

CHAPTER 7: DISCUSSION

7.1. Introduction

This chapter provides detailed technical discussion on the contributions of the research work that are made in this project. The chapter starts by further explaining the formal evaluation and selection process of prognostic techniques which can enable reliability engineers to select the appropriate prognostic technique that suits their requirements and their application. The benefits of selecting appropriate prognostic technique for PHM implementation is also discussed. The selected prognostic techniques BLR and SVR are developed, implemented, and adapted to accommodate maintenance into prognostics. The results from both approaches are further discussed to help reliability engineers to understand the applicability and limitations of both approaches.

7.2. Formal Evaluation and Selection Process

There is no standardised applicable methodology which helps reliability engineers select a prognostic technique according to their requirements. The selection of applicable prognostics technique is mainly driven by the available engineering resources (run-to-failure data or physics-based degradation model), failure threshold, generality or scope of the approach, uncertainty management, and transparency. Proposed methodologies in literature do not help reliability engineers make a collective decision based on all of their user requirements. Thus, they are unable to select a technique that would be the best fit for their overall user requirements. The generic design framework that is used to develop the formal evaluation and selection process is shown in Figure 7.1

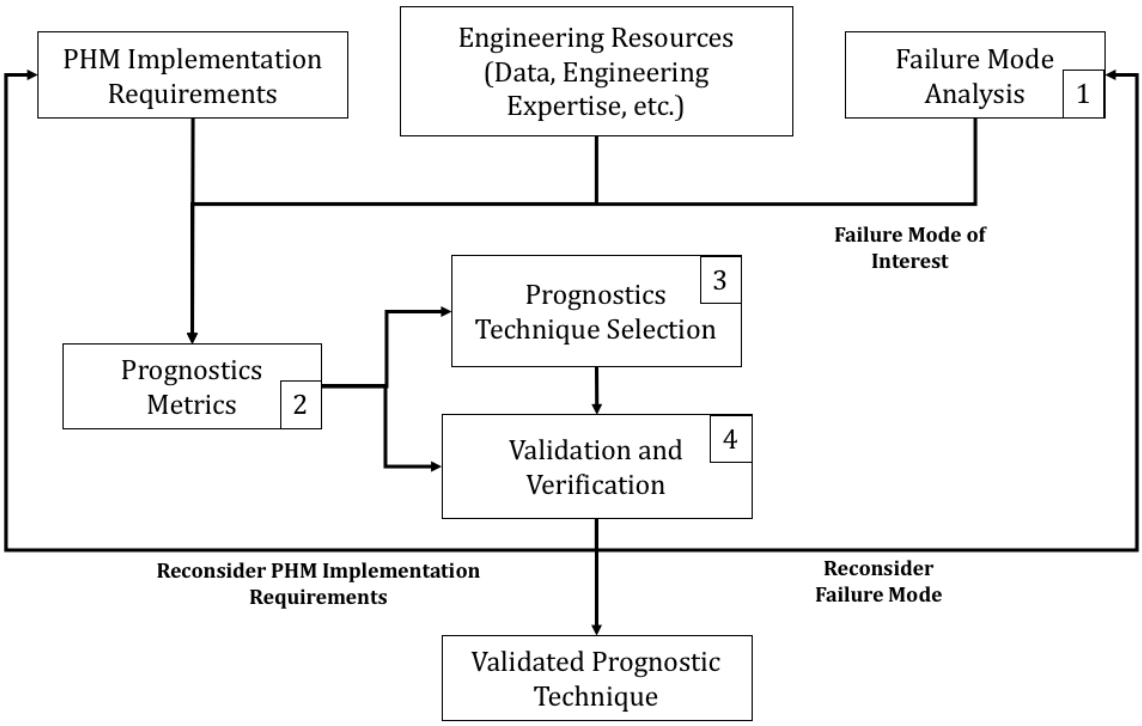


Figure 7.1 - Generic Design Framework for Prognostics

The proposed design framework assumes four stages:

- Failure mode analysis to identify single fault type, aging behaviour, or a number of important failure modes that can affect the operation of an asset. Formal criticality assessment techniques (e.g., FMECA) and importance measurements [154] can help identify failure modes of interest and their criticality.
- Transformation of high-level PHM implementation requirements into application specific prognostic metrics which help evaluate and validate different prognostics techniques under the same criteria. Prognostics metrics can be derived from available engineering resources (e.g. data), based on engineering understanding (e.g. failure mode of interest), model of degradation, and application specific requirements.
- Prognostics Technique Selection utilises the process of evaluating a prognostics technique based on prognostics metrics. This activity determines which prognostic techniques are most suitable.
- Validation and verification of selected prognostics technique using prognostics metrics.

The choices made throughout the design framework impact the immediately connected steps, and may lead to iteration of previous steps. For instance, if system requirements are not met, the designer should reconsider the initial system requirements or the adopted failure mode. While all the outlined activities are important for PHM implementation, this research focuses on the development of an approach for evaluating and selecting a prognostic technique in order to support effective and accurate decision making for maintenance/intervention by accurately predicting failure progression. In this thesis, a simplistic formal evaluation and selection process for prognostic techniques is presented. The process utilises look up tables to select an appropriate metric score for the prognostic metric. The scores in the lookup tables are allocated based on how well the requirements of PHM implementation and prognostic technique characteristics match each other. Therefore, enabling the assessment of a prognostic technique by scoring each and every prognostic metric that are considered for evaluation in the PHM implementation. The formal evaluation and selection process of a prognostic technique is validated through a user requirements driven process. The validation of the process using case studies show that the process can be applied to wide range of industrial applications (i.e. electrical and power industry, aerospace, marine, etc.). The process is dynamic as it allows evaluation of a prognostic technique using any number of prognostic metrics. The process is also extendable and more prognostic metrics can be added to the process by creating lookup tables.

The main benefits of implementing formal evaluation and selection process include better and informed decision making because of thorough consideration of possible options of prognostic algorithms, reduction in time and effort required to implement prognostics, increased adoption of prognostic techniques in other domains/industry, and enabling consistent comparison of prognostic algorithms.

The implementation of the process for the application of steam turbine (i.e. a rotating machine) from a nuclear power plant resulted in scoring the BLR highest. Therefore, the BLR was selected as a probabilistic prognostic technique. Whereas, the SVR was selected as a non-probabilistic prognostic technique as it was scored the second highest technique. The prognostics implementation of both techniques showed relatively similar yet varied results. The implementation of both algorithms generated early and late predictions. Despite the addition of more data, the performance of the algorithms did not improve as the short-term behaviour capturing some additional processes resulted in affecting the performance of both algorithms. The predictions of both algorithms are highly dependent on the trend of the data at the prediction time x_t, and the techniques have difficulty in separating the long term and short-term behaviour. It was assumed that when operating in online mode, the machinery response would be fairly consistent and any unusual behaviour and degradation would be easier to identify. Therefore, the feature case study when machine was operating in online operating mode at full power was extracted. The fault was recognised during the case study time period and maintenance actions were taken. These maintenance actions resulted in reducing the vibration levels which resulted in affecting the degradation path. Therefore, affecting the performance of both algorithms.

The non-linear operational environment of the steam turbine makes it hard to establish efficient prognostics approaches, that are robust enough to tolerate uncertainty, and reliable enough to show acceptable performance under diverse conditions. The prognostics implementation showed that even if prognostic techniques are robust and capable of dealing with the uncertainties, techniques are still required to be reliable enough to be used in the context when the operations of a machinery is non-linear. In other words, prognostics should be able to accommodate multiple operating conditions. Robustness and reliability of a prognostics approach appear to be closely related, and both should be considered as important to ensure the accuracy of RUL estimates. The assessment also shows that perhaps a better prognostics technique which satisfies all the PHM implementation requirements and is reliable enough to predict failure progression of steam turbine more accurately is required.

To address the reliability issue while further enhancing the performance of both algorithms, the algorithms were adapted to accommodate maintenance. In this research, two frameworks for adapting probabilistic and non-probabilistic prognostic techniques to accommodate maintenance are proposed. The probabilistic framework relies on updating the model parameters for the post-maintenance data using the information from the pre-maintenance data. Whereas, non-probabilistic framework generates historic synthetic data based on the model parameters of the pre-maintenance data. This historic synthetic data is then combined with the post-maintenance data to form a new data set which is used for prognostics implementation.

7.3. Adapting Prognostics for Maintenance

In steam turbine degradation, most of the degradation patterns are nearly linear over a longer period of time, however there are cases where the rates of degradation may be non-linear. There are several events that may affect the degradation of a steam turbine. For example, the degradation of a turbine may reduce due to maintenance action resulting in the recovery of the turbine performance. For accurate prognostics, knowledge of maintenance actions which affect the rate and state of degradation is crucial. A generic methodology about this concept is illustrated in Figure 7.2. Prognostic algorithm can be reset if a maintenance has been carried out which results in recovering the performance of a steam turbine. In this case, prior parameters/degradation data can be updated to then restart the RUL estimation.

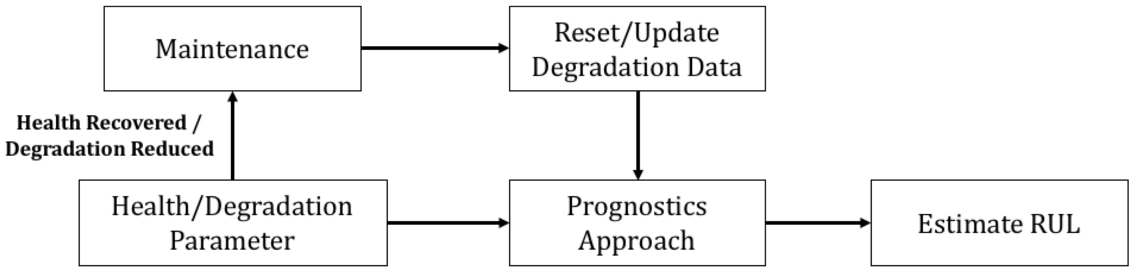


Figure 7.2 - Generic Methodology to Accommodate Maintenance

The proposed methodology resets a probabilistic prognostic algorithm by reconfiguring the prior parameters when a maintenance event is detected. Whereas, for a non-probabilistic prognostic algorithm synthetic historic data based on model prior to the maintenance is used to inform the prognostic algorithm. The main benefits of adapting prognostic techniques to include maintenance are:

- Detection of deviations in degradation path due to maintenance
- Inclusion of degradation deviations into prognostics to increase efficacy and accuracy of predictions
- Prediction of RUL with fewer data points
- Avoiding the loss of RUL through early scheduling of maintenance
- Enabling maintenance practitioners make informed decision for maintenance scheduling

In real world, it is difficult to detect directly any slope change in degradation due to maintenance because they are typically very noisy. Thus, leading to uncertainty which impacts the ability to accurately predict the degradation. In order to overcome the aforementioned issue, sophisticated integrated prognostic approaches are introduced, combining BLR and SVR with the change point detection (CPD) algorithm in order to adapt prognostic algorithms to accommodate maintenance. The CPD algorithm plays an important role to detect any changes affecting degradation's slope due to maintenance.

A change point detection (CPD) algorithm, aims to discover points at which sudden changes occur in time-series data [155]. This method can be classified based on the delay in detection: real-time detection or retrospective detection. Real-time detection is used for applications which require immediate response. On the other hand, retrospective detection can be used for applications, which tolerate longer reaction periods. The latter algorithm tends to give more robust and accurate detection [155]. In this research, retrospective CPD algorithm is used for detecting maintenance events because delay has minor effect on the decision making due to slow and long failure progression in steam turbines. The information from CPD algorithm is utilised accordingly for enhancing the quality of RUL estimation and the performance of prognostics algorithms.

In the following subsections, the implementation of proposed methodology for probabilistic and non-probabilistic prognostic techniques are discussed. For the implementation of proposed methodology, synthetic and real-world cases studies are used to discuss the adaptation of the algorithms to accommodate maintenance. In the discussion, metrics such as run time, number of data points for prediction, training sample, and uncertainty quantification and representation are used to explain the strengths and limitations of both techniques.

7.3.1. Adapted-BLR

The Adapted-BLR is an integrated prognostics technique which combines the BLR algorithm with the CPD algorithm to accommodate maintenance for prognostics while estimating RUL. The CPD algorithm is used to identify the maintenance events retrospectively. This information is then used to reconfigure parameters (i.e. slope and intercept) of the BLR algorithm.

It is assumed that repairs are performed to return machinery to a working condition. A repair is a maintenance action that improves the health of a machinery but it does not completely remove the precursor failure conditions. Therefore, for parameters reconfiguration, same degradation rate (i.e. slope) is assumed for the post-maintenance data. The initial degradation point (i.e. intercept) of pre-maintenance data is selected as the initial degradation point for the post-maintenance data.

Figure 7.3 shows a detailed block diagram of the proposed concept. The degradation parameter is fed into BLR algorithm to estimate RUL. At the same time, degradation parameter is also monitored continuously by CPD algorithm. If CPD algorithm detects significant decrease in degradation, it considers that maintenance action is just performed and parameters of prognostic algorithm should be adjusted accordingly. The reconfiguration of parameters also considers the post-maintenance affect which is the change in degradation rate. If the degradation rate is within the higher and lower threshold limit (i.e. ± 5% of the pre-maintenance data), parameters are reconfigured. However, if the degradation rate is lower or higher than the threshold limit, parameters are reset.

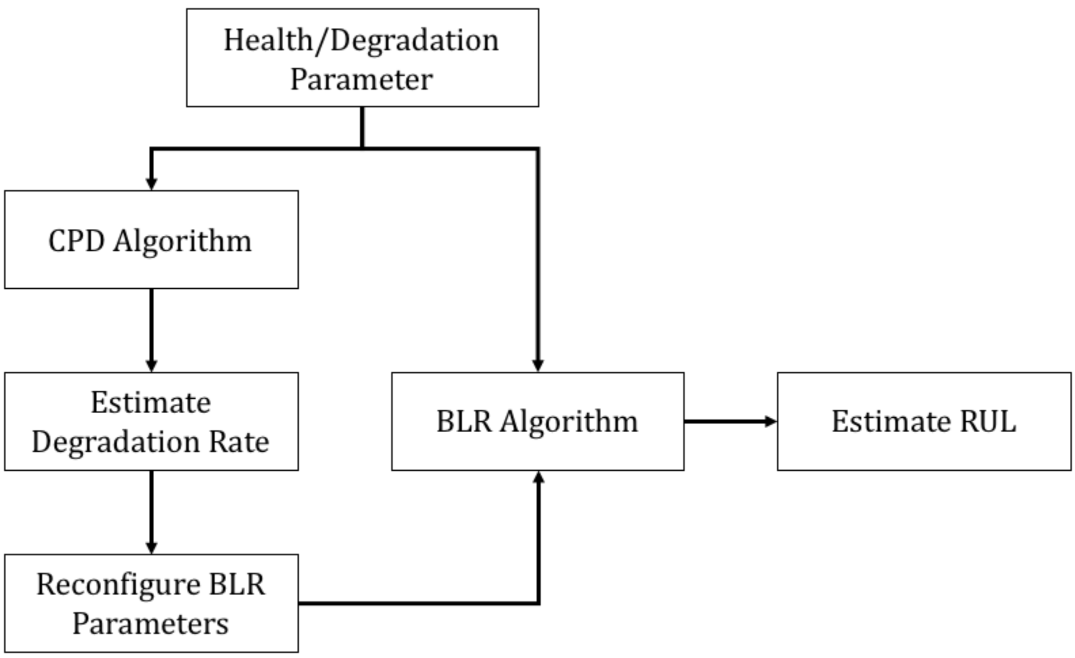


Figure 7.3 - Block Diagram of Combining BLR and CPD Algorithms

The proposed concept was implemented using a real case study from a steam turbine in nuclear industry. As described in Section 4.7.3, maintenance actions such as injection of grease to reduce friction recovered degradation performance. The main prognostic algorithm requires this information when maintenance occurs, in order to reset the algorithm. However, as described earlier, to detect maintenance CPD is applied directly to HP displacement as shown in Figure 7.3. There were two maintenance events that were detected in the real-world case study as shown in Figure 4.29. These maintenance events result in decrease of vibrations due to friction. After the detection of these events, the rate of degradation for the post-maintenance data and the pre-maintenance data were compared. If the difference between the degradation rates is higher or lower than the threshold limit, the parameters of the algorithm were reset or reconfigured accordingly for the estimation of RUL due to the fact that maintenance leads to uncertainty due to a possible change in degradation rate which may affect the accuracy of the algorithm.

The results of the implementation as described in Section 5.3.3 showed improved performance of the BLR algorithm. The parameters of the BLR algorithm remained relatively closer and converged into the ground truth. For the estimation of expected ground truth, linear regression has been used based on consultation with industrial peers. The implementation results as shown in Table 5.4 show that the Adapted-BLR produced RUL estimations with fewer data points. The results also show that the technique results in prognostic gain which is the time (i.e. RUL) for which maintenance can be deferred to maximise the utilisation of a component. This helps maintenance engineers avoid the loss of RUL through early rescheduling.

The Adapted-BLR as an integrated approach allows improved estimation of RUL while tracking uncertainty in the linear model. The BLR algorithm provides analytical framework based on conjugate Gaussian distributions to estimate model parameters using available data, thus allowing estimation of posterior and predictive distributions. The RUL can be estimated from the failure or warning distributions which is obtained based on the predicted values exceeding the failure or warning threshold, thus allowing quantification of uncertainty in predictions. The CPD algorithm allows detection of maintenance events. This information is used to reconfigure the parameters of the BLR algorithm to produce better RUL estimations.

The implementation of Adapted-BLR showed that the running time of the algorithm is very low. The time taken to estimate RUL using 1311 data points (i.e. the number of data points in the case study) is 5.712 seconds which is the highest time taken by the algorithm. Whereas, the lowest time recorded to get reasonable RUL estimation is 2.31

seconds for 50 data points. Table 7.1 shows the time taken by Adapted-BLR to estimate RUL using selected number of data points.

Table 7.1 - Running Time of Adapted-BLR

No. of Data Points	Time Taken to Estimate RUL (s)
200	3.965
300	4.677
400	4.766
500	4.837
600	4.986
700	5.321

The main limitation of the Adapted-BLR is potential uncertainty in capturing noise characteristics. The algorithm assumes that the variation in noise of degradation parameter of an asset over its lifetime is constant. However, the non-linear operational environment of the steam turbine results in varying noise levels which results in affecting accuracy, robustness, and reliability of the Adapted-BLR. The implementation of the technique shows that the technique is performing correctly and produces results that are explicable. Therefore, for further validation of the Adapted-BLR, a synthetic case study was also used. The synthetic case study assumes constant variation in noise level. The results of the implementation were promising. Results showed that the integrated technique is working as intended. The integrated approach detects maintenance events. The approach uses the information from the detected events to reconfigure or reset the parameters of the BLR algorithm in order to provide improved RUL estimations. The results obtained from the implementation are explicable and reliable. This is due to the assumptions of constant degradation and single operational mode (i.e. constant full power) which are used to generate synthetic case study data (See Section 4.6.3).

The implementations using the real world case study and the synthetic data showed that the technique is capable of producing results with uncertainty representation for longer prediction horizon. As shown in Figure 5.11, RUL is estimated from the distribution of future health estimates that exceed the warning threshold. The uncertainty that is associated with the predictions tends to increase with longer prediction horizons. The uncertainty in predictions is also higher when machine is running in non-linear operational modes. The operational modes tend to introduce noise and variation within the data. Thus, resulting in uncertainty. Therefore, to further enhance the performance of the algorithm in terms of reliability, robustness, and accuracy, the prognostic algorithm must also accommodate operational events within the data that result in deviation from the expected degradation path and affecting the performance of the algorithm.

7.3.2. Adapted-SVR

The Adapted-SVR is an integrated prognostics technique which combines the SVR algorithm with the CPD algorithm to accommodate maintenance for prognostics while estimating RUL. The CPD algorithm identifies maintenance events retrospectively. This information is used split the data into pre-maintenance and post-maintenance data. After the segregation of the data, the model for the pre-maintenance data is tested using the post-maintenance data. If the accuracy of the model is higher or equal than the accuracy of the pre-maintenance data, the model parameters of the pre-maintenance data are used to generate historic synthetic data. This historic data is then combined with the post-maintenance data to form a new data set which is then used to retrain the model on the data that contains historic information while fine tuning the hyperparameters for better predicting the degradation trend and remaining useful life. However, if the accuracy of the model when tested with the post-maintenance data is lower than the accuracy of the pre-maintenance data, the model is considered not suitable for generating historic synthetic data. Therefore, a new model must be built for the post-maintenance data.

As mentioned earlier, repairs are performed to return machinery to a working condition while improving the health of a machinery. Repairs do not completely remove the precursor failure conditions. Therefore, for historic synthetic data generation, same degradation rate (i.e. slope) is assumed. Whereas, the first historic data point that is generated based on the model parameters of the pre-maintenance data is selected as an initial degradation point (i.e. intercept) for the historic synthetic data.

Figure 7.4 shows a detailed block diagram of the proposed concept. The degradation parameter is fed into SVR algorithm to estimate RUL of steam turbine. At the same time, degradation parameter is also monitored continuously by CPD algorithm. If CPD algorithm detects significant decrease in degradation, it considers that maintenance action is performed and accuracies of the model must be tested with the post-maintenance data. If the accuracy of the model is higher, historic synthetic data can be generated and combined with the post-maintenance data to retrain the model. However, if the accuracy of the model is lower for the post-maintenance data, the SVR algorithm is reset to estimate RUL.

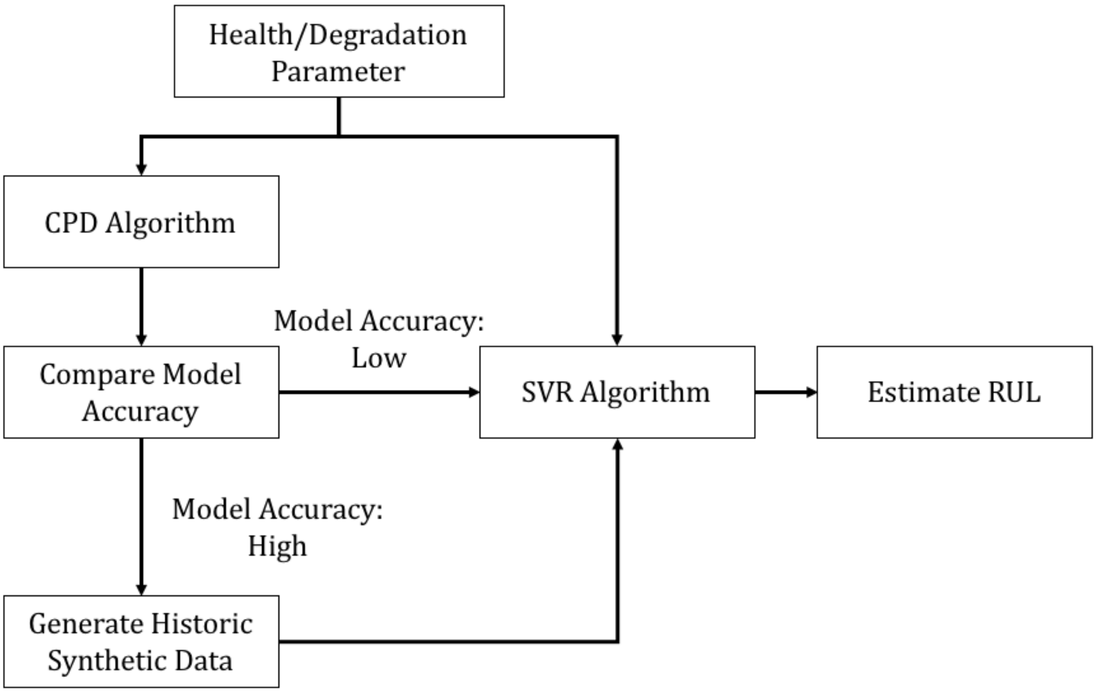


Figure 7.4 - Block Diagram of Combining SVR and CPD Algorithms

The proposed concept was implemented using a real case study of a steam turbine (See Section 4.7.3). The case study contains two maintenance events as shown in Figure 4.29. The maintenance actions were performed to recover health of the machine and reduce vibration levels. The main prognostic algorithm requires this information about maintenance events when they occur in order to either reset the SVR algorithm or generate historic synthetic data. As described earlier, to detect maintenance CPD is applied directly to HP displacement as shown in Figure 7.4. After the detection of these events, the model of pre-maintenance data is tested with the post-maintenance data and the model accuracies of pre-maintenance and post-maintenance datasets are compared. The information from this comparison was then used to either reset the SVR algorithm or generate historic synthetic data to retrain the model.

The results of the implementation as described in Section 6.3.4 showed improved performance of the SVR algorithm. The parameters of the SVR algorithm remained relatively closer and converged into the ground truth. The ground truth of the parameters is estimated using linear regression. A comparison between the model accuracies for pre-maintenance and post-maintenance data was performed to assess and accommodate the post-maintenance affect (i.e. change of degradation rate) for RUL estimation. If the model accuracy is higher or equal for the post-maintenance data historic synthetic data was generated to include historic information while the degradation rate remains same. However, if the model accuracy is lower, the SVR algorithm is reset in order to estimate RUL due to change in degradation rate. The generation of historic synthetic data allowed the parameters of the algorithm tend to converge quicker into the ground truth and remain relatively closer because the hyperparameters were fine-tuned and contained historic information. The results of the implementation as shown in Table 6.4 show that the Adapted-SVR is capable of estimating RUL with prognostic gain using fewer data points. The Adapted-SVR helps practitioners estimate early RUL predictions while avoiding the loss of RUL through early scheduling of maintenance.

The Adapted-SVR as an integrated approach allows improved estimation of RUL while utilising the decision boundary of the SVM. The SVR algorithm provides analytical framework based on support vectors to determine the decision boundary, hyperplanes, and model parameters. The determined decision boundary can be extrapolated using the model parameters to estimate RUL based on the predicted values exceeding the failure or warning threshold. The hyperplanes of the SVR algorithm are sensitive to support vectors (i.e. data points on the hyperplane) as shown in Figure 7.5.

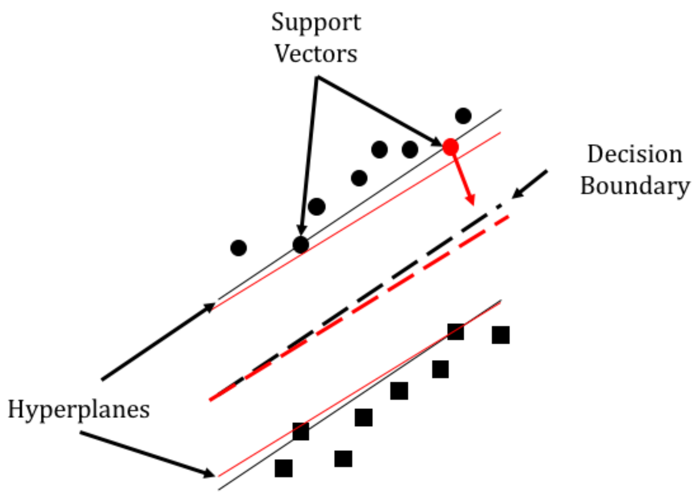


Figure 7.5 - Effect of Data Uncertainty on Support Vectors

The uncertainty relating to the support vectors affects the orientation of the decision boundary. Therefore, changes in orientation of the decision boundary results in affecting the RUL estimations.

The CPD algorithm of the adapted-SVR allows detection of maintenance events. The maintenance events information from the CPD algorithm was used to reset the SVR algorithm when the model accuracy was lower. However, when the model accuracy was higher, historic synthetic data was generated which was combined with the post-maintenance data to form a new data set. This data set was then used to retrain the model in order to fine tune the hyperparameters. The tuning of parameters is a time consuming task and affects the overall run time of the algorithm. Table 7.2 shows the overall time taken by Adapted-SVR to estimate RUL using selected number of data points.

Table 7.2 – Running Time of Adapted-SVR

No. of Data Points	Time Taken to Estimate RUL (s)
200	386.159
300	554.064
400	781.085
500	987.106
600	1121.128
700	1572.170
900	1737.192

On average, 99% of the overall time is spent on training the model. For instance, for the whole case study (i.e. 1311 data points), the adapted-SVR takes 2247.317 seconds to estimate RUL. The time taken to train SVR model is 2243.129 whereas the rest of the time is spent on detecting the maintenance events and making predictions. These results confirm that the training of the algorithm results in higher running time. The running time of a predictive technique can be a limiting factor depending on its application. As the Adapted-SVR is implemented retrospectively, the implementation is allowed to produce predictions in time. However, if the application required real-time results then the running time of the current implementation can be prohibitive.

The main limitation of the Adapted-SVR is its lack of uncertainty quantification that is associated with the prediction of failure because SVR predicts degradation as a single point. The algorithm is also incapable of quantifying uncertainty that is associated with the model due to single point estimations. The assumption that the variation in noise of degradation parameter is constant also affects the performance of the algorithm because the steam turbine of a nuclear power plant operates in a non-linear operational environment where noise levels are varying. Thus, affecting accuracy, robustness, and reliability of the Adapted-SVR. The implementation of the technique using the real-world case study shows that the technique is performing correctly and produces results that are explicable. Therefore, for further validation of the Adapted-SVR, a synthetic case study was also used. For the synthetic case study, constant noise level was assumed. The results of the implementation showed that the integrated technique is working as intended. The integrated approach detects maintenance events. The approach uses the information from the detected events to either reset the SVR algorithm or generate historic synthetic data which is combined with the post-maintenance data and is used as historic information to provide improved RUL estimations. The results obtained from the implementation are explicable and reliable.

The implementations of the technique using the real world case study and the synthetic data showed that the technique is capable of producing results for longer prediction horizon. However, the technique as mentioned before does not consider the uncertainty that is associated with the model and predictions. The uncertainty in predictions is higher when machine is running in non-linear operational modes. The operational modes tend to introduce noise and variation within the data. Therefore, uncertainty associated with the data, model, or future predictions in longer prediction horizon may affect the performance of the algorithm. To enhance the performance of the algorithm in terms of reliability, robustness, and accuracy, the prognostic algorithm must also accommodate events within the data that result in deviation from the expected degradation path and affecting the performance of the algorithm.

7.3.3. Comparative Analysis of Adapted-BLR and Adapted-SVR

In this section, comparative analysis between adapted-BLR and adapted-SVR is presented. The proposed concepts of both techniques provide practitioners with two different ways of accommodating maintenance into prognostics. It enables practitioners to utilise maintenance events information to improve RUL estimations probabilistically and non-probabilistically. However, the performance of both algorithms varies in terms of convergence to the ground truth, uncertainty representation, and running time. Figure 7.6 shows performance comparison of Adapted-BLR and Adapted-SVR parameters after the detection of first maintenance event as shown in Figure 4.28. The algorithms utilised 75 HP displacement data points (i.e. increased levels of vibration data) of the labelled region 3 of Figure 4.29 to estimate RUL.

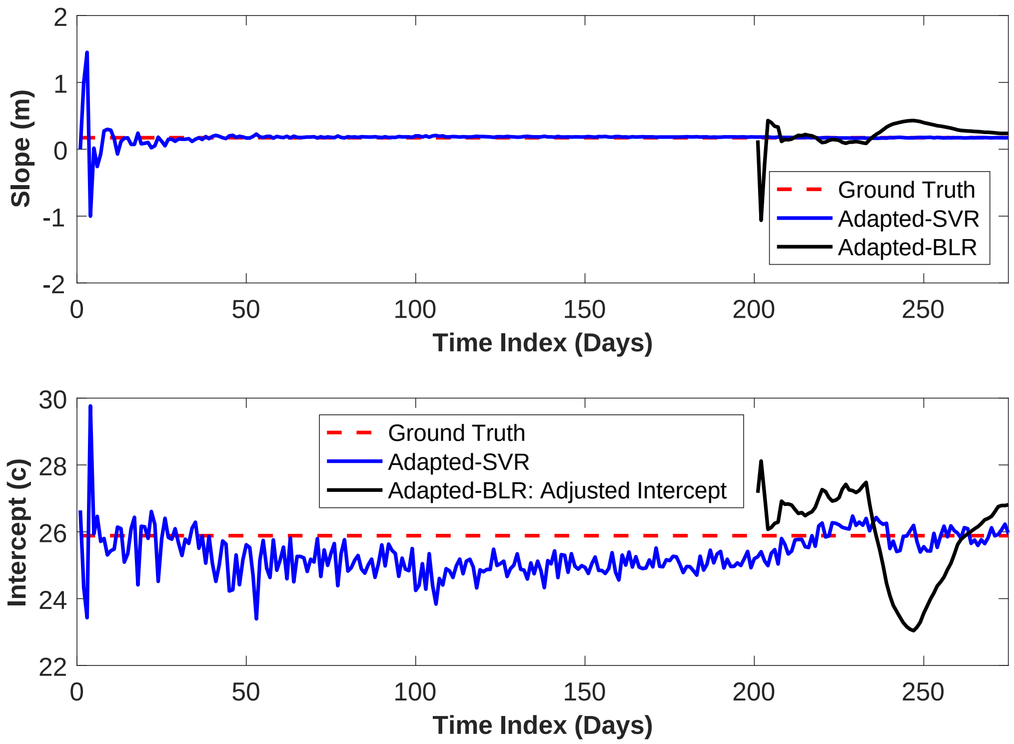


Figure 7.6 – Performance Comparison of Adapted-BLR and Adapted-SVR Parameters

It can be seen that the parameters of the Adapted-SVR tend to remain relatively stable and closer to the ground truth compared to Adapted-BLR. This is due to the fact that there is more data available in the form of historic synthetic data points (i.e. first 200 data points) that were combined with the data from the labelled region 3 to form a new data set. Whereas, the Adapted-BLR algorithm relies on updating the parameters of the prior distribution to accommodate maintenance. The prior distribution gets updated over time due to which variation is seen at the start. This variation in parameters performance tends to settle and converge into ground truth when more data points become available as shown in Figure 5.16 (i.e. the implementation of Adapted-BLR using synthetic data). These results indicate that when parameters are either converged into ground truth or relatively closer to the ground truth, both algorithms tend to produce improved RUL estimates while considering post-maintenance effects.

Both algorithms are capable of producing RUL estimates that are explicable. Adapted-BLR along with the RUL estimations provides means to quantify uncertainty compared to Adapted-SVR. As mentioned before, it utilises conjugate Gaussian distributions to estimate model parameters using available data. Whereas, Adapted-SVR determines model parameters using support vectors (i.e. data points). Both algorithms are capable of producing RUL estimations for longer prediction horizon. However, only Adapted-BLR is capable of quantifying uncertainty that is associated with the predictions because it relies on the distribution of data points exceeding the warning or failure threshold. The Adapted-SVR lacks the ability to represent uncertainty in predictions and estimates RUL by predicting the point in time when predicted degradation exceeds the threshold limit. Both algorithms suffer from potential uncertainty in capturing noise characteristics of the data. The algorithms assume that the variation in noise of degradation parameter of an asset over its lifetime is constant. However, the non-linear operational environment of the steam turbine results in varying noise levels which results in affecting accuracy, robustness, and reliability of the both algorithms when implemented with the real-world case study. The implementations using synthetic data for which constant degradation and noise was assumed showed that the technique is producing correct and explicable results.

The implementation of both algorithms also showed that the running times vary greatly. The running time of a predictive technique can be a limiting factor depending on its real-time (i.e. safety critical) or retrospective application. The running time of the Adapted-BLR is considerably low compared to Adapted-SVR which is due to conjugate Gaussian distributions. The generation of historic synthetic data affects the running time of the Adapted-SVR as more time is spent on training the algorithm. The implementation complexity of both algorithms is low as existing literature and toolkits in MATLAB or Python were used to develop, implement, and test both prognostic techniques.

All the above discussion in this chapter shows that Adapted-BLR has considerable advantages over Adapted-SVR and is a better prognostic technique that is capable of accommodating maintenance at less computational cost. It provides means to track uncertainty in model, predictions, and RUL estimations. It becomes more reliable when more data points are available for estimations and when variation in data is low.

7.4. Summary

In this chapter, detailed technical discussion on the contributions of the research work was provided. The formal evaluation and selection process for prognostic techniques presented in this thesis utilises look up tables to select an appropriate metric score for the prognostic metric in order to enable the assessment of a prognostic technique by scoring each and every prognostic metric that are considered for evaluation in the PHM implementation. The process is dynamic, extendable, and applicable to range of industries. It will facilitate practitioners with better and informed decision making because of thorough consideration of possible options of prognostic algorithms. The evaluation and selection process was implemented and two prognostics techniques were selected. The selected prognostic techniques BLR and SVR were developed, implemented, and adapted to accommodate maintenance into prognostics. The results from the implementation of Adapted-BLR and Adapted-SVR were further discussed and compared to help reliability engineers understand the applicability and limitations of both approaches. The discussion and comparison show that the Adapted-BLR is a better prognostic technique that estimates RUL while considering uncertainties and at lower computation cost.

CHAPTER 8: CONCLUSION & FUTURE WORK

This chapter concludes the research work by summarising issues addressed in the thesis, developments, and contributions. A discussion on possible future work is also presented.

8.1. Contributions and Conclusion

The main objective of this research is to develop generic prognostic algorithms that are capable of accommodating maintenance with applicability in various scientific and engineering domains, where in this particular work, the developed techniques are applied to the degradation data obtained from a steam turbine of a nuclear power plant in the UK. The development of such algorithms is of major interest to manufacturers and operators of critical equipment, for the range of maintenance and operational benefits. These include, reduced maintenance costs, reduced instances of equipment failure, a reduction in ongoing scheduled maintenance activities and costs, and improved equipment uptime and availability. Key to enabling such benefits to be realised are robust algorithms capable of operating within real-world environments. In this thesis, all of the algorithms presented were developed exclusively using data collected from an operational steam turbine of a nuclear power plant. Thus, the developed approaches have demonstrated applicability to the relevant domains for which they are developed and provide future practitioners with insight and guidance in the development of future prognostic algorithms.

The project was conducted in three stages. In the first stage, a literature survey of condition monitoring and prognostics is conducted to identify key issues that affects asset management. The main challenges that also presented opportunities for research included selection of appropriate prognostic algorithms and accommodation of effects of maintenance into prognostics. The survey also allowed identification of prognostic metrics and widely applied prognostics techniques. In the second stage, a formal evaluation and selection process for prognostic techniques is developed, validated, and implemented using the prognostic metrics. The implementation of the process helped in selecting BLR and SVR as probabilistic and non-probabilistic techniques. In the third stage, the selected prognostics techniques were implemented. The performance assessment of the techniques helped in understanding various challenges that arise during the implementation of prognostics for complex systems such as steam turbines. One of the challenges identified is the management of effects of maintenance. In the final stage, two proposals were presented to accommodate effects of maintenance for probabilistic and non-probabilistic prognostic techniques. The proposals were implemented, verified, and compared. The advantages and limitations of both techniques were presented for practitioners.

During the course of this project the following achievements and contributions were made:

- A review on state-of-the-art prognostics techniques with the challenges that are involved during the implementation of prognostics was conducted. This review allowed identification of challenges and opportunities. Out of the identified challenges in prognostics, selection of prognostics technique and effects of maintenance actions are addressed to increase the efficacy of prognostics.
- A formal evaluation and selection process for prognostics technique which is widely applicable to various industries is developed, validated, and implemented. The process will help practitioners evaluate and select prognostic techniques based on available engineering resources, user requirements, and strength and weaknesses of prognostic techniques in mathematical context.
- Adapted-BLR is developed and proposed as a probabilistic prognostic technique that is capable of accommodating maintenance and estimating RUL. The technique is implemented using a real-world case study. The results from the implementation are analysed and discussed in detail to help practitioners understand the applicability and limitations of the technique.
- Adapted-SVR is developed and proposed as a non-probabilistic prognostic technique that is capable of accommodating maintenance and estimating RUL. The technique is also implemented using a real-world case study. The analysis of the results from the implementation is presented in detail to help practitioners understand the applicability and limitations of the technique.
- Comparative analysis of the Adapted-BLR and Adapted-SVR is presented with detailed discussion of the results from prognostic techniques.

The observations from the implementation results and the resulting conclusions drawn from these observations throughout the project are as follows:

- Detailed literature survey of prognostics identified six major challenges for the implementation of prognostics system. These challenges include: selection of prognostics technique; lack of run-to-failure data; management of prognostics uncertainties; effects of maintenance actions; effects of failure interactions; performance evaluation of prognostics. The selection of prognostics technique and accommodation of effects of maintenance actions into prognostics are the two most underdeveloped areas of prognostics.

- A selection of an appropriate prognostic technique is a crucial activity for the implementation of reliable and accurate prognostic system that helps reliability engineers make an informed decision for maintenance. However, there is no standardised methodology in prognostics literature and practice that helps the practitioners with the selection and evaluation of prognostic techniques based on available engineering resources, user requirements, and thorough consideration of the merits of prognostic techniques. The proposed formal evaluation and selection process utilises prognostic metrics to help practitioners make better and informed decisions for the selection of a prognostic technique by thoroughly considering possible options of prognostic algorithms, while reducing time and effort required to implement prognostics. The process utilises lookup tables to select score for prognostic metrics to formally assess the applicability of a technique. The process will encourage increased adoption of prognostic techniques in other domains/industry. It will also enable consistent comparison of prognostic algorithms.
- From the formal evaluation process of prognostic techniques, BLR and SVR were selected as probabilistic and non-probabilistic prognostic techniques for the implementation in nuclear prognostics.
- BLR is a transparent probabilistic prognostic technique in its assumptions, where it provides a clear explicability of the rules that govern the relationships that make predictions possible. For the validation purpose, the transparent solution is important in the field of safety-related applications. BLR also allows incorporation of previous knowledge/experience in a coherent way and avoids over-fitting problems. Furthermore, BLR have been utilised widely and successfully in multidisciplinary fields such as reliability engineering, survival analysis and forecasting.
- SVR is a supervised prognostic technique which provides clear steps for the prediction of RUL. However, SVR lacks the ability to represent uncertainty in

predictions and estimates RUL by predicting the point in time when predicted degradation exceeds the threshold limit.

- For the development of prognostic algorithms, one of the primary challenges is identifying, or inferring, an appropriate signal of interest, for quantifying the current level of equipment degradation and for use in predicting equipment RUL. To track the evolution of an identified fault indicator over time requires that the operating conditions at which times the fault indicator is evaluated are consistent. In this way, the only issue which can be responsible for changes in the value of the fault indicator is equipment degradation, thus enabling the evolution of the degradation process to be tracked and forecasted accurately.
- In steam turbines, vibration signals represent the overall health of the system. These signals are used to monitor the degradation of the steam turbine to detect the changes in performance and to indicate the need for inspection/maintenance. Thus, vibration signal (i.e. HP displacement) that represents degradation is forecasted for RUL estimation of the steam turbine. However, there is a large uncertainty associated with the signal as it gets corrupted with noise due to various reasons, including steam turbine design, manufacturing, operating condition, maintenance actions, etc. Large uncertainty in the data causes inconsistency in prognostic predictions, especially when there is little data available.
- The implementation of BLR and SVR show varying performance due the inability of the techniques to distinguish between short-term and long-term behaviours. The operating conditions of the plant affect the performance of the algorithm. Therefore, for further validation, a synthetic case study is used. The synthetic data of known properties, which mimics degradation data with constant noise level, is generated. This methodology is very effective to validate the performance of the developed algorithms, because it shows that the technique is capable of producing early RUL prediction.
- In steam turbine degradation, most of the degradation is nearly linear, however there are cases where the rates of degradation may be non-linear. In the second case, the engine performance may degrade at approximately constant rate for a period of time, followed by a decrease in rate or the level of degradation. This occurs when steam turbine performance returns due to maintenance action.

Maintenance actions introduce variation within the degradation parameters that are being monitored for condition monitoring. Therefore, for accurate prognostics, knowledge of maintenance actions which affect the rate and state of degradation is crucial.

- To detect and accommodate maintenance actions, two integrated prognostic (i.e. probabilistic and non-probabilistic) approaches that utilise CPD algorithm are proposed. The CPD algorithm helps identification of maintenance events. The information from CPD algorithm is utilised accordingly. For probabilistic algorithms, prior parameters can be reset or reconfigured when a maintenance event is detected. Whereas, for a non-probabilistic prognostic algorithm synthetic historic data based on model prior to the maintenance is used to inform the prognostic algorithm. The Adapted-BLR and Adapted-SVR proves to be promising to be applied in prognostics as they enhance the quality of RUL estimation and the performance of prognostics algorithms by accommodating maintenance into prognostics as shown by the implementation results.
- The implementations of the Adapted-BLR and the Adapted-SVR resulted in RUL estimations with prognostic gain using fewer data points. For instance, using 5 data points of the post-maintenance data of the real-world case study, the Adapted-BLR produced RUL estimation of 42 days compared to the BLR which estimated the RUL of 14 days. Thus, resulting in the prognostic gain of 28 days. This information can be used by maintenance engineers to schedule maintenance while maximising the utilisation of the asset and to avoid loss of RUL through early scheduling of maintenance.
- The analysis and comparison of the adapted algorithms shows that Adapted-BLR has considerable advantages over Adapted-SVR. The Adapted-BLR is a better prognostic technique that is capable of accommodating maintenance at less computational cost. It provides means to track uncertainty in model, predictions, and RUL estimations. It becomes more reliable when more data points are available for estimations and when variation in data is low.
- In a dynamic operational environment, the deterioration process of a machinery can be affected by different factors like engineering variances, failure modes, environmental and operating conditions. The data acquired from such machinery are usually noisy and subject to high level of uncertainty / unpredictability, and

estimation of RUL is usually a hard task. Therefore, for accurate prognostics, these factors must be addressed along with the inclusion of maintenance effects in order to encounter uncertain inputs, engineering variations, etc., and to meet industrial constraints and requirements. Nevertheless, this research work is a step ahead in PHM domain toward maturity of prognostics.

8.2. Future Work

The industrial partner for whom the technologies are developed have expressed their desire to take this work forward and are actively involved in investigating avenues for future research, in partnership with academic institutions. There are several ways the work conducted in this project could be developed and taken forward. This section provides several suggestions for future works:

- Uncertainty due to variable operating conditions can greatly affect the reliability and implementation of prognostics in the real world. Thus, current and future operating conditions should be used as inputs for prognostics, and this topic needs to be further explored.
- In the steam turbine's case, the vibration data represents degradation. However, the supplied vibration data is very noisy and does not always show monotonic increase. As a result, the developed prognostic approaches are subject to large uncertainties when estimating RUL which leads to difficulty in decision making for maintenance. Therefore, either utilising better representative signal or multiple signals representing degradation could help prognostic algorithms perform better.
- To reduce the computational complexity and cost of SVR different optimisation algorithms, difference sizes of training datasets, implementation approaches such ensembling models, etc. can be considered to improve the performance of SVR.
- To deal with the uncertainty, SVR can be implemented in Bayesian probabilistic framework (i.e. PSVR) in order to estimate error bars along with the predictions.
- Implement adapted prognostic techniques using other case studies such as Li-Ion Batteries [156], Bearings [157], Turbofan Engine [158], etc. to further validate the performance of the techniques.
- Implement adapted prognostic techniques using synthetic data with varying level of noise.

- Extend prognostic implementation by implementing latest prognostic techniques such as Recurrent Neural network with Long Short-Term Memory (LSTM) [159] or Temporal Convolutional Network (TCN) [160] for multi-step forecasting while comparing the performance of the technique with the existing prognostics implementation.
- The ground truth data is very crucial to produce true failure-time data as well as an appropriate algorithm validation. In this work, based on consultation with industrial peers and expert matters, linear regression method is applied to the vibration data and it assumes the mean of the regression model as the "expected ground truth". Nevertheless, this practice does not have a strong scientific foundation. Specific research in determining ground truth is strongly required, where the ground truth is rarely available in many situations, especially in a complex system such as steam turbines.
- The formal evaluation and selection process helps identify suitable prognostic techniques. The method is extendable and more prognostic metrics can be included to further enhance the selection and evaluation process. A metric such as cost-benefit ratio can be included in order to help practitioners understand and assess the adoption and application of prognostic algorithms.

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