CAXTON OKOH

A FRAMEWORK DEVELOPMENT TO PREDICT REMAINING USEFUL LIFE OF A GAS TURBINE MECHANICAL COMPONENT

SCHOOL OF AEROSPACE, TRANSPORT AND MANUFACTURING
Manufacturing Department

DOCTOR OF PHILOSOPHY, PhD
Academic Year: 2013 - 2017

Supervisors: Professor Rajkumar Roy, Professor Jörn Mehnen
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This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

ABSTRACT

Power-by-the-hour is a performance based offering for delivering outstanding service to operators of civil aviation aircraft. Operators need to guarantee to minimise downtime, reduce service cost and ensure value for money which requires an innovative advanced technology for predictive maintenance. Predictability, availability and reliability of the engine offers better service for operators, and the need to estimate the expected component failure prior to failure occurrence requires a proactive approach to predict the remaining useful life of components within an assembly.

This research offers a framework for component remaining useful life prediction using assembly level data. The thesis presents a critical analysis on literature identifying the Weibull method, statistical technique and data-driven methodology relating to remaining useful life prediction, which are used in this research. The AS-IS practice captures relevant information based on the investigation conducted in the aerospace industry. The analysis of maintenance cycles relates to the examination of high-level events for engine availability, whereby more communications with industry showcase a through-life performance timeline visualisation. Overhaul sequence and activities are presented to gain insights of the timeline visualisation.

The thesis covers the framework development and application to gas turbine single stage assembly, repair and replacement of components in single stage assembly, and multiple stage assembly. The framework is demonstrated in aerospace engines and power generation engines. The framework developed enables and supports domain experts to quickly respond to, and prepare for maintenance and on-time delivery of spare parts.

The results of the framework show the probability of failure based on a pair of error values using the corresponding Scale and Shape parameters. The probability of failure is transformed into the remaining useful life depicting a typical Weibull distribution. The resulting Weibull curves developed with three scenarios of the case shows there are components renewals, therefore, the remaining useful life of the components are established. The framework is validated and verified through a case study with three scenarios and also through expert judgement.

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PUBLICATIONS

Publications that contributed to this research

i. Okoh, C., Roy, R., and Mehnen, J. (2017), Predictive Maintenance Modelling for Through-Life Engineering Services, Procedia CIRP. The 5th International Conference on Through-life Engineering Services. DOI: 10.1016/j.procir.2016.09.033 https://www.sciencedirect.com/science/article/pii/S2212827116309726

ii. Okoh, C., Roy, R., and Mehnen, J. (2017), Maintenance Informatics Dashboard Design for Through-Life Engineering Services, Procedia CIRP. The 5th International Conference on Through-life Engineering Services. DOI:10.1016/j.procir.2016.09.019 https://www.sciencedirect.com/science/article/pii/S2212827116309532

iii. Okoh, C., Roy, R., Mehnen, J. and Redding, L., and Harrison, A. (2014). Development of an Ontology for Aerospace Engine Components Degradation in Service. 6th International Conference on Knowledge Engineering and Ontology Development, Rome, Italy. DOI: 10.5220/0005090201080119 https://www.researchgate.net/publication/280300563_Development_of_an_Ontology_for_Aerospace_Engine_Components_Degradation_in_Service

iv. Okoh, C., Roy, R., Mehnen, J. and Redding, L. (2014), Overview of Remaining Useful Life Prediction Techniques in Through-life Engineering Services. Procedia CIRP, vol.16, pp. 158-163. The 6th CIRP Conference on Industrial Product-Service Systems. DOI: 10.1016/j.procir.2014.02.006 https://www.sciencedirect.com/science/article/pii/S2212827114001140

v. Roy, R., Mehnen, J., Addepalli, S., Redding, L., Tinsley, L. and Okoh, C., (2014). Service Knowledge Capture and Reuse. Procedia CIRP, 16, pp.9-14. The 6th CIRP Conference on Industrial Product-Service Systems. DOI: 10.1016/j.procir.2014.03.001 https://www.sciencedirect.com/science/article/pii/S2212827114000869

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive–moving-average
BBN	Bayesian Belief Network
CBM	Condition-Based Maintenance
CDF	Cumulative Distribution Function
CI	Computational Intelligence
EPSRC	Engineering and Physical Science Research Council
ETTF	Estimated Time To Failure
EUL	Expected Useful Life
FMEA	Failure Modes and Effect Analysis
FRACAS	Failure Reporting, Analysis, and Corrective Action System
GE	General Electric
GET	Generic Enumeration Technique
GOT	Generic Optimisation Technique
HMM	Hidden Markov Model
HP	High Pressure
IP	Intermediate Pressure
IPSS	Industrial Product Service Systems
ISO	International Organisation for Standardisation
LP	Low Pressure
LSM	Least Square Method
MAE	Mean Absolute Error
MIR	Master Index Representation
MLE	Maximum Likelihood Estimate
mR	Mean Rank
MR	Median Rank
MRO	Maintenance Repair and Overhaul
MSE	Mean Square Error

NGV	Nozzle Guide Vane
OEM	Original Equipment Manufacturer
PDF	Probability Density Function
PHM	Prognostics and Health Management
PLM	Product Life Cycle Management
PoF	Probability of Failure
PSS	Product Service Systems
RCM	Reliability Centred Maintenance
R-Cube	Rejected, Replaced and Reused
RMSE	Root Mean Square Error
RR	Rolls-Royce
RT	Recognition Tool
RUL	Remaining Useful Life
SATM	School of Aerospace, Transport and Manufacturing
SCDF	Symmetric Cumulative Distribution Function
SMC	Sequential Monte Carlo
SVM	Support Vector Machine
TBC	Thermal Barrier Coating
TES	Through-life Engineering Services
TGO	Thermally Grown Oxide
TPM	Through-life Performance Model
WLC	Whole Lifecycle Cost
WTPPM	Weibull Through-life Performance Prediction Model

LIST OF SYMBOLS

Meaning	Symbols
Characteristic life (cycles), Scale; Eta	η
Coefficient of Variance	CoV
Confidence Coefficient	$Z_{a/2}$
Confidence level	$\mathrm{L_{Confidence}}$
Failure times / time to failure	$\mathrm{t_i}$
Inspection/overhaul time	$\mathrm{T_{inspect(i)}}$
Mean	$\bar{\mathrm{t}}$
Mean Absolute Error	$\bar{\mathrm{E}}$
Median Rank	MR
Number of Cumulative Rejected Components	$\mathrm{N_{ARej\_comp(t_i)}}$
Number of Previous Rejected Components	$\mathrm{N_{ARej\_comp(t_{i-1})}}$
Number of Reused Components	$\mathrm{N_{Rem\_comp(t)}}$
Number Replaced at this Overhaul	$\mathrm{N_{Rep\_comp(t)}}$
Number Replaced at this Overhaul Remaining	$\mathrm{N_{Rej\_comp(t)}}$
Observed values	$\mathrm{V_i}$
Predicted values	$\hat{\mathrm{V}}_\mathrm{i}$
Previous /start time	$\mathrm{T_{inspect(i-1)}}$
Rejection/Failure Rate	$\mathrm{F(t)}$
Remaining useful life	T_{RUL}

Sample size	N
Slope, Shape, Beta	β
Standard Deviation	σ
Sum of Squared Error	E
Total number of components After Replacement	$N_{comp(t)}$
Total number of components at Start	N_{comp_to}

1 INTRODUCTION

The 21st century has seen the rise of manufacturers of complex engineering systems provide services of their manufactured products offered to operators – servitisation (Ren and Gregory, 2007; Baines *et al*, 2009; Cheng and Johansen, 2016; Probst *et al*, 2016; Spring and Araujo, 2017). Spring and Araujo (2017) provide insight into diverse forms of servitisation as a process of own it, use it, maintain it and dispose it by incorporating circular economy perspective where products are leased, shared, refurbished, disassembled for different components to be recycled and reused. Product-oriented and use-oriented models, rethinking repair and circular economy are performance offerings of servitisation. Cheng and Johansen (2016) opine servitisation creates competitiveness in the manufacturing space. Ren and Gregory (2007) define servitisation as a transformation strategy whereby manufacturers embrace service orientation, thereby creating better services with the sole purpose of satisfying the needs of the customers, gain competitive advantage and improve organisations' performance.

Probst *et al* (2016) note that service maintenance contracts are increasing because manufacturers are changing their business models from product-makers to product-as-a-service providers. The concept offers added value to products and utilises advance technologies - big data, analytics and the cloud are supporting services such as predictive maintenance for costs reduction and increase efficiency. However, policy-makers can integrate services into manufacturing to support servitisation efforts by delivering collaboration and knowledge platforms to create matchmaking opportunities amongst companies. It provides access to skilled personnel with expertise in the field of IoT, analytics and big data. The concept makes ware of value proposition of predictive maintenance services for growth of businesses. Furthermore, innovation in the supply chains of companies in the nineteenth-century had led to the servitisation modernisations in the twenty-first century, whereby companies provide services bundled with goods and controlled by the same company (Schmenner, 2009).

Innovative servitisation establishes the advent of fusing products and services in the supply chain of large corporations as a competitive strategy, i.e. adding value by adding services to products e.g. Rolls Royce. While “TotalCare” provided the most cost effective, risk-mitigated engine maintenance plan to optimise the support and meet the customer’s operational, maintenance, and administration requirements, “Power-by-the-hour” set in the 1960s aligns the interests of the manufacturers to the operators, who only pay for engines’ operational performance on a fixed-cost-per-flying-hour (Rolls Royce, 2016).

Servitisation is an innovative approach used in industrial product-service systems (IPSS), whereby downtime with associated costs are assessed by applying through-life engineering services Roy *et al* (2013); Redding *et al* (2015); Uhlmann *et al* (2015); Wilkinson *et al* (2009); Addepalli & Tinsley (2015); Farnsworth *et al* (2015); Van Dongen (2015) in the aerospace, automotive, energy, industrial machinery, oil and gas refineries, logistics, maritime, and health care industries.

A through-life engineering services approach referred to as predictive maintenance discussed in chapters 2 and 6 will be introduced to reduce downtime issues, associated costs and spare parts inventory management prompting industry operators and manufacturers to pay attention to Condition-Based Maintenance. Although, the components in-service may fail to perform due to their design specifications, manufacturing processes or through-life use leading to major challenges. These components failures lead to downtime requiring urgent maintenance. The maintenance strategies include corrective and preventive maintenance discussed in section 2.5 of chapter 2. The maintenance strategies affect operations, life cycle cost and downtime. In addressing these challenges, the predictive maintenance strategies known as Condition-Based Maintenance (CBM) and Reliability-Centred Maintenance (RCM). Predictive maintenance strategies are facilitated by the engagement of Through-life Engineering Services (TES) capabilities. Through-life Engineering Services can be described as the ability of creating high-value engineering services based on design and manufacturing aimed at whole life cycle cost for better maintenance decision-making.

This research aims to understand component degradation in a broad context with a focus on predicting the remaining useful life of a component within an assembly. A component degrades because of in-service of complex degradation mechanisms. The design and manufacturing information require investigating in-service components and maintenance histories of the level and nature of the damage. While diagnostics detect the type of the damage, prognostics predict the time whereby a component can no longer perform its designed function.

This applied research seeks to improve the through-life performance knowledge by addressing the issues regarding degradation of assets and predicting their remaining useful life, which are running concurrently and partially repaired with different overhaul times. Difficulty getting appropriate data for modelling and predicting remaining useful life of a component based on assembly data has led to developing a proposed framework for this research.

This chapter gives an overall background of the research. The introductory chapter presents the motivation and scope of the Thesis in Section 1.1. Section 1.2 highlights the problem definition. Section 1.3 gives a list of the research questions. Section 1.4 focuses on the research sponsors. Section 1.5 presents the Thesis structure and Section 1.6 is a summary of this chapter.

1.1 Motivation and scope

Remaining useful life prediction is a growing research field involving techniques from reliability engineering, time series analysis, computational intelligence and regression modelling of assets (Rausand and Høyland, 2004; Majidian and Saidi, 2007; Pecht and Jaai, 2010). Industrial product-service systems are complex engineering systems which include gas turbines, power trains, machine tools and wind turbines.

While gas turbine made of a three-shaft-design is produced by Rolls Royce (RR), a two-shaft-design is manufactured by General Electric (GE). The research aims to investigate degradation mechanisms on a feature of a component/commodity for a specific high-pressure turbine stage one assembly/system of a particular product/engine shown in Figure 1-1.

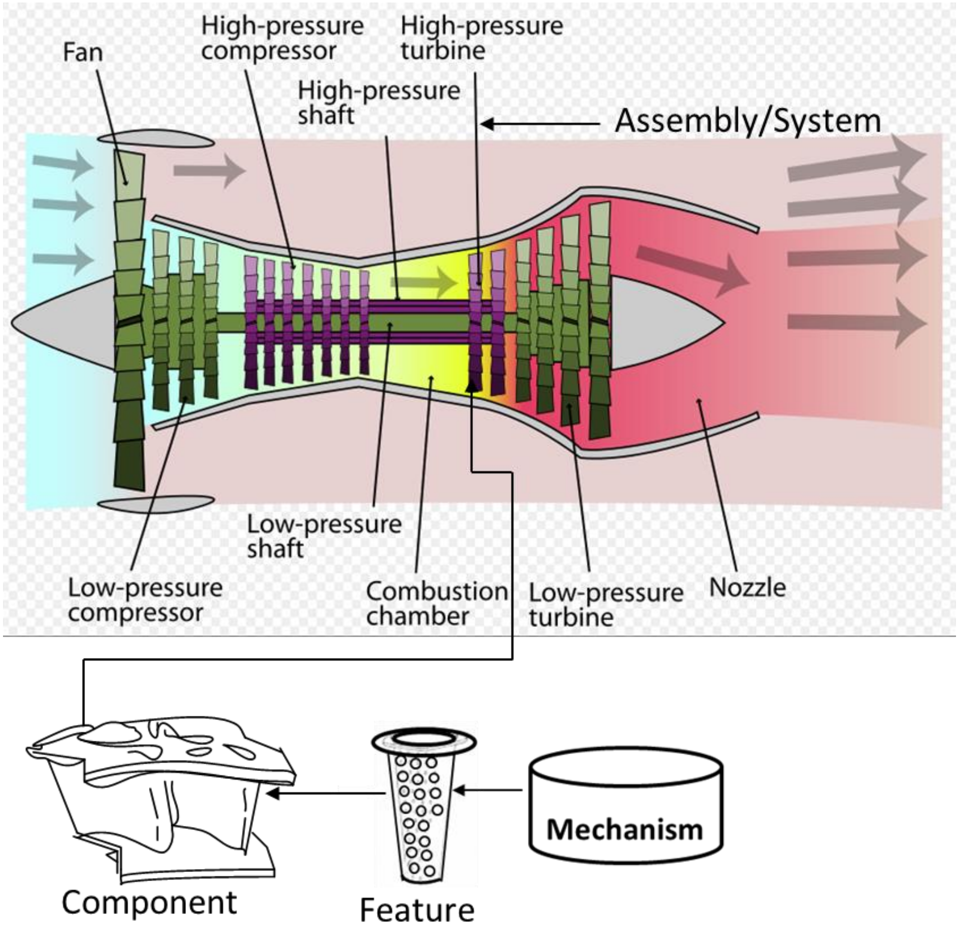


Figure 1-1: A schematic relationship hierarchy

The complex engineering system contains a number of concurrently working multi-component. The multi-component is a collection or group of components such as nozzle guide vanes (NGVs), turbine blades, and compressor fan blades in a gas turbine that degrade by different failure modes. Degradation creates a need for maintenance of a complex engineering system. Failure modes such as corrosion, erosion, oxidation, microstructural change and wear are present in a gas turbine. The gas turbine operating firing temperature of the hot section is 1371^{0}C (Boyce, 2006).

The mechanical component under investigation is High-Pressure Nozzle Guide Vanes (HP-NGV), which is affected by environmental effects, operational component stress, design and manufacture effects (Boyd-Lee *et al,* 2001; Boyce, 2006). The HP-NGV is a family of the turbine component, manufactured from Nickel superalloys and covered in thermal barrier coating (TBC). The TBC is thermal protective ceramic top coat called Yttrium-stabilized zirconia (O'Donnell *et al,* 2017; Lashmi *et al,* 2017). The TBC is high temperature resistance ceramic. A bond coat alloy is deposited on the Nickel substrate to improve TBC adhesion. A thermally grown oxide (TGO) acts as a diffusion barrier, which protects the superalloy from oxidation corrosion (Fukuchi *et al,* 2017; Zhao *et al,* 2017). The temperature is far more than the melting point of foremost Nickel-based alloys. The components deteriorate by corrosion, cracks, damage to the TBC, wear and fatigue. This degradation results from low-cycle fatigue and high-cycle fatigue operating conditions. The degradation mechanisms cause damage to mechanical components of a gas turbine. The purpose of the NGV is to guide accurate thermal flows between their casing mounts (Rolls Royce, 2005). It also maintains effective air seals to protect the gas path and cooling air system from leakage (Rolls Royce, 2005).

In complex engineering systems, prognostic and health management (PHM) is still rare and gradually gaining ground (Balaban *et al*, 2015). In CBM, PHM supports the predictive maintenance strategy to minimise system life cycle losses and life cycle costs (Liao *et al,* 2012). The predictive maintenance aids cost saving over traditional maintenance. Furthermore, predictive maintenance provides proper planning for corrective maintenance to avoid sudden system failures. The development and deployment of remaining useful life prediction frameworks is challenging, hence, the need for a prognostics approach.

The statistical model is required for the prognostics approach, which accepts component life data, overhaul inspection values and the number of components at start, to estimate components rejected, replacement and reuse (R-Cube). A sequence of the state transition (overhaul times) is engaged in calculating the frequency of components replacement. Therefore, the motivation for this research is to develop an alternative approach to remaining useful life prediction of a component based on assembly level data. This approach is necessary for aerospace and defence companies where critical components are found. The failure data are collected at the assembly level. Assembly level components are replaced after a fixed number of used cycles irrespective of their actual health.

1.2 Problem definition

Designers estimate life at the design stage and need realistic basis for the assumptions with the presence of assembly level failure data, but with no trace of component level records. The research provides an approach to convert observed rejection (historical) data into rate of component degradation towards a rejection threshold by modelling the through-life performance to estimate the number of rejections (number of degraded components), replacement (new components) and reuse (existing component). This approach back-fits an observed rejection rate and obtained estimated rejection rate as an error calculation to the initial characteristic life and slope values. The characteristic life and slope values are further applied to predict the remaining useful life of a component in an assembly. Examples of where failure rates are usually collected at the assembly level and not at the component level are marine and industrial engines applications where durability, availability and reliability are of utmost significance.

A model-based (physics-based) model is hard to construct for a complex system to collect degradation data (Brotherton *et al*, 2000; Bolander *et al*, 2010). However, the data-driven model seems appropriate for only assembly level failure data. The research focuses on the components at assembly level because there are no available data at an individual component level. The logical relationship of the mechanism, component/commodity system/assembly and product is shown in Figure 1-2. The purpose of Figure 1-2 signifies the AS-IS current state analysis of historical data to determine nature and level of degradation mechanisms, feature of the component with failure, the component/commodity of the system/module and the system of the product/engine. The TO-BE side implies the proposed component failure and RUL prediction which relate to the engine and components. Damage is assumed to be present in the component, hence, the use of reliability model and no need to show features and damage mechanisms.

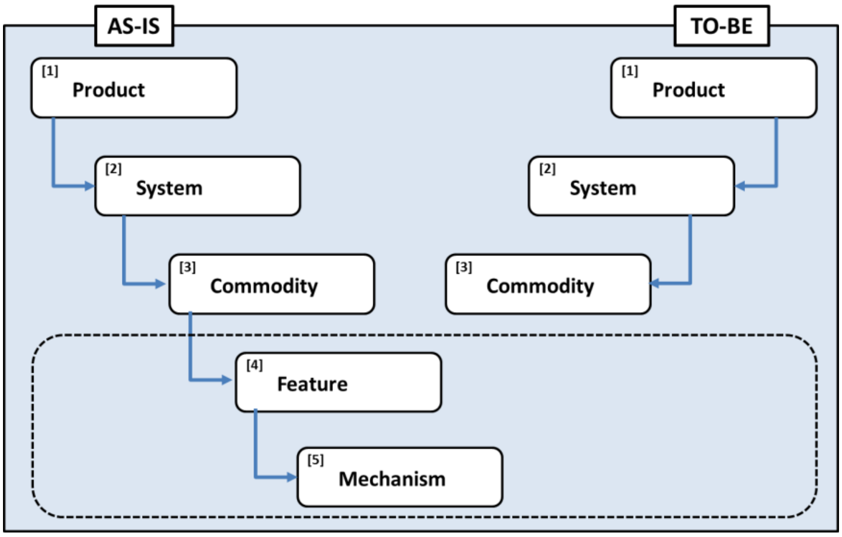


Figure 1-2: Relationship process for existing and proposed scenario

The mechanism and feature phases are assumed and built-in in the degradation model for the component. While the AS-IS depicts the traditional maintenance strategy, the TO-BE relates to the predictive maintenance strategy. In the current practice discussed in chapter 4, the method for analysing component degradation consumes time, reduces the reporting time of spare parts inventory, extends engine downtime and increases manpower cost. There is a difficulty in evaluating documented degradation mechanisms. It is hard to decide when to scrap the entire components in an assembly. In the current practice, it can be difficult to know the expected number of components to be rejected within an assembly until a traditional maintenance assessment is conducted. However, in addressing this challenge, a prognostication approach known as a predictive maintenance strategy is recommended (Rausand and Høyland, 2004). The predictive strategy uses historical and current health data to estimate impending rejections for scheduled maintenance. This predictive strategy is referred to as prognostics and health management in condition-based maintenance.

1.3 Research questions

The research questions are derived from the motivation of the research and problem definition. The research questions reflecting the information in Section 1.1 include:

i. How do we identify, analyse and derive relevant degradation information from service history data sets for the prediction of the remaining useful life a component in an assembly?
ii. How do we evaluate and fuse the identified degradation variables and parameters from disparate sources to assess through-life performance using assembly level data to predict the remaining useful life of a component?
iii. How do we validate the developed framework of through-life performance model systematically for component degradation and remaining useful life prediction?

1.4 Research sponsors

Through-life Engineering Service (TES) Centre

The Through-life Engineering Services (TES) Centre is an Engineering, Physical, Science, and Research Council (EPSRC) Centre for Innovative Manufacturing. The centre is a £15M National Centre which include a £5.7M from EPSRC – grant number EP/I033246/1. The centre conducts world-class research to support manufacturing industries in the UK. The TES centre supports UK manufacturing sector with through-life engineering services for customers worldwide. The centre delivers high value products with predictability, availability and reliability through companies and their supply chain to improve competitiveness with lowest life-cycle costs. The centre (TES Centre, 2013) creates advance and innovative capabilities to: develop technology and processes to improve design and manufacturing for engineering services; reduce whole life cost of high-value products; improve knowledge on interaction amongst electronics, mechanical and software systems; create innovative and potentially disruptive strategies; and expand regenerative manufacturing. The centre aims to conduct state-of-the-art research in maintenance and installation costs reduction, and advise using robotics systems for maintenance, repair and overhaul.

Rolls Royce (RR)

Rolls Royce is a distinguished engineering organisation and worldwide provider of state-of-the-art power and propulsion systems. The systems are manufactured for use on land, at sea and in the skies. The company's operating domain covers aerospace (civil and military), nuclear, energy, marine and services. The company provides maintenance, after sales support, delivery and engine disposal to shipping, logistics, military and airlines for passenger carriers. The company operates a business-to-business model of operation. Examples of engines for civil aviation wide body and narrow body aircraft are Trent 700, 900, 1000 and XWB.

The company offers performance-based business model to ensure engines have prolonged life through innovative and effective maintenance, repair and overhaul, thereby improving durable design. Its business performance model delivers power-by-the-hour showing the essence of circular economy for resources efficiency and long-term sustainability, by selling cycles of flight service. This business performance model is used for civil aerospace wide and narrow body aircraft – Boeing 787 and Airbus A380. The company offers material sustainability strategy through its diverse manufacturing facilities to support spare parts management. Components are manufactured from about 20,000 tons of super alloys metal materials annually. The company reprocesses 90% -100% of titanium and nickel super alloys captured from machining gas turbine materials (Kiser *et al,* 2016). The innovative design and advanced service operations improve performance and reduce whole life-cycle costs (Rolls Royce, 2005).

The company's overhaul activities begin on-wing in-service diagnostics using advanced engine health management practice to identify anomalies. This can lead to further investigation of the engine being taken off the aircraft – off-wing for further overhaul activities including repair of components and replacement.

Rolls Royce an Original Equipment Manufacturer (OEM) has a matchless understanding and knowhow in repair and overhaul of gas turbine engines. These repair and overhaul are conducted in facilities around the world, which include Ansty, Bristol, Montreal, Oakland California and Oberursel in Germany (Rolls Royce, 2017).

1.5 Thesis structure

This chapter discusses the research context, motivation and scope, problem definition and research questions. Figure 1-3 illustrates the layout of this Thesis.

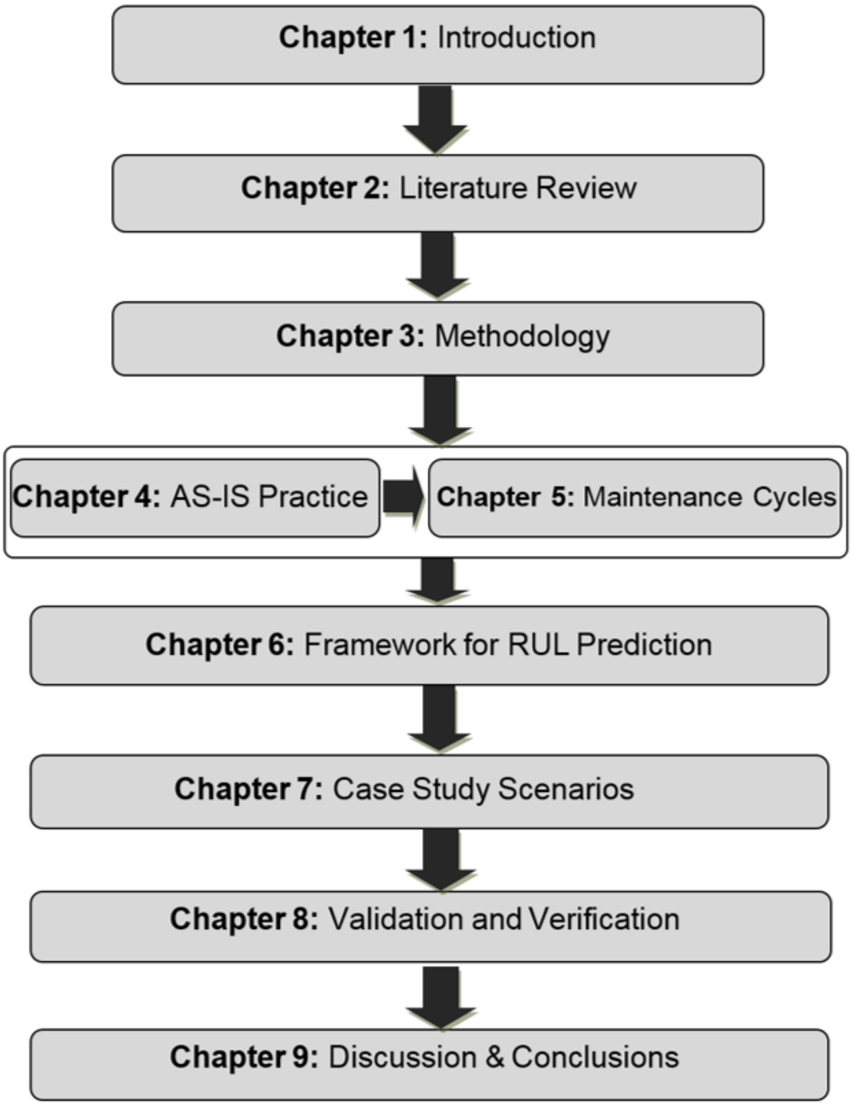


Figure 1-3 Thesis structure

Chapter 2 reviews the literature with respect to remaining useful life prediction methods, techniques and methodologies. This chapter focuses on the specific methodologies; techniques and methods applied in achieving the aim of the research. Other areas covered in this chapter include through-life engineering services, degradation mechanisms, taxonomy and ontology, timeline visualisation of events, an overview of maintenance strategies, renewal theory, parameter estimation, performance metrics and remaining useful life models.

Chapter 3 highlights the aim, objectives and a systematic approach to the scientific research methods applied. Chapter 3 further discusses the methodology, rationales and the scientific research approaches used in this Thesis. The adopted methodology implemented in this research is presented.

Chapter 4 examines and analyses the current (AS-IS) practice on the level and nature of component degradation from a traditional maintenance perspective. Chapter 4 discusses the relationship of the product, system, commodity, feature and mechanism about the service history and current health degradation information. In this context, taxonomies were automatically extracted using terminology recognition and relationship extraction techniques to show a hierarchy of relationship representation and the number of components, features and mechanisms.

Chapter 5 presents an extension from the investigation of the degradation mechanisms taxonomy to events taxonomy to generate an ontology of events relating to multiple engines and multiple overhauls states. The investigation and analysis show the multiple maintenance cycles on a timeline for events visualisation. Furthermore, overhaul sequence and activities are outlined.

Chapter 6 demonstrates prognostic through-life modelling based on knowledge acquired in chapters 4 and 5 to create a generic framework for predicting the remaining useful life of components. The framework outlines the through-life performance of component degradation based on the renewal theory from an actuarial perspective. The pre-processed data were used to estimate the parameters of the Weibull function. The application of renewal theory was introduced in the model to calculate the number of R-Cube at each overhaul state. The through-life model distinctively and accurately forecasts the number of R-Cube components for the next overhaul transition state. The state transition approach utilises the expected R-Cube outcome at the failure time onto the next overhaul. A model evaluation using a back-fitting algorithm was produced using a performance metric to calculate the deviation accuracy of the initial parameters. The application of a cost variable was used to determine the time to replace the entire component assembly. The remaining useful life of the components is predicted using RUL methodologies, techniques and methods discussed in chapter 2. The through-life performance approach reflects on the research objectives and contributions to knowledge stated in Sections 3.1 and 9.2.1.

Chapter 7 discusses results of the framework developed in chapter 6 and the scenarios of a case study. Data-driven methodology, statistical technique and the Weibull method are implemented to analytically model the through-life performance of a set of components in an assembly. The case study scenarios include single stage, single stage repair replacement and multiple stage. The presented results of the case study scenarios are described.

Chapter 8 describes the validation and verification conducted with experts including analysis of the outcomes.

Chapter 9 presents discussions on the various chapters of this Thesis, contribution to knowledge and limitations, implementation challenges, future works and conclusions.

1.6 Summary

This chapter gives an overview of the research problem. The introduction presents the research background and highlights the relevant areas of focus in this Thesis. This chapter includes the motivation, rationale and scope, the research questions, research sponsors and overall structure of the Thesis sections. The next chapter presents the literature review, a research gap and relevant topics essential for this applied research project.

2 LITERATURE REVIEW

This chapter presents a detailed literature review regarding through-life engineering service, maintenance strategies, ontology and taxonomy, timeline visualisation, parameter estimation, modelling, performance metric, degradation and remaining useful life prediction methodologies. In this thesis, the remaining useful life prediction methods and techniques are categorised into methodologies and further discussed in detail. The merits and demerits of the prediction methodologies are highlighted as well as the challenges of current prediction models. Section 2.1 describes the methodology for the literature review. Section 2.2 deals with Through-life Engineering Service. Section 2.3 gives an overview of maintenance strategies. Section 2.4 described taxonomy and ontology. Section 2.5 discusses condition-based maintenance. Section 2.7 relates to visualisation. Section 2.8 gives evidence of parameter estimation. Section 2.9 highlights modelling approach. Section 2.10 describes application of renewal theory. Section 2.11 relates to performance metric. Section 2.12 discusses renewal of repaired components. Section 2.13 give a detail discussion of remaining useful life approaches. Section 2.14 highlights the research gaps. Section 2.15 summarises chapter 2.

2.1 Methodology

This research focuses on developing a technique for through-life performance modelling to predict the remaining useful life of a component within an assembly. Figure 2-1 presents the methodology for this chapter. The study is intended to capture the state-of-the-art research on remaining useful life prediction. Whilst conducting this research, the keywords were searched and discussed briefly are “through-life engineering service”, “maintenance strategies”, “ontology and taxonomy”, “timeline visualisation”, “parameter estimation”, “modelling”, “performance metric”, and “degradation”. The aforementioned keywords were used to establish the context of the research. However, the main aspect is the remaining useful life prediction approach was relevant and a thorough literature search and discussion were conducted in detail, and statistics about the outcomes presented in Figures 2-2, 2-3 and 2-4.

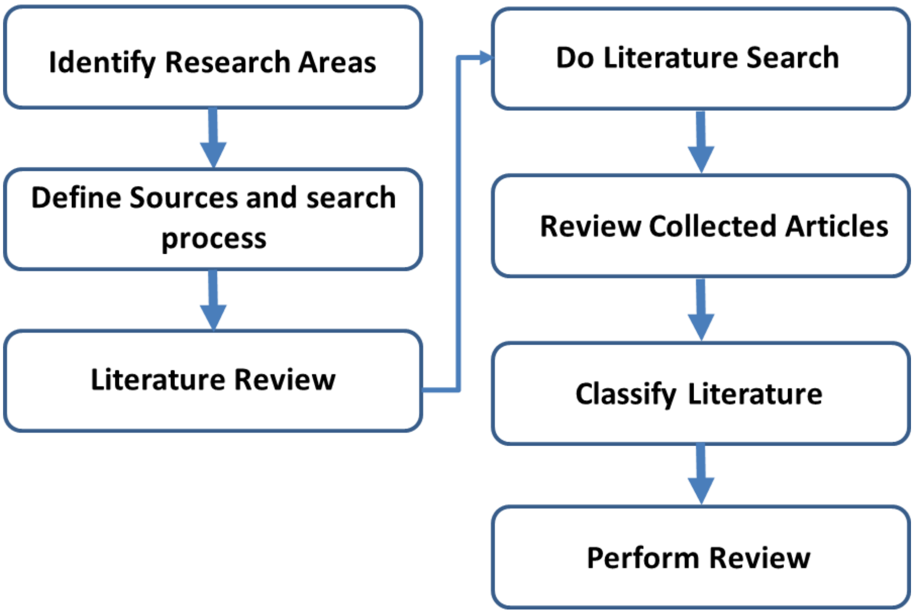


Figure 2-1 Literature review methodology

Content analysis is used as a research method to capture the current practice. The outcome is expected to support a proposed technique for remaining useful life prediction. Marasco (2008) note that content analysis relates to (a) defining the sources and procedures for searching of documents that should be analysed and (b) describing the categories instrumental to the classification of the documents collected. The extensive literature search covers articles from the years 2005 to 2015 as of 26th January 2016, (see Figure 2-3). The survey of literature was carried out using Scopus database and a total of 1,875 documents were analysed based on the remaining useful life keywords. Figure 2-2 shows a search result analysed and scaled down to centre on the pertinent documents.

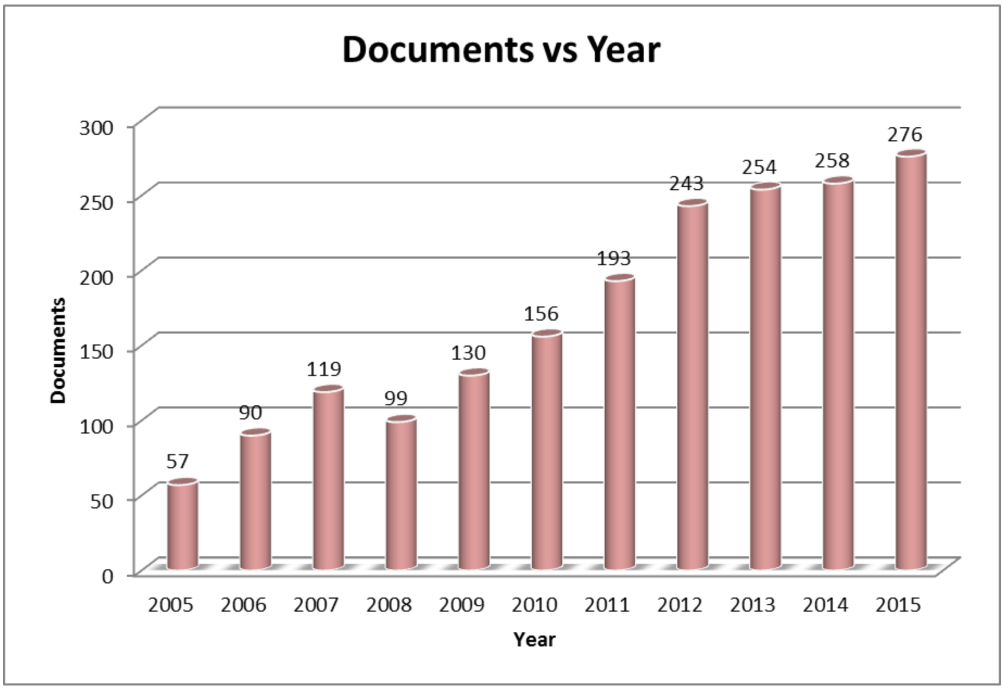


Figure 2-2 The number of literatures on RUL per year

Figure 2-3 shows the document counts of the authors, where Goebel, K., is the most prolific author in the field of remaining useful life predictions followed by Zerhounni, N., and Lall, P.

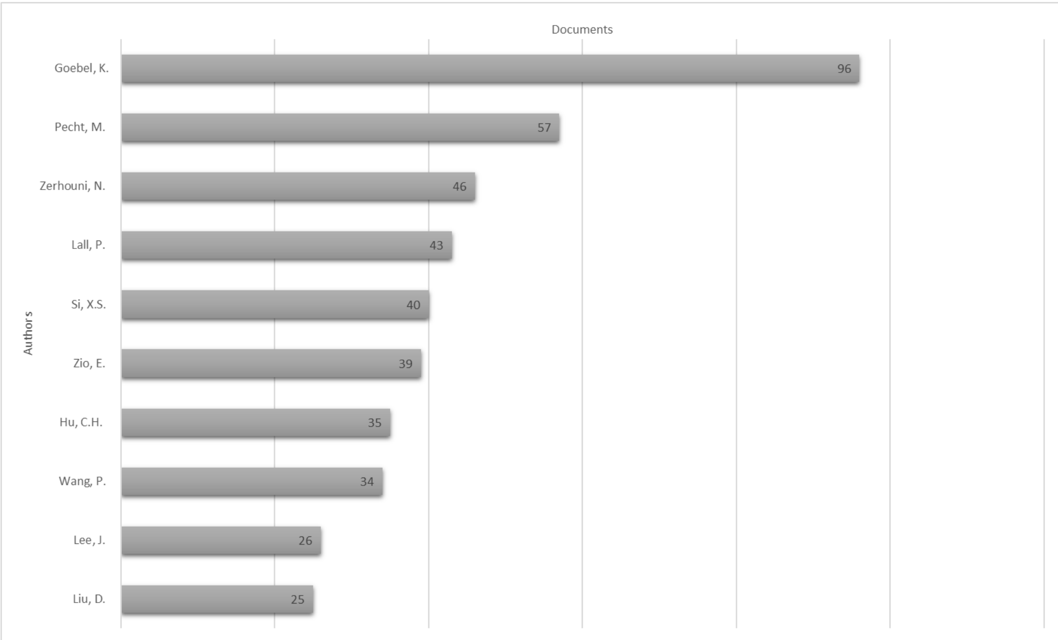


Figure 2-3: A comparison of documents by authors

However, the literature type and the literature presented as a pie chart show a variety of the documents. This pie chart shows conference papers are mostly written followed by peer reviewed journal papers (see Figure 2-4A). A note indicates a document from the Canadian Journal of Civil Engineering.

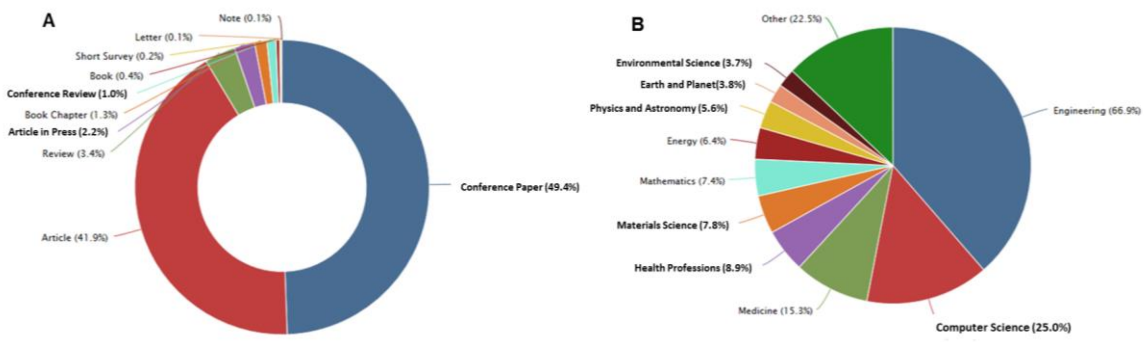


Figure 2-4: Comparative literature by (A) type and (B) subject area

Figure 2-4B shows that the engineering discipline engages mostly on this topic of remaining useful life research closely followed by the computer science field. These documents were reviewed and classified in line with their contents. The outcomes of the findings from the literature review inspired a provision of semi-structured interview questions for industry interaction (see chapter 4).

2.2 Through-life Engineering Services

Through-life Engineering Services (TES) concept is defined as technical services that are necessary to guarantee the required and predictable performance of an engineering system throughout its expected operational life with the optimum whole life cost (Roy *et al*, 2013). TES coordinates and provides the research capability for the creation of high-value engineering systems based on design and manufacturing. TES aims to improve the reliability, spare parts availability, maintainability and safety of products to deliver the lowest possible whole life cycle cost. TES assists in the transfer of best practices between different industrial sectors and extending the life of industrial goods (Roy *et al*, 2013).

However, TES can be suitable for all manufactured industrial product-service systems.

Through-life Engineering Services has themes that allow for maintenance, repair and overhaul functions to align with the operations strategy of an organisation. TES facilitates correct application of technology supported by the efficient use of service knowledge. Significant benefits obtained from accurate life prediction can improve MRO decision making (Farnsworth *et al*, 2015; Uhlmann *et al*, 2015). The simulation tools are used to adapt procedures, modular maintenance systems, and informed disposal decisions that facilitate the prediction of trustworthy life expectancy. Increasing the application of advanced information technology, Product Lifecycle Management (PLM) processes for distribution and collaboration, condition monitoring, and prognosis can significantly improve product availability, thereby reducing cost and downtime (Okoh *et al,* 2014). Degradation management is an aspect of TES and the maintenance of autonomous systems as well as the development of capabilities in a collaborative environment to enhance the lifespan of components. The concept of cost engineering provides a performance-based service approach and whole-life cost model, which applies to the full system maintenance and service delivery systems to deliver effective business solutions. The uncertainty modelling and simulation techniques based on technological and trade uncertainties are used to improve component/product designs. The concepts above and methodologies when supported by obsolescence management, service network for capability assessment and cost estimation have the potential to improve the design function greatly. As a result, there will be an improvement in quality, reliability, availability and safety while yielding feedback to manufacturers (Roy *et al*, 2013; Chopra *et al,* 2016; Morant *et al,* 2016; Zhang and Pham, 2016).

2.3 Degradation Mechanisms

The characterisation of in-service degradation mechanisms analysis requires knowledge of the properties of the titanium and nickel based super alloys which are candidate materials for gas turbine engines. The materials degrade over time at the high temperature associated with aircraft operations. The candidate material is the primary component manufactured for gas turbine engines. The degradation mechanisms which are predominant in metallic components are corrosion, deformation, fracture and wear (Zhu *et al,* 2013; Imran *et al*, 2014; Prozhega *et al*, 2014; Giourntas *et al*, 2016). There is a need to curtail component's failure and a timely awareness of failure mechanism is essential for maintenance decisions with regards to through-life engineering services (Farnsworth *et al*, 2015; Redding *et al*, 2015; Uhlmann *et al*, 2015; Van Dongen, 2015). The types of degradation mechanisms are further discussed in and applicable to chapter 4. Furthermore, the degradation processes discussed are hard to predict, hence, supporting the need for this research.

2.3.1 Corrosion

Corrosion is a chemical deterioration process resulting from an electrical or biological reaction, which includes oxidation and sulphidation (see Figure 2-5). Methods to measure corrosion rates include, for example, an electrochemical technique, which shows the speed at which reinforced steels are corroding and help identify degraded areas (Soleymani and Ismail, 2004; Prozhega *et al*, 2014).

Figure 2-5 Metal discs showing corrosion on the surface

2.3.2 Deformation

Deformation changes the geometry or shape of a component such as shrinking, stretching, bending, and twisting. They have cumulative effects upon strain in a component due to an applied force (Norman, 2013; Zhu *et al,* 2013). Aspects of deformation are time dependent and time independent mechanisms. In Creep deformation, the component gradually accumulates over time with the presence of high temperature and thermal cycles stress until the product fails (Norman, 2013; Zhu *et al,* 2013; Giourntas *et al*, 2016). Monte Carlo-based uncertainty technique, optical measurement systems, digital image correlation, the intensity method and phase shift method are often used for deformation measure (Gåsvik *et al*, 2014).

2.3.3 Fracture

Fracture is separation of a material by means of cracking or disintegration which makes a component incapable of performing its designed functions. It can occur as a result of chemical effects, shock and/or stress. This fracture failure mechanism occurs via loading which is independent of time (Norman, 2013). A slow change (creep) in structure can lead to fracture whereby the presence of crack can grow rapidly in steels and aluminium alloys as shown in Figure 2-6. Johnson and Cook (1985) indicate that fracture increases slightly as strain rate increases in copper, iron and steel using a fracture model, pressure - strain ratio is critical as well as temperature and stress rate.

Figure 2-6 Bearing external ring failure and inner ring failure with fracture (Source: (Medjaher *et al,* 2012)) (see appendix A for permission)

2.3.4 Wear

Wear – material loss over a period of time resulting from component use. The estimation of wear (or resistance to wear) can be achieved by implementing the weighting method to fix and measure wear. This wear failure mechanism can be calculated by weighting the component before and after use. The variables to consider include speed, friction co-efficient, surface finish/texture, surface hardness, load, the number of cycles, and time are all critical in estimating adhesion wear of metallic engine components (e.g. nickel based super alloys, brass, aluminium and steel) (Ameen *et al,* 2011; Zhu *et al,* 2013; Imran *et al*, 2014). This research submits that deformation, fracture, wear and corrosion can be measured to ascertain through-life perspectives of a component using a variety of methods relative to prognostics models.

2.4 Taxonomy and Ontology

Taxonomy involves non-similar words and broadly is a vocabulary, but a collection of controlled terms organised into hierarchical structure. The taxonomy extracted from a service maintenance repository for different degradation mechanisms include for example “fracture” with synonyms as crack, tear, and break (Uschold and Gruninger, 2004).

Ontology (Gruber, 1993) serves as a problem solving tool of the conceptualisation of entities (Maedche and Volz, 2001). The concepts and relations between them are used to reason and describe a domain knowledge. Ontology knowledge repository which may use taxonomy in a controlled vocabulary, but expressed in an ontology representation language by employing a grammar that shows something meaningful for a domain of interest. Ontology can be described as a recognised nomenclature and classification of the different word types, properties, and interrelationships, which are present in a specific domain, for example, aerospace. The ontology hierarchical arrangement represents a more natural means of information management in a unique domain. The content in the ontology aids the identification and retrieval of relevant keywords from sentences and reports based on subject, verb and object approach. The application and analysis are conducted in chapter 4 of this Thesis.

2.5 Overview of maintenance strategies

Brown and Sondalini (2016) describe maintenance as the management, control, execution and quality of activities to reasonably ensure design levels of availability and performance of assets meet business objectives. Maintenance is conducted using different strategies as presented in Figure 2-7. The maintenance strategies are listed and classified as a taxonomy with a focus on the selected strategies in the blue boxes (Rausand and Høyland, 2004).

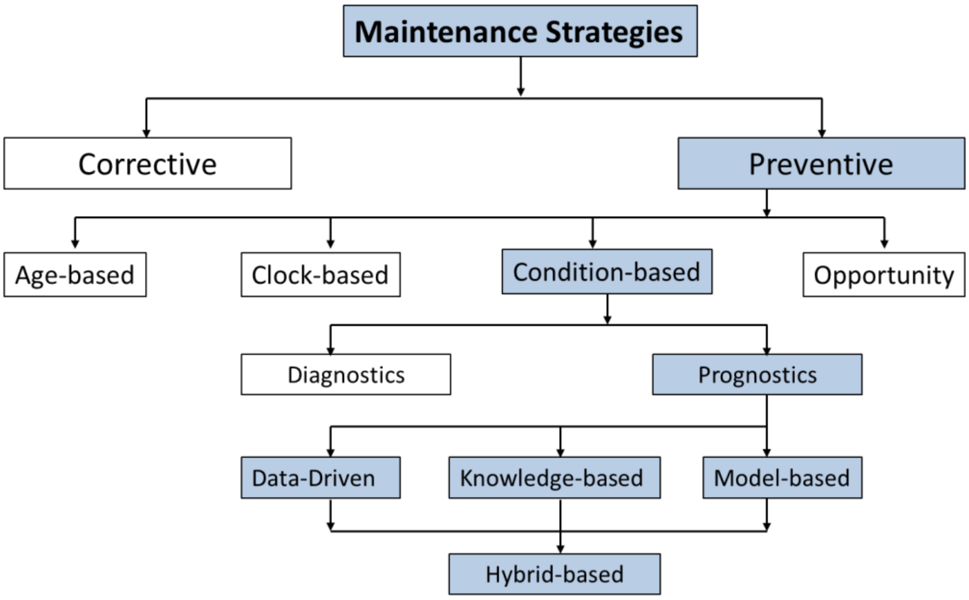


Figure 2-7 A proposed taxonomy of maintenance strategies

Corrective maintenance

Rausand and Høyland (2004) argue that corrective maintenance relates to repair tasks carried out after an asset has failed. Historically, the last sixty year since the second World War, the world has transformed the maintenance perspective (Brown and Sondalini, 2016). Corrective maintenance was the only viable option for engineers to fix or replace breakdown equipment. Though, corrective maintenance is still very much in use currently such as electric light bulbs. Corrective maintenance aims to bring equipment back to its functioning state (Rausand and Høyland, 2004).

Preventive maintenance

Rausand and Høyland (2004) describe preventive maintenance as a planned maintenance performed when an item is functioning properly to prevent future failures. The preventive maintenance strategy consists of age-based, calendar/clock-based, opportunity-based and condition-based. Age-based specifies the age of an asset measuring time in operation such as the number of take-offs and landings for an aircraft, while clock-based maintenance tasks are conducted at specific calendar times; a block replacement policy (Rausand and Høyland, 2004). In the special case, where the downtime due to maintenance and the downtime due to repair/replacement is negligible, the calendar-based and the age-based maintenance policies become alike (Tang, 2012). In practice, clock-based is easier to schedule compared to age-based. The former is less proficient than the latter from random maintenance scheduling before renewal (Tang, 2012). Opportunity maintenance – preventive maintenance applicable for multi-item systems where maintenance tasks on other items give an opportunity for carrying out maintenance, which were not the cause of opportunity (Rausand and Høyland, 2004). Pintelon and Gelders (1992) opine opportunity maintenance replaces equipment components, which are yet to fail based on available maintenance resources. This opportunity maintenance improves system availability and reduce production loss by reducing operations excellence and increases production efficiency (Borges, 2015). Condition-Based describes measurements of one or more condition variables of an asset, which are initiated when a condition variable passes a threshold (Rausand and Høyland, 2004). Rausand and Høyland (2004) state that condition-based is also known predictive maintenance, which determines the state of an in-service system to predict future maintenance when the need arises. The concept assesses the health condition of an equipment continuously and extrapolates to a predefined failure threshold (Camci and Chinnam, 2010; Eker *et al*, 2011). The condition-based maintenance is one aspect of focus in this research with further discussions presented in the next section.

2.6 Predictive maintenance

In the context of this Thesis, predictive maintenance and traditional/conventional maintenance are discussed. However, a predictive maintenance culture adopted for on-time decision making assesses the health of a component in-service before system failure. The predictive maintenance minimises system life cycle losses and life cycle costs. This predictive maintenance strategy can save cost over a traditional maintenance. It provides appropriate scheduling for a traditional maintenance to prevent unpredicted system failures. The advantages of predictive maintenance include optimisation of spare parts management, enhanced system lifetime, guarantees safety and availability of the system. The predictive maintenance strategy reduces the risk of tragic events, remove unexpected outage and minimise the cost of gas turbine components (Di Maio et al, 2011). Figure 2-8 shows a categorisation and the relationship of predictive maintenance as diagnostics and prognostics.

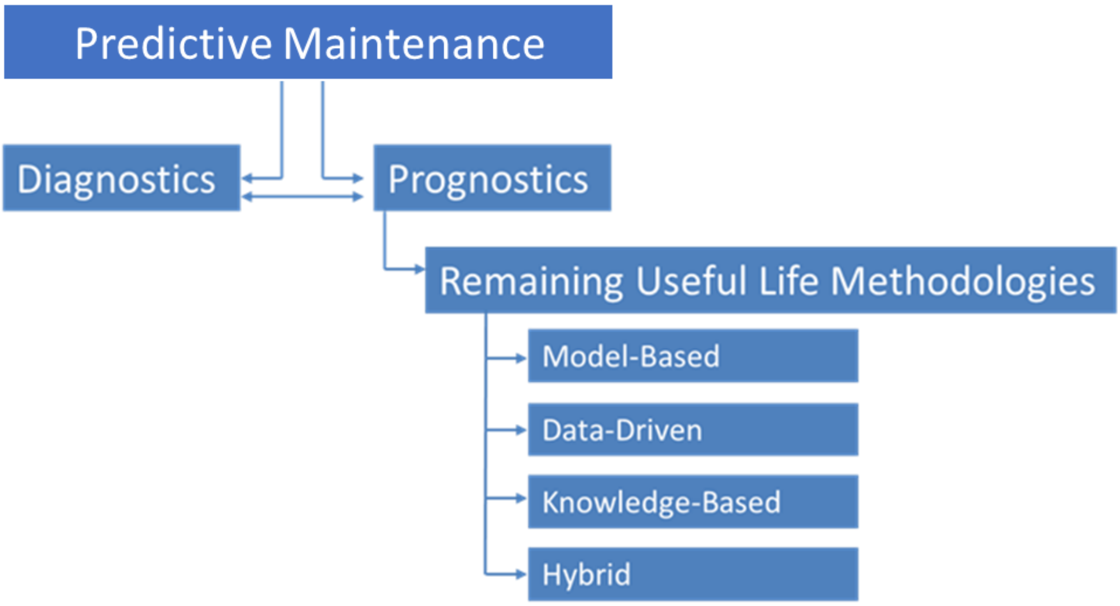


Figure 2-8: A taxonomy of condition-based maintenance

2.6.1 Component degradation diagnostics

Diagnostics is a process for checking faults and the healthy state of sub-systems and units in an operating environmental condition with the aid of sensors. During maintenance, inspection is required to identify damage on components and provide information on the current performance status (Banjevic, 2009).

Boyce (2006) analyses the turbine section of the gas turbine, which houses the first-stage vanes and the last-stage blades. In the turbine section, the effect of corrosion on the first-stage vanes of the gas turbine is a severe and preliminary inspection for cracks or bowings can be conducted. However, this Thesis focuses on the first-stage vanes. The first-stage of vanes are typically superficially inspected using a Borescope for gaining entrance into the turbine through the combustion chamber areas or by removing the inspection plates. Degradation mechanisms are also called fouling mechanisms, which affect the turbine section are described in Table 2-1.

Table 2-1 Failure mechanisms in vanes (Boyce, 2006)

No	Failure Mechanisms	General Description	First Stage Vanes
1	Nozzle vane bowing	• Reduction in the passage area • High temperature • Improper cooling • High wheel space temperature	• The vanes can suffer from hot corrosion • Thermal Barrier Coating (TBC) Spallation
2	Burnt nozzle vane	Uneven combustion creates various hot spots, which lead to melting of the vanes	• Trailing edge melted • Damage to vane platforms is usually due to improper cooling
3	Incomplete combustion or excess fuel	• During start-up, the fuel is not combusted and collects in the stationary vanes, which acts as flame holders • Ensures that the control system has a rate of acceleration and shutdown mode	Vanes totally melted
4	Hot corrosion Type I (over 1500ºF)	• An active form of oxidation, caused by the reaction of the Sodium (Na) in the air of fluid • Sulphur, which is usually in the fluid and oxygen • Intergranular attack • Sulphide particles, • A denuded zone of base metal	• Damage to the leading edge • Erosion of the TBC attack on the base coating
5	Hot corrosion Type II (between 1100ºF to 1450ºF)	• Caused by low melting eutectic compounds resulting from the contamination of Sodium sulphate and some of the alloy constituents such as nickel and cobalt • Layered type of corrosion	Not applicable
6	Hot gas erosion-oxidation	• Caused by small solids in the air or the fuel • With common combustor pattern • Excessive engine gas temperature (EGT) pattern	• Failure of the TBC on the nozzle vane or platforms • Not even around circumference
7	Blade tip rubs	• Due to subtle tip clearance • High metal temperatures in the blades	Not Applicable
8	Blade fretting erosion	• Fretting in the dovetails/fir trees is caused by the rocking action of the blades • Peaking turbines are highly susceptible to this problem	• Several attacks on trailing edge and leading edge • On the concave side of the airfoil
9	Blade and wheel rupture failure	• This failure occurs in high temperature and highly loaded blades (highly stressed) and disks • Disk failure can be catastrophic • Caused by inadequate cooling due to blockage cooling passages	Creep distortion usually at trailing edge
10	Foreign object damage (FOD) Domestic object damage (DOD)	• FOD occurs from materials coming from an external source to the gas turbine • DOD occurs from failure of internal components	Most damage from this point forward
11	Low Cycle Fatigue (LCF)	• Turbine disks • First stage turbine suffering from low steady state stress due to thermos-mechanical fatigue problem • Peaking turbines more susceptible	• Cracks in the Vanes • Single vane segments suffer less than multiple vane segments
12	High Cycle Fatigue (HCF)	• Can Occur in any blades or vanes due to the blade resonance frequency being excited • Occurs in blades where there are no tip or mid-span shrouds	• Not applicable to most designs

2.6.2 Component degradation prognostics

Prognostics defined as "analysis of the symptoms of faults to predict future condition and residual life within design parameters" (International Standard Organisation, 2015). Medjaher *et al* (2012) argue that Prognostics is the estimated-time-to-failure (ETTF) based on the risk of existence or subsequent appearance of one or more failure modes. Prognostics estimate the time after which a component can no longer perform its intended or expected functionality to improve system safety. Physics-based and data-driven approaches can support this process. The data-driven approach engages a collection of maintenance and monitoring data to deduce failure modes, while physics-based model utilises mathematical models to estimate lifespan of components (Chen *et al,* 2012; Daigle and Goebel, 2010). The next section discusses visualisation of events.

2.7 Visualisation

In the field of visualisation, timelines are frequent and powerful form of graphic design which include data maps and time series (Tufte and Graves-Morris, 1983). Tory and Moller (2004) observe scientific, information and knowledge visualisation, while Tufte and Graves-Morris (1983) present a 2D-graphical plot algorithm to display a summary of events on a timeline. Timeline visualisation application has been used extensively in electrical engineering to represent electrical signals as the most common display generator as seen in an oscilloscope (Karam, 1994), interactive documents as interfaces to historical data (Kumar *et al,* 1998), personal histories for medical records (Plaisant *et al*, 1996), novel organiser for digital libraries (Alonso *et al*, 1998), and understanding relationships amongst events for cognitive advantage (Allen, 1995). Due to the limitations of the current practice, the study of the timeline visualisation regarding the analysis of maintenance cycles was conducted to gain useful insights on how to develop the remaining useful life prediction framework.

2.8 Weibull Parameter estimation

Parameter estimation relates to distribution estimation from data. It is processes time-to-failure data in reliability engineering to estimate the parameters of the selected distribution (Abernethy, 2006). The goal of this aspect to establish background knowledge required for this research. There are several parameter estimation methods available. This section presents an overview of the existing methods used in life data analysis. Examples of the parameter estimation methods are least squares, maximum likelihood estimation, a method of moments and Bayesian estimation methods. The least square and the maximum likelihood are used and discussed in this research (see chapter 6).

2.9 Modelling

Modelling is a process of developing a structured procedure that will enable policy makers to predict the effect of changes to the system (Maria, 1997). In this Thesis, the modelling approach demonstrates a system starting at time t = 0 until the next overhaul inspection state. At each overhaul inspection state, the system should be assessed to find out any form of defect on the components using non-destructive testing techniques (Kumar and Mahto, 2013). Roy *et al* (2013) note that during maintenance, repair and overhaul, the components with defects are rejected and/or replaced, while those without defects are reused. The procedures for developing a numerical/statistical model include problem identification and formulation, real system data collection and data processing, model formation and development, model validation and documentation, select and establish conditions, perform calculations and results interpretation.

2.10 Renewal theory

Renewal theory is the study of particular probability problems connected with the failure and replacement of components (Doob, 1948; Cox, 1962; White, 1964; Rausand and Høyland, 2004). In this Thesis, the research relates to multi-component of a one-component system (assembly), e.g., aerospace gas turbine NGV component assembly.

Doob's (1948) argues that renewal theory is based on the theory of probability, which deals with a population of individual components. When any individual component fails (rejection) at inspection, there is an immediate replacement based on scheduled maintenance. Since the components are supposed to survive or fail independently of each other, it is sufficient to consider a population at any time consisting of only a single component. At birth, the future lifetime of the individual component is a chance variable with distribution function *F(t)* (the probability of failure before age *t*). At any age *t*, the lifetime remaining then follows a distribution function. Renewal theory is part of counting processes applied to examine the reliability of a repairable system as a function of time (Rausand and Høyland, 2004). The renewals with respect to time can be expressed as

$$\{X(t), t \in T\} \tag{2-1}$$

For instance, a system start at time T = 0 and when an NGV fails from within a collection of components (NGVs) in an assembly, it is expected to be immediately replaced with new components and the system continues in service. The assumption is that all components are taken as a population, each with the same failure law and must follow an overhaul process.

In this context, the random variables X(t) of the number of components rejected in the time interval (0,t] as a stochastic process {X(t), t > 0}. This work relates to a multi-component in an operating assembly as a series. The multi-component is represented in a through-life performance prediction model. The model is formulated as follows:-

i. The assembly of an engine contains an X number of new components
ii. The X number of components starts off during a test/in-service
iii. At time T, first inspection, X_1 number of components have failed based on progressive usage at T, Y% (percentage of failed components) of X is expected to fail, the more the engine is used, the more of X that will fail
iv. The number of X_1 which failed at first inspection are replaced together with the existing X which becomes X_{reuse}
v. The repair time is neglected

vi. The second inspection occurs at time T_2, T_3, …, therefore the sequence of failures is T_1, T_2, T_3,….
vii. IT_i is the time between failure i-1 and failure i for i = 1, 2, 3….IT_i is the interoccurrence time i for i = 1, 2, 3, … which is the time between failure, current and previous inspection time
viii. The distribution of the rejection (failure) rate is based on Weibull cumulative distribution function. The Weibull functions is selected because a renowned OEM uses it for failure and reliability analysis (Rolls Royce, 2005). The environmental and operating conditions remain constant through life.

The population of a set of component in-service at any overhaul state give R-Cube outcome. The concept of the through-life performance modelling is dependent on a mathematical entity to estimate the R-Cube outcome. The typical two-parameter Weibull cumulative distribution function is used to model through-life performance (Abernethy, 2006). Two events (rejection) can lead to replacement of components (i) end of life and (ii) rejection based on degradation mechanisms (Okoh *et al,* 2014). Survival and reliability analysis determine a “fit for use” of the reused components. The through-life performance model determines the rejection rates. The failure analysis subjects the rejected components to further investigation to gain an understanding of the cause of failure (Okoh *et al,* 2014).

2.11 Performance metric

Performance metric for accuracy measures the “nearness” of a point estimate values to the observed values (Engel *et al*, 2000; Saxena *et al*, 2008). The performance metric is accuracy and precision based (Saxena *et al*, 2008). In this work, the accuracy aspect of the performance metric has been selected. The accuracy based metric includes Bias, Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE) (Willmott and Matsuura, 2005). While MAE seems straight forward and used to obtain better understanding due to its averaging, the MSE happens to be more popular than

MAE. MSE deals with larger errors, while RMSE is most widely used because of the interpretable units. The MAE is selected and applied in this study because it offers better average and widely used by an OEM.

2.12 Renewal with repaired components

Barringer and Associates (2010) explain that the Weibull analysis can be used on both new components and repaired components based on the practical conditions that include

i. Repaired to good as new: If the NGVs are repaired to good as new, then the repaired Weibull trend line should lie near the original Weibull distribution for new components,
ii. Repaired to good as old: If the NGVs are repaired to good as old, then the Weibull line should be displaced to the left (shorter characteristic life, η),
iii. Repaired to something in between good as new or good as old: If the NGVs are repaired to the in-between cases, something between good as new or good as old then a displacement between the old and new Weibull lines with the “goodness” of the repair manifest by the “how much displacement” with a significant displacement, and
iv. Repaired is better than new: Make improvements over the new parts base line and repaired NGVs to a condition which is better than new. A displacement of the Weibull trend to the right produces a new Weibull line when repaired to better than new. This translation of the Weibull trend line would then demonstrate a significantly improved η value.

The Weibull analysis can be used for new NGVs and repaired NGVs, however the concern is getting the time-to-failure correctly identified and addressing the named failure conditions. The repair of gas turbine component is done by third party specialist companies approved by the Original Equipment Manufacturer (OEM). Sulzer (2016) asserts metallurgical procedures provide repair elements to return gas turbine component to their metallic properties. This repair of a component reinstates the health to a more reliable state “as good as new”.

2.13 Remaining useful life prediction approaches

This Thesis categorised RUL prediction methods and techniques into RUL methodology. The primary RUL prediction methodology are model-based and data-driven. Over time, researchers have extended the methodology covering knowledge-based and hybrid as identified in the literature. Figure 2.9 illustrates the RUL prediction methodology classification and simplifies the selection process for specific models to address different cases. Refer to appendix B for analysis of RUL techniques from literatures reviewed for the categorisation. Figure 2-9 is read bottom-up approach where the method(s) such as Weibull requires a statistical techniques and data-driven methodology to perform predictions, while neural network method is utilised by a computational intelligence technique with a data-driven methodology. Parametric instance supports experience technique which is related to knowledge–based methodology. Distributed method is utilised bay fusion technique as a combination of technique and for the hybrid methodology. Figure 2-9 can also be interpreted such that a model-based methodology requires a physics-of-failure technique which in-turn uses a method outlined. A data-driven methodology requires any of statistical or computational technique to perform analysis by selecting the needed methods listed.

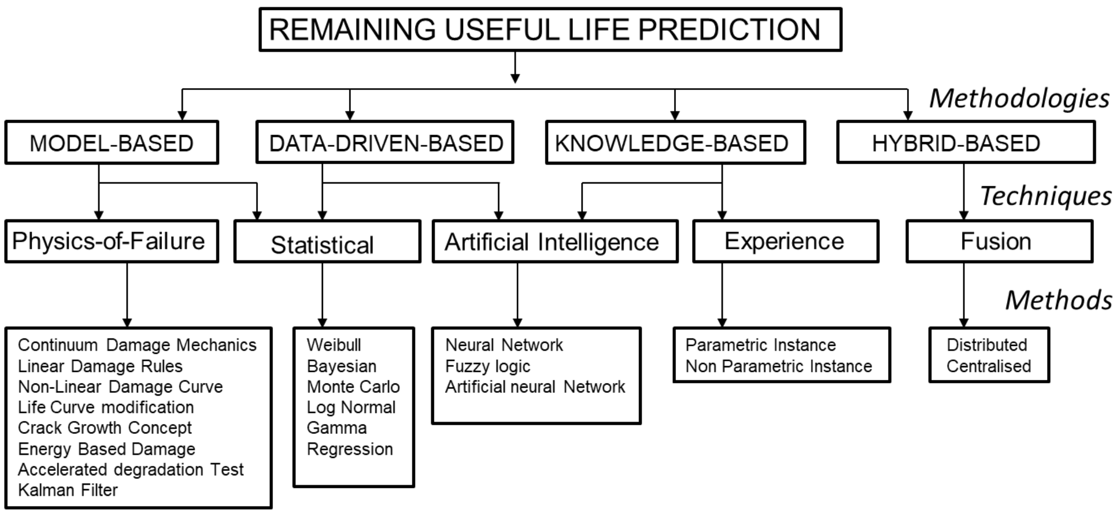


Figure 2-9 Categorisation of RUL prediction methodologies

Medjaher *et al* (2012) state that majority of the literature adopted the term RUL against Estimated-Time-To-Fail (ETTF). These authors concluded that the absolute value of RUL was only about a confidence interval, which is useful for decision making. In this thesis, the research combines multiple methods to generate results critical to designers and manufacturers. These results aid the improvement in optimisation of component design, and the manufacturing processes. The results also enable better decision making with configuration, usage and maintenance data. The application of multiple health indicators offers a more informed basis upon which to classify event data. The representation of remaining useful life on a degrading component in Figure 2.10 shows the feedback to design and manufacture.

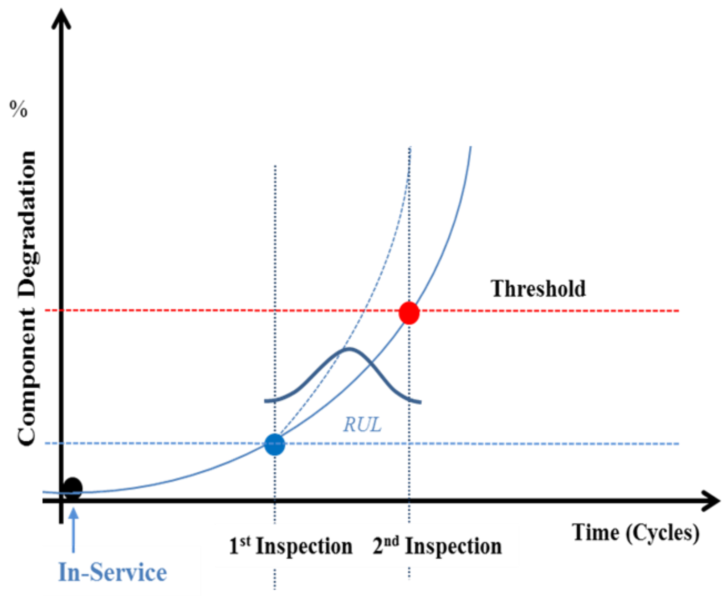


Figure 2-10: RUL showing component health index against time

The remaining useful life approaches embedded in the design of service delivery systems for through-life performance in the servicing, production, and manufacturing sectors are changing at an increasing rate (Liao and Tian, 2013; Di Maio *et al,* 2011; Shao and Nezu, 2000; Yang *et al,* 2012). In the application of diagnostics and prognostics, estimating remaining useful life requires researching on the equipment functional capabilities (An *et al,* 2013; Benkedjouh *et al,* 2013; Bolander *et al*, 2010; Cheng and Pecht, 2007; Xiongzi *et al,* 2011).

2.13.1 Prediction Methods

Prediction methods can be equations or functions for data extraction to estimate the remaining useful life of a component. In this section, the methods highlighted are extracted from the technique based on reviewed literature (see appendix C).

Weibull Reliability Function

The Weibull function is a statistical distribution which can assume different failure distributions when there is a change in the shape determining parameter. The Weibull function is well known to reliability engineers and developed by Waloddi Weibull in 1951 (Abernethy, 2006). The mathematical model for the distribution, failure rate and the cumulative function is the two-parameter Weibull function. The demonstration of the through-life performance model uses the knowledge of system reliability to represent the behaviours of components degradation. The degradation modelling is based on Cumulative Distribution Function (CDF) of the Weibull distribution to assess through-life performance. The Weibull distribution can take one, two or three input parameter(s) to model failure rate (Abernethy, 2006). The three-parameter Weibull includes a location parameter which traces the distribution alongside the distance from a point to the vertical (abscissa scale). A change in the value of location parameter can have an effect by moving the distribution and its related function from right to left. The two-parameter Weibull is when the location parameter is zero and the one-parameter Weibull is the slope becomes a constant. The Weibull distribution is a continuous distribution used in various applications to model lifetime of components such as bearing (Bechhoefer *et al,* 2015).

In the operation of complex mechanical engineering systems, an increase in the rate of failure shows the characteristic life and the mean-time-to-failure of the system can have approximately equal values (Abernethy, 2006).

The Weibull Probability Density Function (PDF) can be written as

$$f(t) = \eta \beta^{\eta} t^{\eta-1} e^{-(\beta t)^{\eta}} \qquad 0 < t \leq 0 \tag{2-2}$$

$$F(t) = 1 - \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{2-3}$$

where t is time (cycles), η denotes the scale parameter > 0, and ($\beta > 0$) denotes shape parameter. The Weibull CDF is governed by the Equation (2-3), which is the probability of failure or component rejection rate in an assembly between (0 to t]. Equation (2-2) is a two-parameter Weibull function for PDF, while Equation (2-3) is a two-parameter for CDF, which used for this research.

Therefore, Equation (2-4) introduces the probability of surviving to time *t* as

$$Pr_{sur}(t) = 1 - F(t) \tag{2-4}$$

For the Weibull distribution, the mean time to failure (MTTF) is the First moment,

$$MTTF = \eta * \Gamma(1 + \frac{1}{\beta}) \tag{2-5}$$

where Γ denotes a gamma function, which is defined for complex positive numbers. The Weibull distribution Second moment is calculated using Equation (2-6)

$$Var_{Weibull} = \eta^2 * \Gamma(1 + \frac{2}{\beta}) \tag{2-6}$$

where $Var_{Weibull}$ is the variance. The Weibull distribution is a continuous probability distribution with a statistical reliability modelling capability of fitting life data. The Weibull distribution parameters can be estimated with extremely few samples. If the Weibull is not a good fit for the data, then sample size provides little assistance. The Weibull is capability of estimating parameters from 3 to less than 20 samples (Abernethy, 2006). The Weibull reliability function facilitates failure forecasting, maintenance planning strategies and costs, effective replacement policies, spare parts forecasting and recommendation to management in response to service problem (Abernethy, 2006). Advantages of Weibull analysis include provision of reasonable failure analysis and forecast of with extremely samples, the Weibull tests are whenever an initial failure happens in a batch of components. The Weibull generates other distributions such as Poisson, Normal, Exponential Binomial, and Rayleigh. The drawbacks include lack of failure data, unidentified failed components and mixtures of failure modes. For example, where there is a trend in data, the Weibull model will be an inappropriate choice. The selection of the Weibull distribution is purely due to the choice of the OEM. Other reliability functions which exist are as gamma distribution and log normal distribution are not part of the Weibull group of distributions. The log-normal can a likely choice for materials analysis, crack growth rate, accelerating system degradation and non-linear systems.

When transferred to remaining life prediction, the Weibull Cumulative Distribution Function is used by researchers to illustrate behavioural patterns, performance loss and equipment performance degradation (Kim *et al*, 2012). In analysing the model, the Weibull distribution demonstrates through-life performance of components in an assembly for which the failure rate is proportional to a power of time. The feature parameters β and η were derived from the Weibull distribution which depicts the bathtub model in Figure 2-11. The shape parameter β which is power plus one is interpreted as:

i. A value of $\beta < 1$ indicates that failure rate decreases over time. Rolls Royce (2005) describe a failure risk with substantial "infant mortality" further than a definite life of early failure. The failure frequency declines over time as defective assets are rejected from the population
ii. A value of $\beta = 1$ indicates that failure frequency is constant over time. Rolls Royce (2005) suggest component failure occurs randomly through life
iii. A value of $\beta > 1$ indicates that failure frequency increases with time. Rolls Royce (2005) submit that no component failure risk at minimal life, while significant failure risk occurs resulting from aging assets as wear-out failure. The mechanical failure modes are low cycle fatigue, corrosion and erosion.

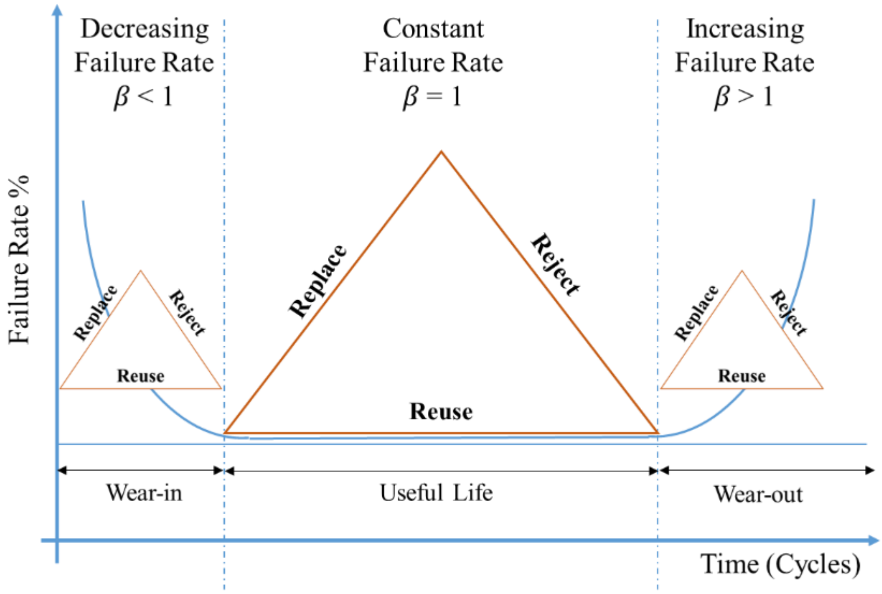


Figure 2-11: Weibull bathtub model with state transition approach

The estimated parameters from a through-life performance of the service history and current health data are used in the model to forecast the rate of rejections. The rate of rejection is based on the failure modes, which indicate infant mortality, random and wear-out. However, certainty in ages of failure results from high β values, while lack of predictable failure times results from low β values. The outcome of rejections can be interpreted in both cost and safety directions with respect to reliability and maintenance for prognostics purposes. The Weibull distribution is applied as a regression model to estimate failure rate of components (Peng *et al,* 2010). The Weibull distribution assumes and interprets different failure behaviours using β and η parameters. Whereas the η represents the characteristic life, the β signifies the degradation rate of 1, less than 1 and greater than 1, which affects the shape of the distribution (Rausand and Høyland, 2004). Cox (1962) applies actuarial function (Baye's theorem) in describing the survival time remaining.

Monte Carlo Method

Monte Carlo method involves using random numbers and probability to solve problems. The term Monte Carlo method is about the game of chance in a popular

Casino in Monte Carlo, Monaco (Metropolis and Ulam, 1949). The Monte Carlo algorithm facilitates physical simulation and computational statistics by taking random samples. In the model evaluation section, the Monte Carlo method was used to generate random number. The simulation was conducted by generating random numbers using the Equation (2-7) (Microsoft, 2008).

$$\mathrm{MC}_{\beta} = \mathrm{Rnd}() * \beta * 10\% \tag{2-7}$$

where MC_{β} denotes the sensitivity, Rnd() denotes a method for generating random numbers, β is the varied determinant of sensitivity.

The Monte Carlo simulation is carried out for sensitivity analysis. The sensitivity analysis can be used for qualitative and quantitative reasoning of a problem. This sensitivity analysis assesses the rate of change of the β degradation parameter. The β parameter is the single operating point for the evaluation and assumes that η performance parameter remains constant. This assessment helps observe the through-life performance prediction model behaviour. The sensitivity can result from fuel type, unexpected impacts and unexpected accidental braking. If there are catastrophic events, the prediction of remaining useful life of components would not hold.

2.13.2 Prediction techniques

Prediction techniques are designed to provide guidance on addressing a problem situation by analysing the data aspects and how things interact (Avison and Fitzgerald, 2006). As a result, a remaining useful life prediction technique can be a fundamental analysis of a method used to predict the remaining useful life of a component, and to assess its functional capabilities before failure happens. However, choosing an appropriate approach to address specific issues in a particular domain can be difficult (see appendix D).

Statistical

Statistical techniques relate past and present data duly observed and analysed with methods such as exponential smoothing autoregressive moving average

(ARMA), and for effective prediction of the result (Okoh *et al,* 2014). Coppe *et al* (2012) apply random variables to new data, which improves distribution of unknown parameters. Inferential statistics are crucial for extrapolation and interpolation of time series events. Samples of data extracted during an experiment exercise are used for descriptive and inferential statistical analysis. Graphical representation of the arithmetic mean, median, mode, correlation and standard deviation describes continuous data type, e.g. length of a crack. Relevant to the frequency of possible values of categorical data are ‘fair’, ‘good’, and ‘better’ apply to descriptive statistics (Bechhoefer *et al,* 2008). Abernethy (2006) draws statistical inferences by estimation and prediction of unobserved values data patterns, while regression analysis provides answers to hypothetical questions and information modelling of relationships. Least square estimates and maximum likelihood estimates are techniques for regression analysis.

In a similarity-based prognostics approach for remaining useful life estimation of engineered systems, Wang *et al* (2008) deduce that remaining life of a test unit is to estimate the actual life of the training unit with similar degradation pattern. Regression and ARMA techniques have been introduced to extrapolate the curve to certain criteria. These predictive methods are deterministic to producing an estimated output at a given time. However, ARMA method is used to fit data showing an exponential degradation pattern. Cheng & Pecht (2007) identify regression of the relationship of the parameters to forecast remaining life. In unvarying operating conditions, ARMA is used to recognise the dynamic behaviour of components (Tran *et al*, 2012). The alternative statistical approach used in medical and biomedical fields include Proportional Hazard Model (PHM) whereas, when applied to lifecycle issues, can accurately and reliably predict RUL (You *et al*, 2010).

The time series statistical technique depends on previous values rather than future values. Auto Regressive and Moving Average (ARMA) is a time series analysis technique requiring past and present observation data for exponential smoothing to predict results based on the dynamic behaviour of a component (Tran *et al*, 2012). Shao and Nezu (2000) introduce auto-regressive integrated moving-average (ARIMA) model as another time series approach to forecast life of bearings. The time-series method forecasts future signatures prediction (Liu *et al*, 2007, 2012), while estimating is more accurate, forecasting is reliable in the medical and biomedical fields (You *et al,* 2010).

In statistical technique, Bayesian technique merges probability and graph theory. Both Dynamic Bayesian Network (DBN) and Hidden Markov Model (HMM) use historical sequential data to predict future failure. As a result of the conditional independence, the methods are affected by the diffusion, where effect of past experience makes credible prediction (Ferreiro *et al*, 2012; Gobbato *et al*, 2012).

In (Ahmadzadeh and Lundberg, 2014), Dynamic Bayesian Network method is used within a statistical technique with graphical representation of stochastic processes. It helps users to assess and update a system to predict further states of a system, while Dynamic Bayesian Network (DBN) is applied to predict the remaining life of vertical machine drill bits (Dong and Yang, 2008). However, Bayesian Belief Net (BBN) was applied to simulate remnant life (Przytula and Choi, 2007). Bayesian update and expectation-maximum were employed to obtain an exact closed-form distribution for remnant life (Si *et al*, 2013). Bayesian regression uses a linear technique to process past and current data to predict the likelihood failure-time (Bernstein Distribution) for consistent improvement of results with higher prediction accuracy (Zaidan *et al*, 2013). The Hidden Markov Model is a stochastic process model and a powerful method to estimate remaining life (Ahmadzadeh and Lundberg, 2014). This HMM is a parametric model with distinct features for both diagnostics and prognostics, the technique simulates sensor signals, identifies the health conditions and predict remaining life (Chinnam and Baruah, 2003). Wang (2002) establishes use of stochastic gamma process and hazard rate to estimate the remnant life.

In (Goode *et al,* 2000) a reliability function is applied in a statistical technique to estimate RUL of pumps in a hot strip of the steel mill. Wang (2010) submits that reliability function accepts data with specific failure modes to generate significant historical information. The Weibull distribution is used to model time-to-failure to estimate the RUL by fusing vibration and reliability data between potential and functional failure boundaries regarding reliability. The Weibull distribution adequately illustrates observed run-to-failure data to define a probability density function and cumulative density function that uses the shape and scale parameters for RUL prediction (Yang *et al*, 2012).

In (Bechhoefer *et al,* 2015), a failure rate is used to predict the η and β parameters of the Weibull distributions in estimating remaining useful life using actuarial methods. Historical data and product life cycle operating hours are used to predict the remaining useful life based on a conditional survival function, whereby a 90% probability of surviving for the next time is generated by an actuarial method with regards to opportunity cost. The distribution describes fatigue failures of the bearing. A regression estimate used data efficiently with few data sets to predict life, but has poor extrapolation capability. Besides, domain experts can correctly interpret the application of this technique, whereas non-domain experts may experience difficulty in interpreting statistical results. Statistical techniques are significant to investigate causality (cause and effects) of various domain specific events. The run-to-failure data generates the distribution for confidence bound that is dependent on the volume of data.

Artificial intelligence

Artificial Intelligence (AI) is described as reasoning, knowledge, learning, natural language processing and communication processes which are dependent on input and output. This technique is also known as machine learning. Examples of artificial intelligence include fuzzy, neural networks (NN) and artificial neural network (ANN) (Schwabacher and Goebel 2007). An understanding shared in literature attribute NN to black-box techniques which analyses the computational complexity of components without foreknowledge of the internal structure (Xiongzi *et al,* 2011). Traditional artificial intelligence uses symbolic knowledge and modelling to reason the way humans do and act rationally, while computational intelligence uses numeric coding.

Computational intelligence (CI) is mainly numerical with NN, Evolutionary Algorithm (EA), Genetic Algorithm (GA), Fuzzy Logic (FL), while artificial intelligence is for reasoning, planning and making intelligent machines e.g. Expert systems, NN, FL, intelligent agent. The technique uses performance conditions to estimate the future state of an asset.

Yang *et al* (2012) confirm that observation (condition monitoring) data are used as input, outputs as function can be used to predict some features of future data, permits separate implementation and supports theoretical learning and decision boundary. However, artificial neural network (ANN) is used to train and learn data collected from sensors via networks to predict the RUL of an asset. Support Vector Machines (SVM) use an interconnected functional relation between input variables and expected output to incorporate statistical estimates of conditions with limited samples for predictive learning.

Saha *et al* (2007) conclude that SVM supervised learning is used for classification and numerical regression, while a Relevance Vector Machine (RVM) learns and uses a set of input vectors to predict accurately unseen values. Unsupervised learning has the ability use patterns as input streams. In order to estimate imprecision of pattern matching process Di Maio *et al* (2011) introduce fuzzy logic to deal with vagueness of reasoning based on the rule classification in bearings.

Physics of failure

Physics-of-Failure (PoF) is an approach based on reliability, designed to reduce risk of maintenance by understanding the performance of a component (Varde *et al,* 2006). The PoF technique requires parametric data with formulas for estimation, that is, in the process of developing and implementing latest technologies, both unknown and new defects, and failure modes can be deduced. Fatemi and Yang (1998) have explicitly reviewed Continuum Damage Mechanics, Linear Damage Rules, Non-Linear Damage Curve and Two Stage Linearization, Life Curve Modification Method of Stress and Load Interaction, Crack Growth Concept and Energy-Based Damage Model as prediction theories. Against this background, Yang *et al* (2012) opine that physical failure models are quantitative and analytical regarding degradation mechanisms with the understanding of failure modes, while a detailed physical modelling based on engineering judgement, established wear database and Lifecycle support is enumerated in (Greitzer and Ferryman 2001).

While Saha *et al* (2007) suggested a Particle Filtering (PF) method to estimate a set of points regarding sampled values from unknown state against weights, Xiongzi *et al* (2011) reiterated that PF provides a robust framework for long-term prognosis of accounting for uncertainties relevant to forecasting – the procedures include a collection of input data, a chosen algorithm and an expected output, but, can be used for non-linear model with non-Gaussian noise in prognostics (An *et al,* 2013). Tang *et al* (2011) introduced a classic PF-based prognosis also known as a Monte Carlo algorithm for accurate and precise RUL prediction of a component.

Kalman Filter is a state estimation method for features tracking to minimise error between state transition equation and a measurement to predict future feature behaviour, but used for short term estimate (Byington *et al,* 2004). It can also give exact PDF in analytical form in a linear model with Gaussian noise (An *et al,* 2013). It can be used for normal distribution assumption for noises (Xiongzi *et al,* 2011).

Variables such as temperature, stress, test level and duration, humidity, sample size and radiation are required as input to perform physical accelerated tests. This technique helps to understand the root cause of the failure during the investigation and solves the problem of uncertainty based on sound scientific knowledge. Design of experiments requires parameters such as material properties and geometry information with a number of samples for accelerated test to ascertain RUL. However, the modification of routine maintenance depends on the predicted health of the component.

Experience

The experience technique is specific to judgment of subject matter expert (SME) for maintenance decision-making. This technique is based on sound reliability analysis from non-parametric to parametric probability distributions (Fernandes *et al,* 2011). A non-parametric instance is when the processes and objects are consistently under constant observation to ascertain the length of time before failure, data acquisition – service knowledge of failure events. However, the parametric instances require few parameters to analyse acquired data, but extrapolation is possible in the lower and upper segment where parametric instances are distributed (Fernandes *et al,* 2011). Based on experience, parametric instances deliver accurate and precise failure distribution.

Furthermore, an analysis of the extracted data from the degradation mechanisms would provide a meaningful dataset for classification to determine the RUL of an asset directly by predefining threshold level (Si *et al,* 2011). Thus, a continuous monitoring of the system and processes to ensure information gathered is updated and guidelines are established for feedback to designers.

Fusion

The fusion technique uses a combination of two or more data from disparate sources required to estimate RUL of an asset. The fusion technique is either distributed or centralised. Data classification is a way to incorporate fusion. The uncertainty RUL estimate, on-demand data collected from different sensors are fused to accurately predict useful life using Principal Component Analysis (Cheng and Pecht 2009, Wei *et al,* 2011). However, decentralised fusion uses each sensor to predict RUL according to its information based on stochastic filtering, then fuses prediction results from all sensors with fusion weights at a subsequent update time. Centralised fusion allows measurement between sensors to independently predict RUL to reduce the parameter estimation uncertainty and obtain the final fusion of all sensors as a single input data for RUL prediction. Thus, a fuzzy approach improves accuracy of an estimate of a structured data when compared with an unstructured data representation (Di Maio *et al,* 2011).

Liu *et al* (2012) implemented a fusion method to improve transparency of methods to properly manage prediction of RUL uncertainty. It incorporates a PF learning process to provide a more accurate forecast, but the fusion technique also uses the PoF and experience techniques to predict damage and analyses stress factors. The PoF can be combined with statistical to predict uncertainty bound based on parameters used in the design of experiments. However, a representation of the various parameters from disparate sources can be fused.

2.13.3 Prediction methodology

The prediction methodology justifies the collection of phases, procedures, rules, methods and techniques (Avison and Fitzgerald, 2006). In reliability-centred and condition-based maintenance, prognostics methodology is fundamental to remaining useful life prediction of components to prevent unnecessary downtime and costs. Remaining useful life (RUL) prediction methodology is a systemic analysis to evaluate prediction techniques and estimation methods to determine time remaining for a component to perform its functional capability before failure occurs.

In literature, authors adopted prognostics approaches such as data-driven and physics-based approaches (Daigle and Goebel, 2010; Chen *et al,* 2012; Gasperin *et al,* 2012; Zhao *et al,* 2013). The data-driven approach engages a collection of maintenance and condition monitoring information to deduce the models, while physics-based approach utilises mathematical formulas to estimate the lifespan of the component under investigation. Researchers have unveiled new prognostics models for RUL prediction, which include data-driven, experience-based, knowledge-based and model-based approaches (Gorjian *et al*, 2009; Fernandes *et al*, 2011). Both papers discussed the same RUL approaches about reliability, but in a different context. While the latter Fernandes *et al* (2011) focus on life prediction suitability of product life cycle and concluded that increased modelling accuracy is a function of the life cycle, the former Gorjian *et al* (2009) consider RUL estimate in engineering asset management by providing a potential application to asses health and reliability prediction. RUL prediction is analysed based on data-driven, model-based and fusion approaches with a conclusion that the choice of fusion approach estimates life of a single system; the fusion of more than one RUL distributions is required to estimate new RUL based on probabilistic methods (Xiongzi *et al,* 2011).

Hybrid

Hybrid methodology combines different prognostics methodologies and various techniques. The hybrid methodology uses several techniques for RUL estimation to improve accuracy. The hybrid methodology uses parametric and non-parametric data to perform and improve RUL estimations, accuracy and precision. RUL estimated individually and through methods based on probability theory facilitates the fusion of two or more RUL prediction results to attain a new RUL (Medjaher *et al,* 2012).

In the work of (Ahmadzadeh and Lundberg, 2014), two or more methodologies can be used to extract data, analyse data and model problems relating to RUL; reduces computational complexity, thereby improving RUL prediction precision. The data gathered over time are input, while the RUL becomes the output from the model. A combination of fuzzy logic with a neural network identifies current health condition of an asset used as input to the neural networks with RUL as output. Combination of statistical models with a neural network, Fourier transforms with a neural network, dynamic wavelets with neural networks, and wavelet transform analysis with statistical models have also been reported.

Liao and Kottig (2014) propose a hybrid prognostics model with a combination of experience-based, data-driven and physics-based models. The authors extensively reviewed hybrid prognostics models for remaining useful life prediction of engineering systems and application to battery life prediction for performance. In their work, three models are fused to incorporate different types of data and established results for fusing multiple approaches to significantly improved RUL. Data quality and wholeness can be insufficient for the data-driven model, however, in the case of recently designed systems historical knowledge needs to be acquired.

Ahmadzadeh and Lundberg (2014) review three state-of-the-art models for RUL prediction about the experimental-based model, data-driven model and physics-based model as well as Hybrid approaches. The authors presented taxonomy with advantages and disadvantages of the approaches. Bagul *et al* (2008) initiate a blend of methodologies to estimate a more accurate result. Jardine, Lin and Banjevic (2006) review machinery diagnostics and prognostics, and implemented condition-based maintenance to show that statistical, artificial intelligence and model-based prognostic approaches can be used to estimate remaining life with accuracy, precision and confidence limit.

Data-Driven

RUL prediction methodology applies to statistical and artificial intelligence (AI) techniques which rely on historical and current health data to match identical patterns. These techniques derived from the configuration, usage and historical 'time/run-to-failure' data for maintenance decision making. Components analysed and documented in literature include bearings and gear plates from manufacturing industries. Data-Driven methodology is often used to estimate RUL, thereby informing maintenance decisions based upon failure threshold.

Gåsvik *et al* (2014) propose a 'wavelet packet' decomposition approach and/or Hidden Markov Models to predict RUL, where the time-frequency features allow more precise results than using only time variable. Xiongzi *et al* (2011) note that approaches consequent from historical data are used for predicting RUL of a useful asset without foreknowledge of the physics formation of a component. Malinowski *et al* (2015) argue that remaining useful life estimation of turbofan engines and performance be different from classical similarity-based approaches with training ones. Patterns are designated based on RUL-shapelets relationship for predicting the RUL of an equipment.

Javed *et al* (2015) propose improving accuracy of long-term prognostics of Proton Exchange Membrane Fuel Cells (PEMFC) stack to estimate remaining useful life. Their work contributed to data-driven prognostics of PEMFC by an ensemble of constraint-based Summation Wavelet-Extreme Learning Machine (SW-ELM) algorithm to improve accuracy and robustness of long-term prognostics. A new framework was presented for remaining useful life estimation using support vector machine classifier and the Weibull function for general degradation of an equipment due to aging (Louen *et al,* 2013).

In (Majidian and Saidi, 2007), fuzzy logic and ANN are used to predict RUL of boiler re-heater tubes with a closeness of outcome observed, while ANN method applies to the neurones present, and the suitable design of the membership relates to fuzzy logic. Further analysis of the extracted data from the degradation mechanisms provides a useful dataset for classification to predict the RUL of an asset directly by predefining threshold level (Si *et al*, 2011). The mean residual life computes a function of the current health based on conditional reliability function, and the outcome uses advanced maintenance planning of complex engineering systems (Ghodrati *et al,* 2012). There are difficulties in proper domain knowledge and practical applications which requires simulation and longer training times without transparency.

Model-Based

Physical model-based RUL prediction methodology represents the physical failure technique. The analytical-based methodology refers to an understanding of techniques, which aid reliability estimates of the physics-based model attributed to Physics-of-Failure (PoF), physical science of components and generated empirical equations (Bolander *et al*, 2010). Coppe *et al* (2012) propose use of a simple crack-growth-model for predicting RUL of a system affected by fatigue failure mechanism. Failure measures such as crack by fatigue, wear and corrosion of components relate to mathematical laws used to estimate RUL (Medjaher *et al,* 2012). Thus, huge costs and components specifications, which are not reusable earned this methodology these limitations (Brotherton *et al*, 2000).

The analytical-based methodology requires the combination of experiment, observation, geometry and condition monitoring of data to estimate any damage resulting from a particular failure mechanism. The model-based methodology requires an equation to recognise specific parameters to monitor tools to identify and extract features by using failure modes, mechanisms and effect analysis. Lesieutre *et al* (1997) design a classified modelling approach for system simulation to predict RUL. Model-based approach extracts the relationship between the lifetime and condition variables for RUL prediction of helicopter gear in a mechanistic modelling (Jardine *et al,* 2006).

In (Peng *et al*, 2015), a real-time composite fatigue life prognosis framework was proposed to integrate detected stiffness degradation. While a Bayesian fatigue life prediction approach was used in an inference framework to predict remaining useful life, the prediction performance on experimental data validation was conducted using prognostics metric. Kulkarni *et al* (2015) apply prognostic technology to determine the health status of a system and estimates its remaining useful life. A testbed was used to implement the prognostics methodology on cryogenic propellant loading systems for pneumatic valves. This pneumatic valves testbed subjected to magnitude-varying leaks follow a progression damage pattern.

Chiachío *et al* (2015) present a condition-based prediction of time-dependent reliability in composites to find the remaining useful life of composite materials subjected to fatigue degradation. The stiffness reduction and an increase in matrix micro-cracks density sequentially estimated through a Bayesian filtering framework. The prediction of the remaining useful life was obtained as a probability from estimating the time-dependent reliability. Multi-scale fatigue loss data from a cross-ply carbon-epoxy laminate for validation.

Fan *et al* (2014) describe the Particle Filter-based (PF-based) prognostic approach of both the Bayesian and Sequential Monte Carlo (SMC) statistical techniques to predict the lumen maintenance life of LED light sources. The proposed PF approach analyses the preparation of factors influencing the prediction accuracy and uncertainties. In sum, a careful comparison shows the PF approach achieved better prediction performance to the TM-21 method (Fan *et al,* 2014). In a similar vein, Balaban *et al* (2015) propose prognostics and health management system development for electromechanical actuators. Moreover, the authors employed prognostics algorithms to track fault progression and predict the actuator's remaining useful life. The validation experiments were conducted in both laboratory and flight conditions using a flyable electromechanical actuator test stand.

Model-based RUL methodology depends on the theoretical knowledge where models are designed for specific systems. These systems are monitored and simulated based on factors and responses. In predicting RUL, accuracy, precision and confidence interval are practical issues in engineering services (Engel *et al*, 2000). Peng *et al* (2010) design models which can be revised to increase accuracy and enhance performance using understanding of the degradation mechanics of a system. Oppenheimer and Loparo (2002) determine RUL of a machine by merging fault strength-to-life model with crack growth law for rotor shafts. A combination of the physics-based simulation model and wear prediction model were implemented to predict the RUL of a high dynamic power dry clutch system using double exponential smoothing future values (Watson *et al*, 2005). Again, three models namely gear meshing stiffness identification, driving gear and fracture mechanics were incorporated to estimate the RUL of a gear with a fatigue tooth crack (Li and Lee, 2005). The model-based methodology requires more assumptions about a component and its operating conditions. It also requires specific mechanistic knowledge and various parameters estimate, which depends on a component parameters.

Knowledge-based

The knowledge-based methodology combines computational intelligence and experience by collecting stored information from databases, subject matter experts and interpretation of the rules set (Chen *et al,* 2012). Expert system for decision support can be regarded as a performance service system for service delivery based on the principles of service feedback analysis. Parameters of reliability are estimated using an experience-based technique to gather information from understanding the operations of an asset (Medjaher *et al,* 2012).

Knowledge-based approach assesses the similarity between a temporary situation and a databank of prior failures to infer the life expectancy from previous occurrences using an expert and fuzzy systems (Sikorska *et al,* 2011). Knowledge is the through-life accumulation of data from experience based on stochastic and probabilistic models of degradation of components (Keller *et al,* 1982). An expert knowledge based on experience is used to develop an expert system, which is applicable in plants diagnosis and prognosis by using fuzzy inference system to define easy-to-understand rules based on IF-THEN statements (Biagetti and Sciubba, 2004). In the context of consumer products, a two-phase approach namely Weibull analysis and artificial neural network methods respectively predicts RUL of components. While the first relates to mean life component assessment based on run-to-failure data, the second is used for condition monitoring, degradation analysis and RUL prediction (Mazhar *et al,* 2007). There are difficulties in converting domain knowledge to rules, which require other techniques for prognostics and rules building.

There are several prognostics prediction approaches reviewed in literature, which determines RUL of subsystems or systems. Vachtsevanos *et al* (2006) define prognosis as the ability to predict accurately and precisely the remaining life of a failing component or subsystem. Data-driven, model-based and hybrid models are classified as prognostics approaches (Vachtsevanos *et al*, 2006). The data-driven approach requires no peculiar physical model and solely depends on measured data. However, the model-based approach describes the behaviour of degradation available for the physical model by combining the approaches with measured data to identify model parameters. Hybrid methodology utilises the two approaches above to enhance the prediction performance. Table 2-2 shows the merit and demerits of the methodology and requirements.

Table 2-2 Methodology, Requirements, merits and demerits

Methodology	Requirements	Merits	Demerits
Data Driven (Statistical and Artificial Intelligence techniques)	Extensive data on the challenge and conditions	• Required for static and dynamic component prediction • Can withstand stochastic and complex degradation process • Incorporates statistical techniques for life prediction • Captures complex processes without prior knowledge • The accuracy is dependent on the quantity and quality of the data to predict accurately and precisely RUL	• Challenging to fit domain knowledge in practical applications • Requires simulation • Requires longer training times and not transparent
Knowledge-based (Experience and Artificial Intelligence Techniques)	Expert knowledge	• Incorporates uncertainty, vagueness and inaccuracy using Fuzzy logic • Used where mathematical models are usually difficult to build • Suitable for problem-solving by domain specialist • Requires IF... THEN statement for decision-making	• Problematic to convert domain knowledge to rule • Requires other technique for prognostics • Difficulty in building rules
Model-based (Physics-of-failure and Statistical techniques)	Mathematical representation (component, degradation mechanisms, and operating condition) Parameters, e.g. material properties and geometry	• Establishment of direct relationship between explanatory variables of degradation process and life prediction • Calculates the damage to critical components as a function of operating conditions • The flexibility of the logic, system behaviour and operating condition. • Easy to establish standard algorithms • Substantially high accuracy	• Requires more assumptions about the component and its operating condition • Requires specific mechanistic knowledge • Requires estimation of various parameters • Depends on component parameters
Hybrid	Selected requirements	• Combination of methodologies to improve prediction performance • Overcomes limitations by reducing uncertainty issues	• Inability to use a single method • Requires more data for prediction

2.14 Research gap analysis

In academia, the definition of “Remaining Useful Life” is well established and standardised through the International Standard Organisation – Remaining Useful Life (RUL) is "remaining time before system health falls below a defined failure threshold" (International Standard Organisation, 2015). However, the term remaining useful life comes in various forms such as “remnant life”, “excess life”, “remaining life”, “mean residual life” and “lifetime remaining”. In literature, RUL results have been presented as a probability density function, regression, value, confidence limit or a proportion of the likelihood of failure. In this Thesis, the presented results will have the form of a value based on a 95% confidence limit. While a well-established approach in remaining useful life prediction can be found in the aerospace avionic/electronic domain, research shows this discipline is still developing in the maintenance context. However, the maintenance prognosis is gradually gaining ground. The research gap relates to predicting the remaining useful life multi-component in an assembly.

Nguyen *et al* (2015) propose a novel predictive maintenance policy with multi-level decision approach. Their work focused on multi-component systems with complex structure by using a system level and a component level for decision-making. A Monte Carlo simulation technique is used for evaluating maintenance costs. They argue that the approach is robust, but computing time can increase when the number of components is high.

Rodrigues (2017) estimates remaining useful life prediction of multiple-component systems based on a system-level performance indicator. In his work, a system-level performance indicator is calculated based on the performance of each component and the system-level RUL predicted. The focus is on hydraulic system containing multiple pumps with an air conditioning system for aircraft containing various components. The method used is Particle Filter known as Sequential Monte Carlo.

Lee and Pan (2017) present a predictive maintenance of complex system with multi-level reliability structure, where data generated from on-board sensors are utilised. A discrete time Markov Chain model for modelling multiple degradation processes of components and a Bayesian network model for predicting system reliability is applied. A probabilistic inference is conducted at the system level.

Hafsa *et al* (2015) emphasise the essence of interactions between complex system components RUL by conducting a prognostics of health status of multi-component systems. Their work focused on a Lorry system and the Weibull model is applied to estimate the remaining useful life of the system.

Bian and Gebraeel (2014) present stochastic modelling and real-time prognostics for multi-component systems with degradation rate interactions. In their work, the behaviours of condition-degradation-based sensor signal relating to each component are modelled. The model estimates the residual lifetime distribution of each component using a Bayesian model.

Furthermore, the prediction methodology described in literature for estimating the remaining useful life of residential appliances incorporates Weibull analysis (Welch and Rogers, 2010). This methodology actually solves fraction of units remaining using a β factor to reasonably estimate the RUL of a residential appliance based on a particular Expected Useful Life (EUL) and years in service instead of remaining useful life. The systems under investigation are air conditioning units and the methodology can be applied to other appliances such as refrigerator, freezers clothes washers and dryers (Welch and Rogers, 2010).

Louen *et al* (2013) propose a two-step RUL framework which requires acceptable and unacceptable performance data for training. A support vector machine (SVM) method detects faults and monitors health of an equipment in operating mode, while the performance degradation is Weibull distributed. The Weibull distribution produces a trajectory for the performance degradation, which is the distance to the SVM's separating hyperplane. The trajectory performance degradation is the performance indicator. The RUL is described as the difference between the end of life and the current time focusing on a single asset.

In (Bechhoefer *et al,* 2015), the RUL is estimated using actuarial methods. The failure rate is initially used to estimate the parameters for the Weibull distribution. The conditional expectation of the truncated survival function of the Weibull is used to estimate the time-to-failure: given that the equipment has survived to time *t*, the probability that the same equipment would survive to time *t* plus *y*. The RUL is calculated as the difference in the expected time of failure from current time. The RUL compares the simulated and the experimented time of failure to give the RUL. An opportunity cost is linked with lost productivity due to a failure in order to calculate the associated cost. This cost is based on the safety margin on the equipment.

The researchers above developed a framework to predict the RUL of a single component and appliance using a Weibull function and data-driven methodology. In their research, the single component or appliance is run and assessed until failure. However, in this research, RUL prediction of a component is conducted by assessing the same components in an assembly – multi-component using the Weibull reliability function, statistical technique and data-driven methodology. This research is conducted in the TES centre to identify the qualitative and quantitative factors from the historical information, which is likely to affect maintenance prognosis of mechanical component degradation.

In academia, prognostics focus on the performance of a system, subsystem, or component to estimate its remaining useful life, while this Thesis aims to assess the mechanical multi-component degradation to predict their remaining useful life. Research in academia provided only the framework structure and data analysis of remaining useful life. However, in literature, no evidence relative to the RUL prediction of multi-component in an assembly, which has led to undertaking this research.

2.15 Summary

This chapter gives a review of through-life engineering services, degradation mechanisms, taxonomy and ontology, maintenance strategies, condition-based maintenance parameter estimation methods and remaining useful life prediction. The overview and explanation of the Through-life Engineering Services regarding complex system maintenance and maintenance strategies describe the types of maintenance, namely corrective and preventive with a focus on condition-based maintenance. In this Thesis, the identified methods and techniques of remaining useful life prediction are categorised in the remaining useful life prediction methodologies.

The review of the techniques requires a variety of methods to interpolate and extrapolate data. The ARMA, ARIMA, time series and linear regression statistical techniques are used to plan and infer results. The techniques are used to manipulate known and unknown parameters to accurately and precisely predict RULs. The experience technique explains the knowledge gathered from failure events about continuous monitoring while computation intelligence techniques deal with vagueness and imprecision regarding machine learning and training. The Physics of Failure technique explains the analytical processes, whereas the fusion approach uses distributed or centralised methods to merge data from multiple sources, classify, and manage uncertainty to accurately estimate RUL precision. The PoF technique uses the Failure Mode and Effects Analysis to monitor deterioration trends, failure definitions and identifies failure mechanisms. On-demand databases define the failure mechanisms if mock-ups are not available.

The remaining useful life prediction literature review is the main part of this chapter. The other areas (sections and sub sections) described in the literature review chapter have been applied in chapters 4 and 5. The next chapter relates to the research aim, objectives and methodology of this Thesis.

3 RESEARCH AIM, OBJECTIVES AND METHODOLOGY

This chapter describes the aim, objectives, application of the selected research methods and the research methodology adopted.

3.1 Research aim and objectives

This research aims to develop a framework for predicting the remaining useful life of a gas turbine mechanical component in an assembly. The assembly level historical data are required to model the through-life performance of components degradation. The purpose of this research is to develop a framework to assess component deterioration and predict the remaining useful life of the component in the assembly based on historical (assembly level) data. The life of the assembly is determined by the life of a component failing in the assembly at any overhaul inspection time. However, the proposed framework contains an approach to convert rejection rate data into an understanding of the underlying component degradation occurrences towards the rejection threshold.

The through-life performance of component degradation engages a reliability function to improve the modelling application to predict the number of rejected, replaced and reused (R-Cube) components. This through-life performance model increases the applicability of remaining useful life with the following core objectives:

i. To perform a critical analysis of existing research relating to remaining useful life prediction
ii. To investigate the current (AS-IS) practice of the level and nature of degradation information available on the aero component deterioration service;
iii. To model component degradation for through-life performance on assembly level data, thereby forecasting the expected component failure to predict component remaining useful life

iv. To develop a framework for the assessment of through-life performance assumptions taken at the design stage, thereby predicting the remaining life of the mechanical component based on assembly level data;
v. To validate the framework through expert judgement and an industry case study.

The proposed framework focuses on component degradation based on predictive maintenance, predicting the number or frequency of R-Cube and remaining useful life of the component. A literature review is conducted to gain understanding of the research domain followed by an investigation (AS-IS practice) of the degradation mechanism study based on traditional/conventional maintenance. This investigation of the AS-IS practice captures the types of damage and the relationship with components. The captured information such as the types of components, damage and number of components. The historical data can be fused into the through-life performance model. The efficient and effective capture, interpretation, transition, storage and fusion of a vast volume of complex data from disparate sources represent an enormous challenge on many levels.

The research attempts to estimate the life consumption of components by assessing the through-life performance of components in an assembly. Furthermore, checking the valuable time remaining for future use requires certain parameters to determine the time to replace the entire batch whilst predicting remaining useful life. A scheduled maintenance, repair and overhaul (MRO) at the shop floor supports detection of events of both high and low levels for components' rejection, replacement and reuse (R-Cube).

Consequently, an engine usage is dependent on several factors such as temperature, pressure, relative humidity, contaminants, and flight cycles. Subsequently, the parameters of the engine operating conditions include failure modes such as high and low cycle fatigue and foreign object damage. In industrial product-services systems (IPSS) such as gas turbine engine, comprises systems, sub-systems, and components. The IPSS gas turbine engine incurrs costs in the operation phase, which dominates the whole product life cycle (Fernandes *et al*, 2011).

3.2 Research methodology

The research selection includes the chosen research methods and the rationales as detailed in this chapter. The research methodology explains the justifications for choosing the appropriate research strategy (see Figure 3-1). The research strategy describes the data collection methods for the study.

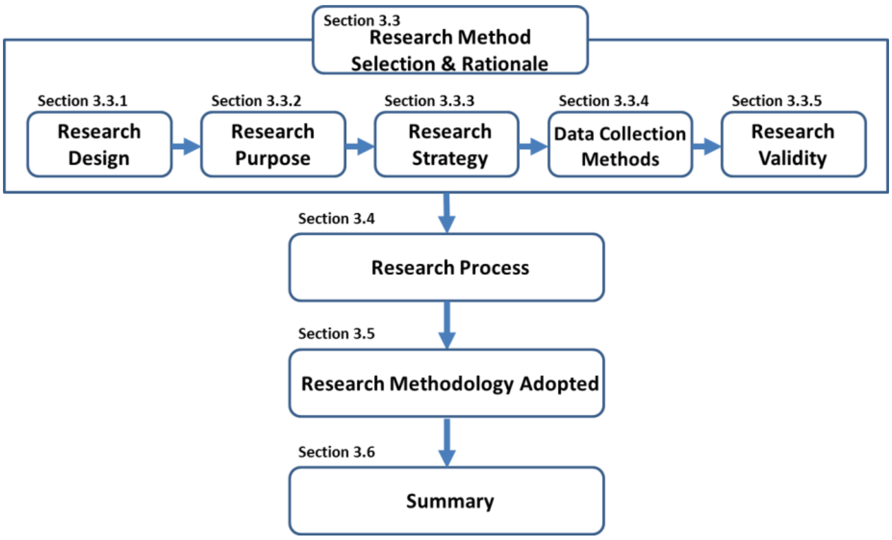


Figure 3-1: Layout of the methodology section

Avison and Fitzgerald (2006) argue that methodology reasonably justifies the process for collecting and managing different procedures and methods. However, methodology describes and analyses the procedures used in conducting qualitative and quantitative research (Clough and Nutbrown, 2012). The application of methodology justifies the research questions and explains the methods utilised in this research. While methodology articulates applying specific research methods, a method is a data gathering tool for research (Sachdeva, 2009). Examples of methods in qualitative research are interview and survey, while methods for quantitative research include questionnaires.

However, this research aims to develop a framework to predict the remaining useful life for a component based on the assembly level life and overhaul data.

This research focuses on the concept of remaining useful life prediction within the field of Prognostics and Health Management for Condition-Based Maintenance. The background of this research is the analysis of mechanical component degradation. In this research, the Weibull method is applied to the model-building data available to develop the through-life performance prediction model. The Weibull method is adopted to approximate the targeted random process. The Weibull method will also be used in the validation data available to estimate parameters for cross-validation purposes. The research gaps identified in the reviewed literature and the industry challenges captured would direct the research to reduce the preconception contained with any ambiguity. The next section relates to the research method selection and justification.

3.3 Research method selection and rationale

The methods applied in this research are highlighted in the blue boxes with white text in Figure 3-2. The research technique identified include exploratory, explanatory, mixed (qualitative and quantitative), case study, brainstorming / workshop, documents review and analysis, interviews and literature review. The research technique defines aim and outcomes to clarify techniques for conducting this research (Wisker, 2007).

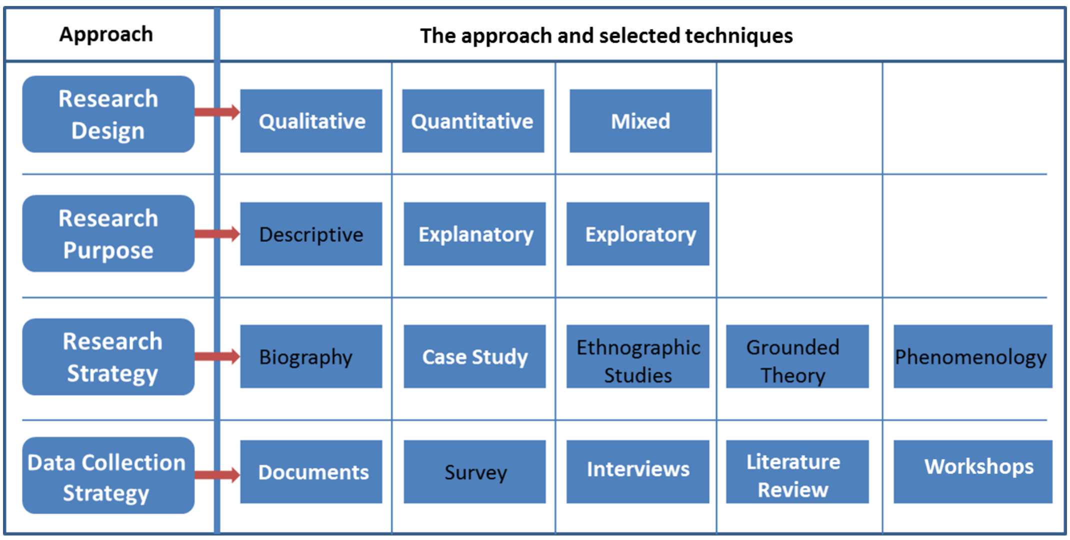


Figure 3-2: The research selection approach (the blue boxes with white texts were used in this thesis)

3.3.1 Research design

The research design discusses qualitative, quantitative and mixed research techniques (Robson, 2002; Wisker, 2007; Lapan *et al,* 2011; Bernard and Bernard, 2012; Symon and Cassell, 2012; Bryman, 2016). The quantitative techniques deal with the certainty of the research theme before design, whereas the qualitative research design engages a generic strategy to describe the research subject and the mixed deals with both design techniques.

i. Quantitative technique

In this study, the researcher engages a significant knowledge of the research theory in the research process. The quantitative research relates to fixed designs (Robson, 2002). In quantitative technique, data collection method is either experimental, correlation, survey or descriptive, whereby numerical data are collected for analysis using statistical methods. Statistics resulting from quantitative research are used to establish the presence of chance relationships between variables (Walliman, 2005). Another method associated with quantitative research includes questionnaires (Wisker, 2007). Data collection was conducted in a structured manner to eliminate bias (Robson, 2002).

ii. Qualitative technique

The qualitative research referred to flexible design (Robson, 2002).The author applied the qualitative technique, which provides a platform for theory-building. The qualitative research design meant gathering and interpreting relevant information. The researcher seeks to understand the notion of the challenge by engaging this research design which changes over the progression of the project. Data collection methods include interviews, case study, focus groups, participant observation and personal learning logs (Wisker, 2007; Symon and Cassell, 2012). In this research, there is a significant degree of engagement with stakeholders for the success of the study.

iii. Mixed technique

The mixed research design is a hybrid of both the qualitative and quantitative research techniques. The hybrid technique allows a fusion of the approaches mentioned above to assist the researcher in managing and documenting this research properly (Wisker, 2007). The researcher used a qualitative design in the initial stage followed by the quantitative design at a later stage of this study.

Based on the rationale, both qualitative and quantitative research designs were not simultaneously applied in the research. However, the qualitative design was primarily used to explore the background of the research to gather relevant information, while the quantitative research design was used for the analytical and numerical applications. The mixed research design allows the application of a two-stage research process whereby one is used before another. With the nature of this study, both the qualitative and quantitative research designs are in line with the aim and objectives of the research, hence, the selection and use of the hybrid / mixed research design in this PhD Thesis.

3.3.2 Research purpose

Robson (2002) argues that research purpose addresses research questions. The purpose of the study informs readers what the research should accomplish during a discussion on the theme. The research purpose includes descriptive, explanatory and exploratory approaches. The researcher has selected the explanatory and exploratory research purpose for this study.

a. Explanatory

The explanatory research purpose are causal (Zikmund *et al*, 2012; Yin, 2013). As suggested by Zikmund *et al* (2012) the major aim of this research purpose identifies a cause-and-effect analysis. For the purpose of this study, the researcher used an illustrative method in the context of either qualitative, quantitative or mixed research designs (Robson, 2002). The explanatory research purpose applies to the AS-IS practice discussed in chapter 4 to understand the cause and effect analysis of the components degradation.

b. Exploratory

The exploratory research purpose addresses the nature of the problems to gain a better understanding of problem dimensions in a current practice (Zikmund *et al*, 2012). This research is exploratory qualitative research design exploring the how in an AS-IS industry practice (Robson, 2002; Symon and Cassell, 2012; Bryman, 2016). The exploratory research design will be applied in chapter 4 highlighting the nature of degradation in relation to cause and effect analysis of failure mechanisms regarding mechanical components. The exploratory process supports identification of parameters required for input in the proposed framework in relation to the literature findings.

The rationale for applying a combination of the exploratory and explanatory research purpose in this study addresses the aim and objectives of this research. The initial phase of this research reports maintenance strategies, and challenges in academia and industry, but rarely discusses the connection of the complexity and project resources. This research introduces the exploratory research purpose. Changes within this research led to explanatory research purpose based on the complexity and resources of the relationship between conventional and predictive maintenance for components degradation and remaining useful life prediction.

3.3.3 Research strategy

Robson (2002) argues that a case study illustrates a credible means and new ways of addressing challenges and problem solving to facilitate learning. The research strategy should be compatible with the research purpose and research questions (Robson, 2002). As indicated by Robson (2002), the research strategy concerns potential research questions. The data collection methods should provide solutions to the research questions.

A case study focuses on the study of a person, a group, a setting and an organisation with the intention of providing viable solutions involving detailed development knowledge (Robson, 2002; Symon and Cassell, 2012). The case study supports involvement of decision makers by depicting real life situations either through questions or discussions. In essence, a case study enables thorough analysis and understanding of the case (Symon and Cassell, 2012). It simplifies complex concepts and improves analytical thinking and communication, but unsuitable for a short-term programme. The research strategy includes collection and reporting descriptive information about the event histories and present occurrences. The researcher uses various types of data, which are possibly accessible to deliver fairly comprehensive information about the investigation.

Yin (2013) asserts a case study supports investigation of complex cases, which are difficult to understand in research laboratories. It provides rich qualitative extensive information; creates new ideas and skills (e.g. data scientists) for further examination to initiate change (Gummesson, 2000). Case studies lack redundancy and are time-consuming, while the results generalised by researchers to a wider community and influence impact on the case outcome.

In a case study, processes, procedures and activities recreate events in a structured manner. In the process of conducting a case study, tasks are investigated in detail for better comprehension. The case study is a useful method for data collection and analysis. The case study methods for gathering data include workshops / brainstorming, observations, unstructured and semi-structured interviews, and official document are suitable for the case.

The rationale for selecting the case study in this PhD Thesis is that predictive maintenance strategy is a relatively new concept when compared to corrective maintenance as discussed in Section 2.5. The predictive maintenance strategy requires an understanding of PHM to perform through-life performance modelling of mechanical component degradation. The case study conducted in this research adopts an approach based on the characteristics of degradation analysis and expert knowledge. Case studies concern the development process that applies to condition-based maintenance application. The case study strategy appears appropriate for capturing existing knowledge from experts and creating new theories. The dominant research purpose is exploratory by introducing a qualitative research design. Semi-structured interviews were conducted to identify the nature of component degradation in an AS-IS industry practice in this study.

3.3.4 Data collection strategy

This section describes the various data collection methods for this research. The data collection methods such as literature review, documents, interviews and workshop/brainstorming session were applied in this research and the rationale presented.

a) Documents

Documents were reviewed, analysed and utilised as evidence of the findings in the data collection phase of this research. Documents is a data collection method for supporting other methods. The content of the articles undergoes quantitative analysis. The analysed contents of the documents concern reliability and validity of this research (Robson, 2002). The articles were utilised to support the findings of the case study and defined the parameters for assessment of the through-life performance.

b) Interviews

Interviews are often preferred for data collection in research (Robson, 2002; Marshall and Rossman, 2016). Dialogue is an interview process with purpose and is qualitative, which researchers strongly depend upon (Marshall and Rossman, 2016). Participants in the interview process describe the topic of interest in their own context (Marshall and Rossman, 2016). The research reveals participants’ opinions by exploring universal topics (Gerson and Horowitz, 2002; Marshall and Rossman, 2016). Robson (2002) describes different interview types as follows:-

i. **Structured:** Prearranged with fixed questions and wording, usually specific

ii. **Semi-Structured:** Prearranged flexibility to adjust the direction and wording based on researcher's discernment. Usually relates to qualitative research design
iii. **Unstructured:** Usually relates to qualitative research design. Researchers allow the discussion to emerge and evolve around the topic of interest

Semi-structured and unstructured interview methods were applied to collect data from participants in the organisation. Interviews with different participants at different times help to gain understanding of the area of study and to obtain views, which others did not disclose.

Methodology for interview questions design

In designing the interview questions, the interviews types were highlighted, and the semi-structured interview chosen. Semi-structured interview has been selected to put together specific qualitative non-numeric data. This type of interview questions creates a sense of balance of open-ended questions for an interview. The semi-structured interview clarifies the research domain and the specific research questions. The designed questions support exploration of the research at the early stage of this research. The designed interview questions for this research facilitates the uncovering of descriptive data on the personal experience of respondents. The information gathered from the use of interview question can create specific insights from generic domains.

The process for designing the interview questions is as follows

i. The researcher created open-ended questions to gather descriptive responses unlike closed-ended questions with "Yes" or "No"
ii. The researcher prevented the use of leading questions
iii. The researcher utilised terms which respondents could comprehend based on their language skill, knowledge, age, gender, and experience. The researcher ensured cultural and social contexts are considered

iv. The researcher constructed questions based on the keep it, short and specific approach. The researcher avoided asking two-in-one question type.
v. The researcher restricted questions with strong positive and negative connections. The researcher discouraged the use of negative questions. The process for participants' selection for the interview is discussed in chapter 4.

c) Literature review

Through literature reviews, the researcher gained knowledge of the current and previous research regarding the topic area (Hart, 2001; Marshall and Rossman, 2016). Literature provides an avenue for the researcher to define the research theory (Marshall and Rossman, 2016). A comparison of research findings with other literature was conducted to identify research gaps in existing research, which produces contributions to knowledge to this research (Hart, 2001). Evidence of gaps in the industry is available in chapter 4 assisted the researcher in the avoidance of errors from prior research (Hart, 2001). Literature reviews support the investigator's research design methodology to identify the significant challenges and data collection strategy relevant to this research (Hart, 2001).

d) Workshop

The workshop is a brainstorming session (Brock *et al*, 2016; Shokri, Bradley and Nabhani, 2016) for collecting data. The process gives individuals opportunity to provide independent responses based on the facilitator's presentation and the questionnaire presented. The process allows free-flow of ideas and open-discussion in order to respond to the questionnaire without bias. The data collection strategy support collation of large data in a single setting rather than one-to-one interview.

Data collection strategy selected for the Thesis

The researcher uses data collection methods as described above. The major strength of a case study data collection is the opportunity to use disparate sources as evidence (Yin, 2013). The introduction of triangulation reduces threats to validity (Robson, 2002; Symon and Cassell, 2012). Triangulation uses either multiple methods or sources. A combination of qualitative and quantitative research techniques enhances investigation and feasibility of this study. Robson (2002); Symon and Cassell (2012); Bryman (2015) conclude triangulation is a valuable and widely used strategy for checking results of qualitative technique with that of quantitative technique.

In this research, the application of triangulation aided proper collection of data from disparate sources. This process ensures the engagement of more than one observer should be present during the study. The triangulation applies to both qualitative and quantitative research techniques. This triangulation engagement mitigates bias and improves research outcomes. However, triangulation assesses literatures reviewed, experts' knowledge, results of reviews, interviews, observations, and discussion sessions. The threats to research validity are mitigated using strategies of prolonged involvement, peer briefing, member checking, audit trail and negative case analysis (Robson, 2002; Symon and Cassell, 2012) as shown in Table 3-1.

Table 3-1: Mitigation strategies

Strategies to mitigate threat to research validity	
Prolonged involvement	Interaction over an extended period
Peer debriefing	Reduce researcher bias through debriefing sessions
Member checking	Checking transcripts, accounts, and interpretations made by respondents through various means (e.g. Email, face-to-face)
Audit trail	Keeping a full record of the conducted activities during a study
Negative case analysis	Searching unproven developed theory

3.4 Research Process

The validity of qualitative research concerns its accuracy, correctness and trustworthiness (Robson, 2002). The accuracy of qualitative research design describes the outcomes and findings (Robson, 2002). Tests for assessing the quality of the research design include internal, construct, reliability and external (Kirk and Miller, 1986; Harrison, 2002; Yin, 2013). In the process of conducting this research, a causal relationship was created within the organisation to gain the most valuable outcome during the interview sessions. Construct the concepts of the prediction by identifying the correct operation measures. The reliability of the research design is key to assess and minimise bias; validate the data collection procedure, conduct an audit by tracking the consistency of methods and practices, and use of standardised research instruments to measure reliability. Robson (2002) outlines the threat to validity in flexible research design to include description, interpretation, theory, reactivity, respondent biases and researcher biases (see Table 3-2).

Table 3-2: Threat to validity in the research design

Threat to validity	
Description	Avoidance of inaccuracy of the data seen or heard, for example, audio and visual recording of interviews
Interpretation	Provision of the happenings rather than emerging from one's involvement within the research environment.
Theory	Proactively search for discrepancies in available data which are not in line with one's theory.
Reactivity	Researcher's physical presence could affect the environment and the people involved
Respondent bias	Obstructing and withholding information; an example is a researcher perceives as a threat and the respondent would not want to share relevant information
Researcher bias	Preconceptions and assumptions brought in a research environment that refers to the behaviour of the types of questions asked

Addressing these threats require effective triangulation strategy in this research. This triangulation strategy was employed to create a balance in the rigour of this research based on a case study, workshop, observations and interviews.

The research process framework reviews the relationships amongst the different segments (see Figure 3-3). This research framework includes situation, research topic, research method, data and conclusion (Walliman, 2005). The research process illustrates the key phases, methods, rationales and deliverables presented in Section 3.2.

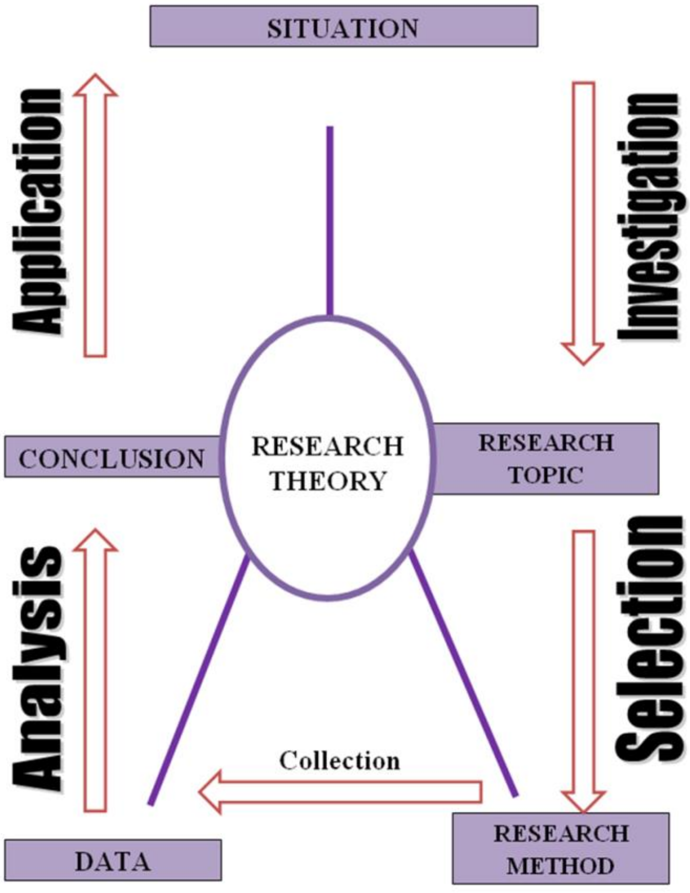


Figure 3-3: The research process. Source: (Walliman, 2005)

The research methods in the research design were used in collecting and collating relevant data for analysis. The data analysed were critical to the research decision-making. The outcome of the information analysed applies to the situation by verification and validation. This research process is a continuous cycle of a product at the end of each phase of the methodology. The next section explains the research methodology adopted for this research.

3.5 Research methodology adopted

The research methodology adopted for the research purpose, research design and research strategy is described in this section. The research process engaged in Figure 3-3 includes three stages represented systematically in Figure 3-4. The process of the research methodology comprises the review of the literature, industry interviews, workshops and case study scenarios. The three phases are

i. Phase 1: Understanding context and current practices
ii. Phase 2: Framework and tool development
iii. Phase 3: Framework and tool validation

3.5.1 Phase 1: Understanding context and current practices

The research involved a partnership between Cranfield University, manufacturing department and an aerospace industry based in the United Kingdom. The project relates to through-life engineering services of a gas turbine performance. The project focuses on the stator of the turbine as highlighted in chapter 1. The project aims to address prediction of component degradation and remaining useful life of component before failure happens. The project focuses on individual components within a multi-component assembly of a gas turbine engine. Literature review shows evidence of remaining useful life prediction for a single component, however, in this study, a framework is developed to assess the component degradation and overall remaining useful life of components at component level using only assembly level. Furthermore, failure data at component level is unavailable, while only assembly level is available in this context, hence the research. Historical and overhaul data from literature, reviewed documents and findings from industry investigation are used in building a through-life performance model from a statistics standpoint. The validation data is the data used in the scenarios of the case study. Since the case study is used to validate the framework, the "data" from industry is utilised as validation data. This means the data used for model-building is completely different from the validation data. The approach of using "model-building data" and "validation data" reflect partitioning in cross-validation. The research addresses issues regarding single stage assembly with replacement of pristine components, single stage assembly with replacement of repaired components and multiple stage assembly with component replacement.

The inability to conduct experiments to mirror the operating conditions and the operational pattern in determining degrading components of a gas turbine at assembly level is difficult, expensive and time-consuming. However, data collection for statistics and computational analysis of the component degradation for complex engineering systems such as gas turbine stand as a suitable approach.

In understanding the context, the situation observed in the current practice led to the identification of problems relating to the research questions. The investigation in the current practice in industry led to the knowledge discovery of degradation mechanisms. The approach improved low-level events capture and categorisation of degradation mechanisms as taxonomy. The taxonomy of deformation, corrosion, fracture, wear and their causes is described in the data collection phase to address the first objective. The process to identify the taxonomy is based on a set of questions validated by an interview with experts. An understanding of the degradation mechanisms affecting different components is significant in the through-life performance modelling to know how many components are fitted in an assembly and the likely number of degraded components. Based on the investigation, low-level events at component level are identified.

Prior to the case study, industry visits, document reviews and interviews with partners, the researcher conducted a literature search in the areas of PHM and CBM, in related field such as aerospace, medicine, manufacturing, electronics and maintenance to address the second objective. The research process employed in Figure 3-3 has been applied to achieve the outcomes – relevant prediction methods, techniques, and methodologies; identify and categorise high-level events at system level; and maintenance cycles of multiple overhauls and engines. The findings show a linkage between components and assembly/systems assets whereby a component is required for a system to perform its expected function. Based on regular overhaul maintenance, the research aims to predict the remaining useful life of a component in an assembly. Furthermore, the observation is tailored towards conventional maintenance strategy, which is a complex and time-consuming approach to maintaining complex engineering system of industrial product-services systems.

3.5.2 Phase 2: Aero component based framework development

The first phase delivers an understanding of the context regarding conventional maintenance approach on component degradation practice and challenges. The identified challenges led to the discovery of the importance of having a predictive maintenance strategy for assessing component degradation before failure. Furthermore, investigation in an analysis of multiple overhaul maintenance cycles conducted reveal a timeline visualisation of high-level maintenance events. Overhaul sequence and activities are highlighted to gain knowledge to build a timeline visualisation. The introduction and utilisation of entity relationship diagram (ERD) and association of the relations are key in developing a maintenance database. The visualisation environment which displays the information on a single page screen is developed with a web technology (PHP). The essence of this investigative analysis is to provide actionable insights regarding root cause and swift retrieval of relevant information for maintenance decision making. The reason for the MRO and replacement of any components are entered in a log. This log is stored in the database and can be retrieved during an investigation. The insights created in the analysis is used to deliver the approach for developing the through-life performance model.

The second phase identifies types of data and variables needed to model the through-life performance of the components in an assembly, which addresses the third objective. The selected remaining useful life prediction methodology, technique and method in this research are the Weibull method, statistical technique and data-driven methodology. The through-life performance prediction framework is derived from the data-driven prognostics approach. The through-life performance framework combines the basic characteristics of a component for a RUL prediction. In this context, the outcome of the modelling results from the third objective to feedback to policy makers. A framework to predict remaining useful life includes algorithms to fuse maintenance parameters collected from disparate sources.

In this Thesis, the Weibull cumulative distribution function is applied as a conditional probability for modelling the through-life performance of components in an assembly. According to literature, where the shape value is greater than 1, overhaul of components is appropriate. The stochastic (random probability distribution) process indicates frequency of the individually degraded component. The Weibull CDF contains two parameters, namely Eta (η) is a scale, which describes the time a large percentage (63.2%) of the components are expected to experience performance loss, while the Beta (β) is a failure rate (shape) with positive constants defining the characteristic life of a location. The Eta or characteristic life (η) equals the mean-time-to-failure (MTTF) when the failure rate is constant. This approach does not perform a model fit test such as the Weibull plot.

The data-driven prognostic approach facilitates the predictive maintenance for through-life performance prediction. The implementation of an estimation algorithm shows overhaul activities using a statistical technique which supports the generation of a distribution to estimate rejection rate, thereby predicting the remaining useful life, which takes care of the fourth objective. The proposed Weibull Through-life Performance Prediction Model (framework) is a data-driven prognostic methodology for:-

(i) Data preprocessing and parameter estimation of processed failure time data
(ii) Statistical modelling of prior overhaul of observed rejections

(iii) Applying renewal theory to predict the expected number of components rejected, replaced and reused

(iv) Predicting remaining useful life of components given that components survived until time *t*, the probability of surviving until the next overhaul period with the inclusion of renewals

(v) Incorporating cost variable as a threshold to calculate when the entire component in the assembly should be replaced

A case study has been utilised to validate the final version of the theoretical design. Real data are used in this case study which serve as the default data in the Through-life performance prognostic modelling.

3.5.3 Phase 3: Framework validation

An industrial case study and expert judgement are used to validate the framework to demonstrate the effectiveness of the prognostic tool, which addresses the fifth objective. A test run of the working application is conducted at the EPSRC Centre for Innovative Manufacturing in Through-Life Engineering Services. At this stage, verification and validation of the time/run-to-failure maintenance data are required to test the developed framework. The results are either in cycles. A comparison of the fused input and output results data with user expectations is conducted. An evaluation of the outcomes is based on domain expert's knowledge (in academic and industry) relative to the sourced data using questionnaires.

The validation process involved the collaborating industry and academic. The industry case study focuses on servicing to feedback to design and manufacture. The purpose of the validation includes: -

i. to ensure the tool meets user expectations in term of assessing the mechanical component degradation and estimating the remaining useful life in cycles;

ii. to check the underlying mathematics for the prognostics and RUL of the mechanical component;

iii. to assess the technique used for the development of the through-life performance framework.

The next section gives a summary of this chapter.

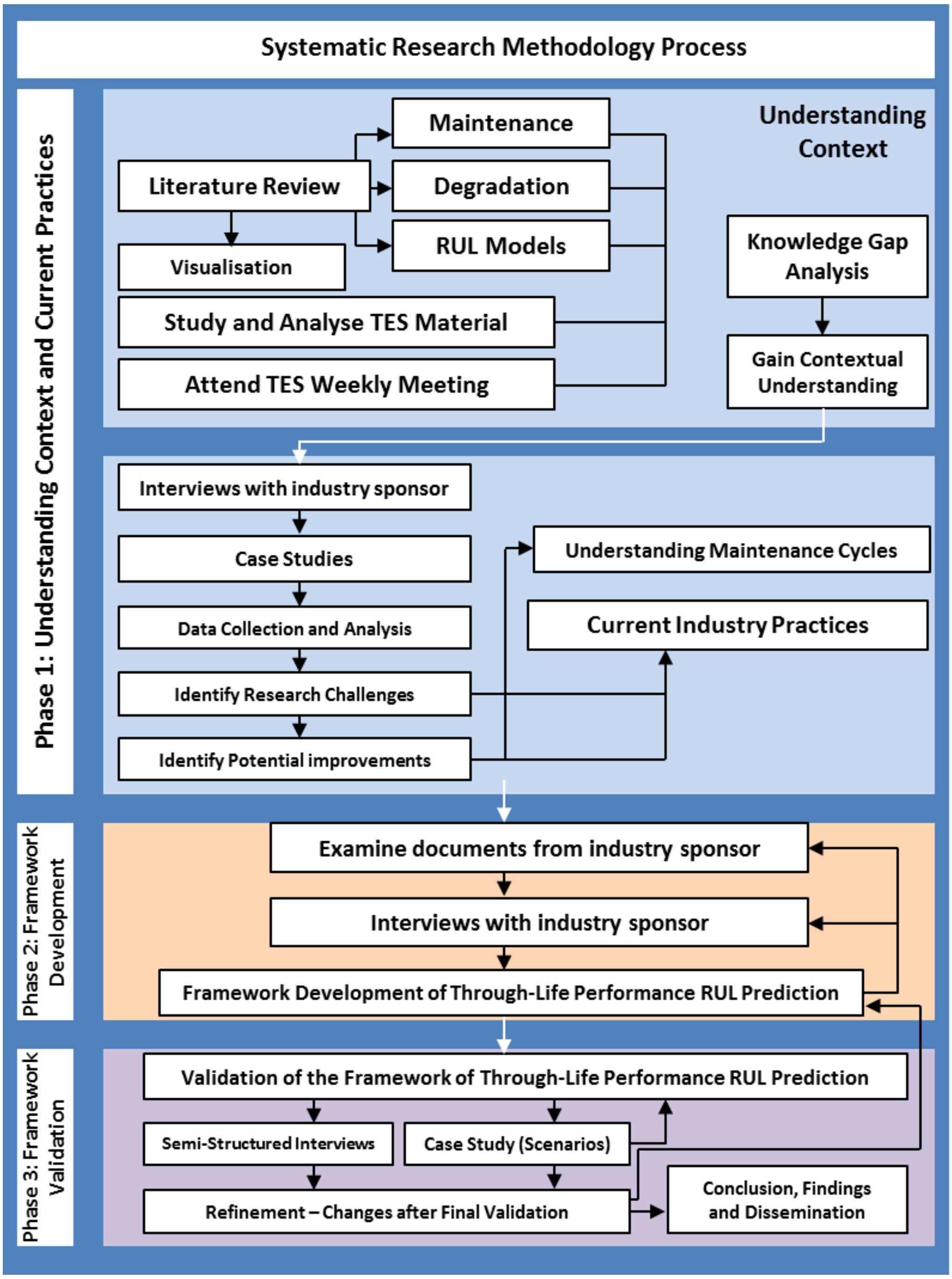


Figure 3-4: Adopted research methodology (Light blue colour is the phase 1, pink colour is the phase 2 and purple colour represents activities conducted in phase 3)

3.6 Summary

This chapter presented an adopted methodology in line with the industry nature of the research. The research design, purpose, strategy and data collection methods are the research methods applied in deciding the methodology.

A research design through exploratory and explanatory perceptions of the case study approach is conducted. This chapter emphasises issues relating to validity of a qualitative design covering strategies to improve this research. The research utilised the data collection methods; document, workshop/brainstorming, literature review and interviews. The rationale for selecting the research approach and data collection methods were enumerated. The discussion of the research methodology adopted includes understanding the context and current practices, framework development for aero component prediction and framework validation. The next chapter discusses the current practice of maintenance strategy in through-life performance of component degradation from industry interactions.

4 CURRENT INDUSTRY PRACTICE

This chapter investigates current industry practice and captures findings of through-life performance events. Data mining from historical sources, forecast of component degradation and remaining useful prediction of a component in assembly has become crucial. Prognostics on degrading component are predicted to ascertain future rejection for on-time maintenance, which is crucial in the aerospace sector with a focus on gas turbine engine multi-component system. This chapter provides initial introduction of the current industry practice in the context of component degradation and remaining useful life prediction. In relation to the investigation and interviews conducted, findings show the current approach in analysing component and maintenance data, but identifying and categorising failure mechanisms from historical sources seem complex and labour intensive (Okoh *et al*, 2014).

In this chapter, Section 4.1 presents the scope of participant selection for the study and industrial association with the collected information for the current practice. Section 4.2 centres on development of the questionnaire. Section 4.3 discusses results of the semi-structure and unstructured interview and analysis. Section 4.4 is a description of the current industry practice. Section 4.5 highlights vital observations including challenges. Section 4.6 summarises this chapter. The following section presents the scope of the current practice.

4.1 Scope of participants' selection

In this study of AS-IS industry practice, the scope relates to the selection of the participants for interview in the course of the investigation. The selection of the participants is in conjunction with the project sponsor, based on this research project. However, since the research context is a stator of a gas turbine engine, the relevant individuals with key responsibilities in this area were identified. Again, another area of interest is assessing component degradation and the major degradation mechanisms found in gas turbine engine. While the study focuses on gas turbine, the assessment of the nozzle guide vanes is eminent. The relevant experts in charge of the design and maintenance of the components were located in the department in different teams. The teams responsible for maintenance of Trent 700, 900, XWB, engineering for service, knowledge management and lifecycle engineering were identified. The identified personnel were later contacted through a face-to-face meeting to briefly discuss the research project and a proposed interview date was set. The interviews were conducted as part of the investigation to further gather relevant information about this study. The roles and years of experience presented in Table 4-1 are experts who were interviewed using unstructured and semi-structured interview questions presented to them, but due to confidentiality the names of persons were not specified in this Thesis. The next section describes the methodology for developing the questionnaire for the study.

Table 4-1 Experts, role space and experience

Experts	**Role Space**	**Experience (years)**
A	Chief Lifecycle Engineer – Trent 900	30
B	In-service Event database	20
C	Design for Service - Trent XWB	22
D	Information Manager - Engineering for Services	12
E	Design for Service - Trent 700	10
F	Rolls-Royce Engineering Associate Fellow - Life Cycle Engineering	30
G	Knowledge Management Technologist	4

4.2 Methodology to develop interview questions

In this research, the methodology for developing the interview question and conducting the study is described. A systematic research methodology was adopted in conducting the investigation of the current practice of through-life analysis and producing the questionnaire. The tasks include questionnaire / interview questions development – literature review, initial discussions with sponsoring organisation; an initial question – pilot research 1-2-1 (organisation and participants); outline of the questionnaire; conducting the data collection – on-site, number of hours used for note taking, teleconference and no recording allowed. The systematic methodology for developing the questionnaire is presented in Figure 4-1.

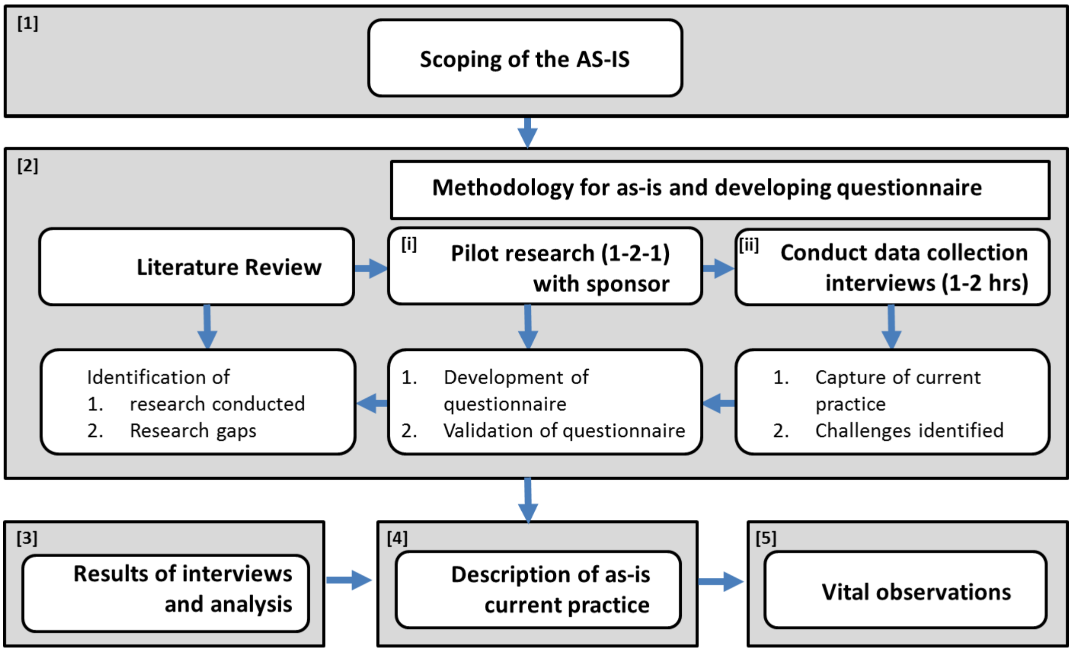


Figure 4-1 The systematic research methodology for phase two

This research aims to investigate the current practice relating data mining of maintenance information, component degradation knowledge and predicting failure of components using historical data. The purpose is capturing relevant and significant information required for prediction and maintenance within an aerospace domain. A review of literature further enables the questionnaire development, comprehension of the research area and identify limitations.

Literature review enhances selection processes by choosing the appropriate approaches to address prevailing challenges of the study. Discussions with industry sponsor began with attending a meeting to initiate this research project. The meeting was attended by relevant stakeholders. The meeting started with an introduction of the study and relevant requirements from the sponsor. However, the aim of the meeting was to relate with stakeholders, to identify and capture vital requirements. Subsequent meetings were attended to further gather and understand compositions of the investigation to address the research questions and to meet the objectives of this research.

4.2.1 Pilot research

Pilot research are conducted as part of initial communications with a participant (Lifecycle Engineer) with 30 years of experience from the sponsor organisation. Two meetings were conducted, while the first meeting took an hour, the second lasted for two hours. Both meetings were essential to further discover the context and scope relevant questions for the research. During the meetings, unstructured interviewing method was implemented. The participant stressed the need to data-mine historical data of components, feature and degradation mechanisms from maintenance information databases to assess health status of different components. The assessment analysis of textual data is to further identify, recognise relevant information and conduct a component, feature and mechanism categorisation. There is cultural impact on the way historical data are stored and utilised in the organisation for component degradation investigation. Based on the knowledge acquisition and discovery, data maintenance team happens to be the right stakeholders for the study.

However, as a result of the initial meetings and literature review, an array of questions was designed for interviewing specific stakeholders in the organisation. The subsequent meetings relate to reviewing and structuring the interview questions. The purpose of the interview questions is to assess how the organisation analyses and estimates component degradation based on failure modes using historical data from disparate sources including merits and demerits. The questions support capturing current procedures utilised to reflect component degradation and remaining useful life prediction. Whilst conducting interviews with the participants, the designed questionnaire is presented to provide realistic information in a two-hour period. The outcomes from the interview were validated through a report submitted to the sponsor. While tasks carried out during the study were joint efforts with the project team, an analysis of the investigation was conducted by the author. Examples of the questions include

i. How would you describe the degradation data?
ii. How are degradation data managed?
iii. What are the component degradation mechanisms?

A comprehensive full list of the questions is presented in section 4.3.

4.2.2 Conducting the data collection

Subsequent to pilot research in Section 4.2.1, semi-structured interviews are initiated for data collection. With respect to initial project meetings, stakeholders' attentions were considered to support identification of relevant personnel to be interviewed. In the process of the study, resource provision from sponsor provided opportunities to invite the right specialists for interview. During the meeting, the sponsor identified and listed would-be professionals for the interviews. The interviews are designed to happen between one and two hours. Additionally, the adopted process for requirements gathering from a semi-structured interview is shown in Figure 4-2.

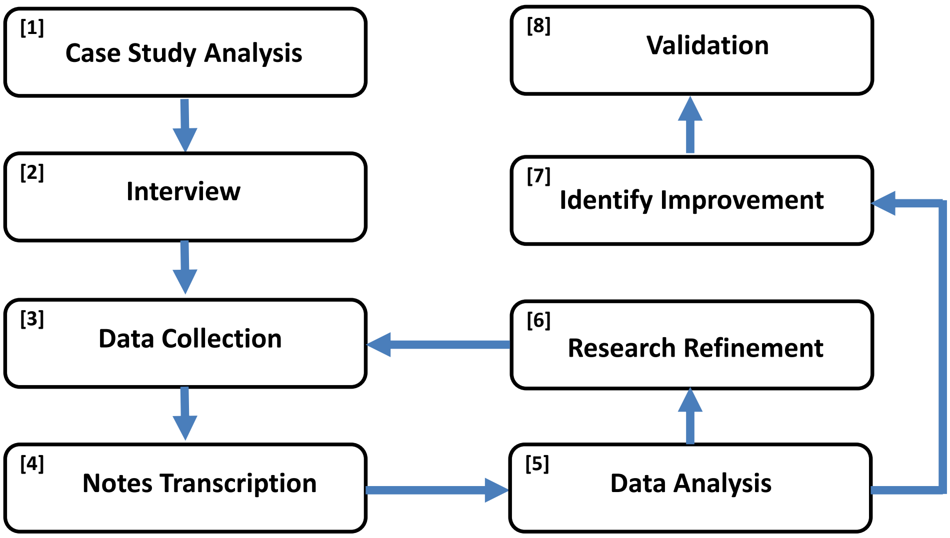


Figure 4-2 Process for information gathering from organisation interaction

In conducting the investigation in the AS-IS industry practice, early stages of the research were a joint approach with other researchers in the characterisation of component degradation project. The preliminary stages aim to deduce and gather relevant information for the project. The joint approach was useful during the initial stages of the research because it facilitates the provision of a clearer picture of the AS-IS practice and issues within an organisation. As the researchers in the overall project worked collectively, the project became individualised (specific focus) as the research progressed.

i. ***Task 1*** relates to a case study as a formation given detailed descriptions of component degradation based on historical data. While this study assesses component degradation relatives to diagnostics – problems examination. It also focuses on gaining understanding by conducting an analysis on maintenance cycles relating to engine availability from a timeline visualisation perspective as a scope and a case study relating to Prognostics – when something erroneous occur.

   In this study, a prior investigation of the current practice relating to the ontology and taxonomy of degradation mechanisms in this chapter followed by an analysis of events at various maintenance cycles in chapter 5. The investigations conducted provided relevant complimentary outputs for the project. The study involves the investigation of the component degradation to assess the level and identify types of damage. A categorisation of degradation mechanisms found includes component type, degradation type, and number of degraded component. Documents and databases were provided to enable delivery of the project. The study is further extended and supported by previous findings and available documents regarding maintenance informatics. Interviews and brainstorming sessions were conducted to ensure the required inputs are identified and outputs produced.

Component degradation and other relevant information are captured such as time of inspection/overhaul, life of component at design stage and flights cycles. The study validates the application of a generic framework. It emphasises the application of predictive maintenance strategy for prognostics. The historical data of specific degraded components in an assembly of the same product which travels on specified routes are statistically analysed. The applied model estimates the numbers of components expected to degrade at certain future flights cycles before failure occurrences to predict its remaining useful life.

In the course of the communication, importance was more on the presentation of the connection with the degraded component, the features of the component and the mechanisms which affect specific features and components accordingly. The interaction was based on capturing current processes of data mining and analysing component degradation from a convention maintenance strategy, while estimating the number of components expected to degrade and predicting remaining useful life of the components in the assembly.

ii. ***Task 2*** refers to the semi-structured interviews developed for data collection process, interviews, case studies and documents gathering. In this task, questions were developed to identify and extract relevant information during interviews and case study from a holistic perspective.

During the interview process, the author made handwritten notes, but did not record the interviews.

iii. ***Task 3*** uses developed interview questions to facilitate and conduct face-to-face conversations with stakeholders. The roles of the management personnel include subject matter experts and life-cycle engineers. Several meetings were initiated. Data collection methods were engaged during the process. Communication methods used in the investigation process are unstructured and semi-structured as highlighted in chapter 3 include face-to-face meetings, telephone interviews, video conferencing (WebEx), email and teleconferencing.

iv. ***Task 4*** shows notes transcription from interviews during the investigation. An example interview question is – **How would you describe the data?** – *The data relates to the complex data representation and storage in both structured and unstructured format. The data is a combination of numeric and text. The text refers to the taxonomy of the different deterioration. Examples of the taxonomy of the deterioration include tear, wear, rust, and crack*. Triangulation is utilised to process the effect from different communication sources of the data. The process illustrates transcription of the handwritten interview notes and report writing, which signifies learning.

v. ***Task 5*** describes the analysis of the data. The responses from the interviewees are handwritten as the conversation progresses.

vi. ***Task 6*** uses collected data to refine the research procedure.

vii. ***Task 7*** acknowledging areas of improvement during data analysis.

viii. ***Task 8*** supports validation using email and face-to-face meeting to contact participants and producing reports. The reports presented findings which were achieved through this study, interviews and documents on component degradation, through-life engineering services and prediction in the aerospace sector.

4.3 Analysis of interviews and findings

The section examines results and interpretation from interviews conducted with experts mentioned in Table 4.1. However, in the course of interview process, the researcher presented a list of pre-stated and additional interview questions in the line of remaining useful life prediction.

i. How would you describe the degradation data?
ii. How do you manage the data?
iii. What are the component degradation mechanisms?
iv. How are the data extracted?
v. What is the process of extracting data?
vi. How would you describe taxonomy and ontology in this context?
vii. How would you describe the degradation mechanism?
viii. What are the prominent degradation mechanisms?
ix. What are the components which are prone to these degradation mechanisms?
x. What are the key features of nozzle guide vanes component and described it?
xi. What is the essence of development test event?
xii. How would you describe the degradation model for prediction?
xiii. Is there a link between component level and assembly level data in a multi-component system?
xiv. How would you demonstrate component rejection, replacement and reuse?

The interview questions were validated with my supervisors, members of my research team and colleagues from research centres. The researcher discussed the interview questions with supervisors, who in turn assessed the questions before approval to ensure it is in line with the research and follows the required standards, ethics and processes. The researcher conducted a one-to-one interview with centre colleagues to ascertain the validity of the questions as a test case for further interviews with experts in sponsoring organisation. The responses to the face-to-face and semi-structured interview questions posed to the experts are presented. A total of 11 semi-structured interviews questions were used to conduct the interviews with different experts listed in Table 4-1.

Based on question 1, Participant A described degradation data as large set of structure and unstructured data. Participant B and D emphasised that degradation data are complex containing numeric and textual data. Participant C referred to degradation as deterioration, which includes tear, crack and wear.

Regarding question 2, Respondent A opined that degradation or maintenance data are stored in databases. Respondent B highlighted that degradation data are managed using Maximo and FRACAS databases. Respondent C noted that data are stored in different locations depending on the nature of the maintenance information. Respondent D provided a clear response by indicating the in-service data used for resolving customers' issues are available in the Maximo database, while FRACAS database contains specification and design work information. Respondent E highlighted that data are stored in different locations or sources e.g. hardcopy documents archives and softcopy in Excel. Furthermore, the data stored in these databases are components, features, and deterioration for capturing the understanding of the physical system.

Relating to question 3, Participants A to G noted some of the component degradation mechanisms including corrosion, deformation, wear and fracture. A request was made to view the database for more mechanisms.

With question 4, Respondents F and G responded to this question. While Respondent F emphasised that data in databases are extracted using an in-house application, Respondent G reiterated that extraction tool is a "recognition tool" designed by an in-house expert using Java. Respondent G also noted that the database contains different modules called containing concepts / terms of deterioration (taxonomy). Database contains information such as the names of products, customers, service types, system types, components, features and mechanisms. This study focuses on products, components / parts / commodities, features and mechanisms.

In question 5, Respondent F explains the process of importing data into excel and using the tool to select the concepts add-on to identify and extract relevant terms. Respondent G opined that the data extraction include (i) concepts/terms only and (ii) relationship extraction between a component and mechanisms. While concepts are currently being extracted using add-ons to recognise and retrieve terms, relationship extraction based on subject-verb-object (SVO) add-on is applied to retrieve components and mechanisms (Jiang, 2012). Example "a blade has crack" ("blades" as component and "crack as mechanisms").

For question 6, Participants F and G responded to this question. Participant F described a taxonomy as synonyms of degradation mechanisms and ontology as a collection of different taxonomy for specific space e.g. ontology module can be a deterioration process containing synonyms of degradation mechanisms. Respondent F emphasised that study should focus on corrosion, deformation, fracture and wear as the major degradation mechanisms affecting gas turbine mechanical components in the hot section. Respondent G highlighted that 'split' can be another name of 'tear' or 'cut', but the underlying meaning might be different from the nature of the mechanisms. Respondent G noted that ontology in this context relates to the different excel sheets, which are used to store the taxonomies for each ontology module.

Regarding question 7, Respondent D relates degradation mechanisms to loosing performance depending on usage. Respondent E noted degradation mechanism results from use of an asset and when the limit or end of life is approached, the rate of performance tends to reduce. Respondent F described degradation mechanisms as a process which makes an item to lose its strength. Respondent G highlighted that degradation mechanism affects the functionality of assets.

In question 8, Respondent A noted that nozzle guide vane and turbine blade are prone to degradation mechanisms in the hot section. Respondents F and G made mentioned of the nozzle guide vane, blades and seal segment.

For question 9, Participant A gave a vivid description of the nozzle guide vane as the central focus of this study. Participant A stressed that components are mainly in compressor, combustor and turbine segments of an engine. However, a jet engine is a multi-component system. For example, nozzle guide vane (NGV) can be either single or in pairs. The NGVs can be between 16 and 20 pairs depending on the manufactured engine. Additionally, a gas turbine is a pressure energy system for velocity and the function of NGV is tuning high pressure gas out of the combustion at 1600^0C, which undergoes a uniform burning. Participant A gave key features of the NGV, which include leading edge, trailing edge, gill holes, shroud, cooling holes, TBC and fir tree root. Participants F and G requested reference to the specific experts such as participant A. Other participants made reference to the engine manuals to get the acceptance limit for engine usage, technical variance of the engine, and events recording management system.

With question 10, Respondents A and F provide responses to this question. In the engine testing process or programme, various events occur during testing. Both participants noted that development test event is the test in progress with the sole task of validating the system based on the specified operating conditions. Participant F provided further insights illustrating that degradation model such as the Weibull function is suitable for degradation, reliability and maintenance issues and it is widely used in industry especially aerospace. Participant F described the operation of an engine in a start and stop mode depicting the numbers of component rejection, replacement and reuse. This question provides information to the case study relating to prognostics.

Relating to question 11, Participant F showed that there is link between component level and assembly level. In this context, an individual component is unable to power a system, while collection of components as an assembly has capability to fire a system. Though, at the component level no insight on data, while assembly level has insight on data such as how many were scrapped, how many were reused and replaced and how many repaired components were replaced.

4.3.1 Comparative analysis of participants' views

A comparison based on participants' views is presented and emphases on the current practice relating to component degradation and remaining useful life prediction. The similarities, differences and unique features relating to the experts about the component degradation and failure mechanisms considered are highlighted.

Similarities

i. Use in-house application for data analysis
ii. No set standards for analysis of complex data to predict component failure existed
iii. No standard methodology for estimating component degradation for future replace existed

Difference

i. Terminologies of different terms and concepts are present in the database
ii. Definition for failure modes and failure mechanisms vary

Distinct

i. Each participant happens to have distinct level of experience in reliability, which results to difference in interpretation of understanding failure analysis.
ii. The advantages of lessons learned are applicable to different individuals by providing enhancement to existing practice

4.4 Description of current practice in industry

The corrective maintenance strategy discussed in chapter 2 relates to conventional maintenance strategy. The domain experts gained a better understanding of gas turbine jet engine during overhaul maintenance and development engine testing (Rolls Royce, 2005). In the course of maintenance, repair and overhaul (MRO), historical and current health data are gathered such as the time (flight cycles – start and stop of an engine), the number of components which had failed and types of damage found during inspections (Rausand and Høyland, 2004; Rolls Royce, 2005; Roy *et al*, 2013). All recorded events encountered during inspections are analysed to give insights enabling domain engineers understand behaviour of the system. In this case, the historical and current health data are both qualitative and quantitative. Examples of the data include component, degradation mechanisms, time of failure in cycles and the number of degraded components. The data are stored in events database and Failure Reporting & Corrective Action System (FRACAS) (Rausand and Høyland, 2004).

The research aims to recognise the current challenges in conventional maintenance for estimating the life of mechanical components. The research justifies the objective to investigate the level and nature of mechanical component degradation available in the historical evidence. This research identifies the following based on objective one: -

i. The level and nature of predominant mechanical component degradation mechanisms
ii. The challenges encountered in classifying the level and nature of mechanical component degradation mechanisms
iii. The visualisation of components with features and nature of failure mechanisms

The research conducted in conjunction with an aerospace company – an original equipment manufacturer. The company provides TotalCare® and Power-by-the-Hour® maintenance services to operators as described in chapter 1 (Rolls Royce, 2005). The focus of the study is on a specific commodity in a product; refer to section 1.1 of chapter 1. In this research, service data containing various components of an engine (e.g. Trent 900) which had been in service and had MRO data were investigated. The service documents and reports were examined and analysed. This study was conducted using semi-structured interviews supported by observations. In relation to Section 1.1, a logical descriptive language was applied to grasp the interaction between different aspects outlined in Figure 4-3 from a single case or multiple cases (Gummesson, 2000). The investigation was systematically conducted across different sections in the same department, which were identified in relationship with service data required for the research. The discoveries made during the investigation were analysed and reported in a universal case study approach (Robson, 2002). The universal approach in conducting the study of a research project is complex with an impossibility to conduct multiple case studies (Gummesson, 2000).

The issues presented in literature and by subject matter experts emerged during and after the course of the study. These issues resulted from conventional maintenance strategy leading to high downtime, man-hours and cost. The conventional maintenance strategy has been previously discussed in chapter 2, which can make gas turbine maintenance and spare parts availability difficult to manage. This strategy is reactive instead of proactive. The designed and manufactured gas turbine representative relationship is outlined in Figure 4-3 illustrating the structure of the data management from product, system, commodity, feature and mechanism per the findings. The data management structure can be read top-down and bottom-up. The top-down approach is an hierarchy showing different connections as steps that transform one into the other (Crespi, Galstyan and Lerman, 2008). The procedures can help in the analysis of the product into another segment to identify the type and nature of failure mechanisms which is responsible for the component damage. The bottom-up approach in Figure 4-3 focuses on the details of the type and the nature of the mechanism affecting the component in the specified product to assess the root cause of the incident (Biederman, Glass and Stacy, 1973; Crespi, Galstyan and Lerman, 2008).

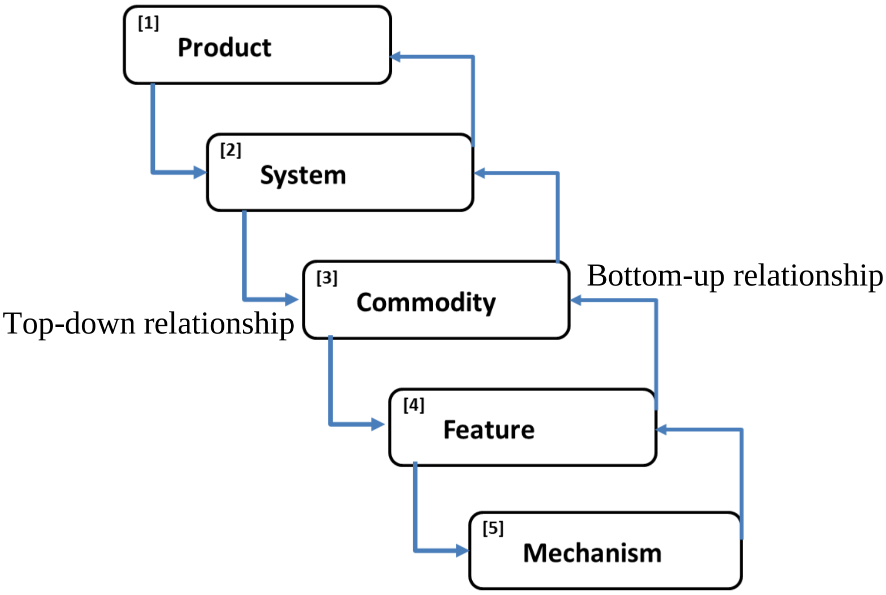


Figure 4-3 Outlined relationship of the AS-IS practice from product to mechanism

The AS-IS practice describes the relationship associated with: -

i. Product – described as the engine type, e.g. Trent 900
ii. System – defined as the module based on shaft type. The product can contain 1, 2 or 3 shafts. However, in this study, all system shafts are examined. The fan, compressor and turbine are the major systems which make-up the product.
iii. Commodity – refers to components or parts, e.g. nozzle guide vanes, fan blades, etc.
iv. Feature – defined as a different segment of the commodity, e.g. leading edge
v. Mechanism – refers to damage or failure modes, e.g. fracture, deformation, wear, corrosion, creep.

For instance, as indicated in Section 1.1, the HP-NGV is a group of individual commodities within an assembly (system). The focus of this study is to review the AS-IS practice relative to degradation mechanisms – fracture, corrosion, deformation and wear from a traditional maintenance perspective, and identify the number of components with features of damage mechanisms.

Ontology for taxonomy of degradation mechanisms

The findings from this study recognises types of damage and approach used in conducting the analysis. Figure 4-4 contains the taxonomy in the ontology showing a typical component to system relationship, various failure causes and failure modes.

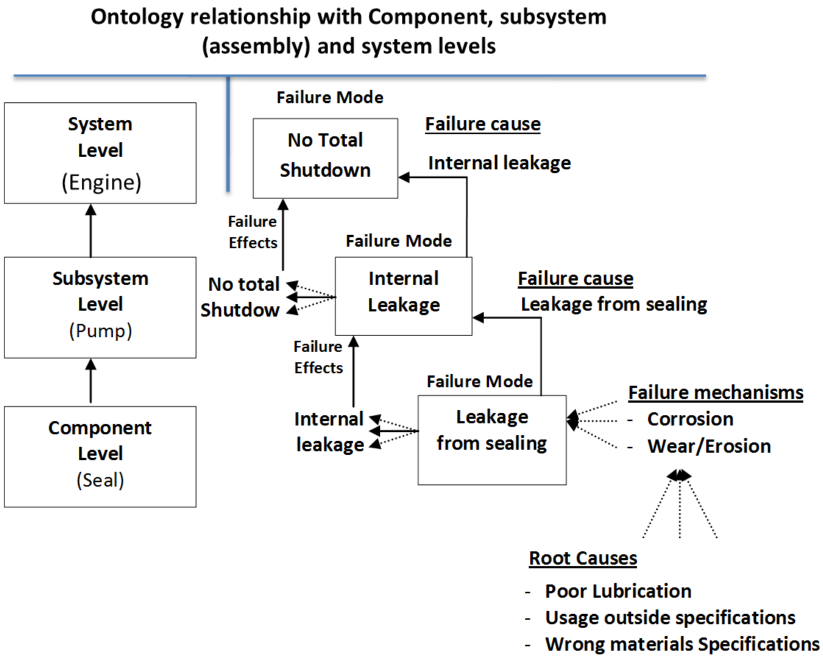


Figure 4-4 The relationship between failure cause, failure mode and failure effect. (Adapted from Source: (Rausand and Høyland, 2004))

This analysis informs decision making when seeking to consider the choice to either scrap or continue to use the component under investigation. The connections created assist in detecting failure mechanisms easily based on the approved and agreed threshold. It relates to the use of the monitored operating and maintenance information as inputs to determine through-life performance in terms of remaining useful life of the component under investigation by observing geometry, property loss and material loss (Okoh *et al,* 2014). The list tends to grow depending on the number of synonyms available. The findings emanated from the model application to the existing data repository for reuse and sharing as seen in Figure 4-5. The purpose of reuse and sharing of data is to deliver consistent approach to problem solving and decision making. Tangible results can be extracted from knowledge sharing and reuse.

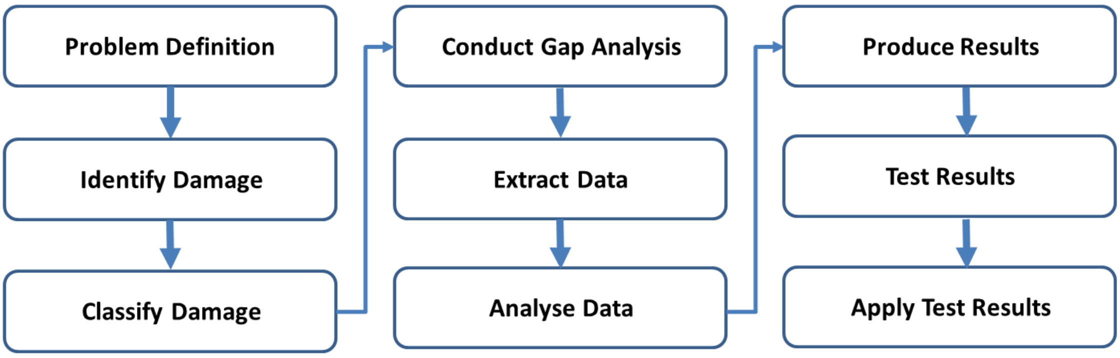


Figure 4-5 A model to modify and develop the existing data repository

(a) Damage characterisation (Problem definition) – the initial idea of the challenge is conceived and reasoned. An example of such is *"What kind of damage affects mechanical components?"* The procedures to modify ontology (Gruber and Gruber, 1993) relates to the process, meaning of the types of damage and how /where damage should be classed. The issue of how identified terms should be uploaded for a rerun and re-analysis is addressed.

(b) Damage identification – the damage identified relates to the damage characterisation. Documents are assessed to identify and retrieve relevant damage based on predominant degradation mechanisms for knowledge sharing (Dadzie *et al,* 2009). The information gathered is then pre-processed and filtered from the raw 'on-demand' textual data. The data contain various terms and concepts which are systematically and hierarchically arranged for use in the engineering for service domain. The process starts with observing issues with material loss, change in shape and properties and questions to understand the nature of damage.

(c) Damage classification – the classified damage in (b) are categorised into class and subclass (see Table 4-2). The definitions and the questions provided domain experts with the how and where to allocate the identified damage. The identification process includes: -

i. Define and seek specific meaning of the types of damage to ensure better understanding of taxonomy of degradation and causes;
ii. Attempt to ask and answer questions to ascertain whether an identified keyword is relative to a specified category of degradation mechanisms;
iii. Identify, assess and filter damage based on material loss, separation, change in geometry and property maintained.

In the course of this study, the identification process determines whether the material under investigation is affected by either corrosion, deformation, fracture or wear to generate a taxonomy (Okoh *et al,* 2014). In this context, a class is attributed to degradation mechanisms, while subclass relates to examples of damage based on the findings.

Table 4-2 Sample concepts, meanings and questions

Class	Subclass	Definitions	Questions
Corrosion	Blistered	Change in the texture – presence of uneven surface or raised bubbles	Is there a variation in colour, weight and appearance or are there elements of deposit on the surface of the material?
Deformation	Bent	Change geometry - Altered from an originally designed shape	Is the material altered from its original shape?
Fracture	Cracked	Material separation - Split without coming apart	Is there a separation within the material?
Wear	Abraded	Material loss - Scrape or wear away by friction or erosion	Is there a removal of some material particles?

(d) Gap analysis – introduced to compare current and future states of the ontology. A framework to modify and develop the ontology serves as a guide to help understand current position, future position and approach to get there (Rosemann and Vom Brocke, 2015). In applying the framework, the current state of the ontology and the iterative reality check process is what to do to get to the future state – the desired robust ontology. The original data sets of the knowledge representation are the maintenance information extracted during the AS-IS investigation, which needs to be updated and maintained, while the proposed future knowledge representation is the TO-BE (Rosemann and Vom Brocke, 2015).

(e) Data extraction – use of a recognition tool to automatically identify and retrieve relevant terms for data analysis. The recognition tool is applied to text mining. The procedures to extract data are described as: -

i. *Context - the application domain where the interrogated report resides*

ii. *Metadata - information about the identified knowledge*

iii. *Feature - is the knowledge of specific damage area*

iv. *Concept - alternate knowledge and relationship with feature in the metadata*

v. *Message - the specified request to extract knowledge represented in the events document with related types of damage*

vi. *Knowledge Extraction - the recognition tool is used to data-mine and return results*

vii. *Update - when* ontology is amended with any newly found terms/knowledge

(f) Analyse Data – data analysed using an iterative reality check process to assess and retrieve actual terms for taxonomy creation. An introduction of a systematic process to iteratively execute "*before update"*, "*during update"* and "*after update"*. A reality check technique is used to get precise number of similar terms present/omitted in the database during analysis with the recognition tool. A reality check technique is manually searching and identifying knowledge discrepancy with a search function.

i. *Before Update* – when results of damage are initially processed to capture mechanisms

ii. *During Update* – current state when results and failure knowledge are manually checked to find the number of precise and accurate mechanisms captured.

iii. *After Update* – checking results and damage knowledge against the events information to identify the mechanisms present in the '*during* *update'*. The relevant knowledge which the recognition tool could not capture is identified by the investigator (writer). The newly found terms are then updated in the taxonomy within the ontology. The uploaded knowledge takes effect immediately after the next run, while the recognition tool automatically runs in the background to effectively update changes.

The AS-IS and TO-BE architecture in Figure 4-6 shows the procedures for translating the current state to the future state. The results show the current and future states (AS-IS and TO-BE) of the deterioration process (ontology module) datasets shown in Figures 4-7 and 4-8. The presence of exclusion represents '!!' in the deterioration process because some words are not mechanisms (see appendix E). The current structure allows assignment of words (taxonomy) anywhere in the deterioration process (ontology module), hence, a proposed agreed structure and arrangement by policy-makers is available in appendix E. The taxonomy for predominant deterioration mechanisms and their causes are available in appendix F.

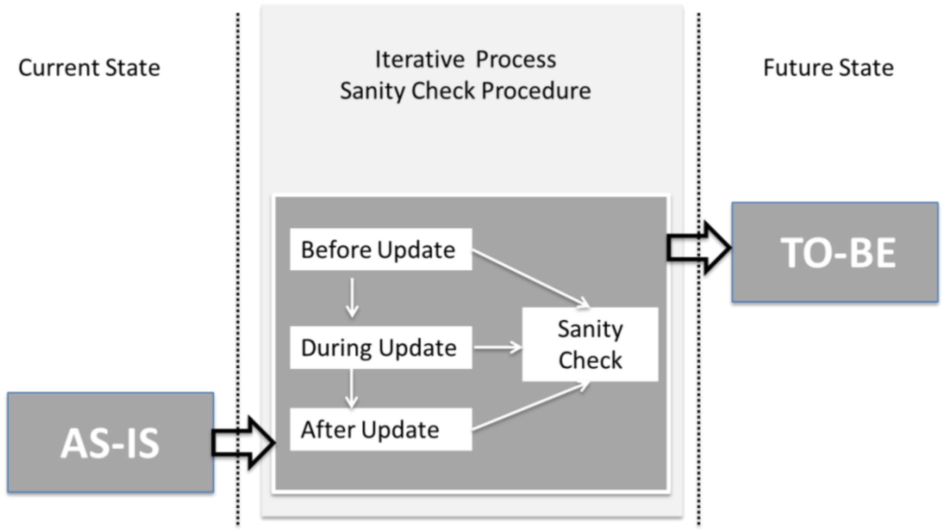
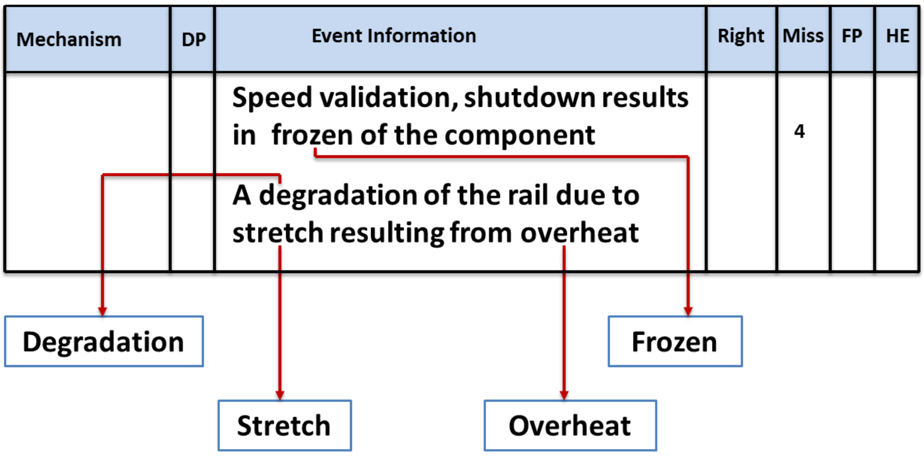


Figure 4-6 Representation of iterative reality check process

A reality check technique ensures data integrity and eliminate redundancy (Boritz, 2005). The reality check technique in this context identifies, captures and stores terms – taxonomy within the ontology. The knowledge extracted from events report should be accurate and consistent irrespective the number of times the tool is applied, when the ontology is updated accordingly. The audit is done on the update section as presented within the architecture. A reality check was conducted by physically counting the identified concepts and by running the embedded recognition tool. The researcher used the following criteria: -

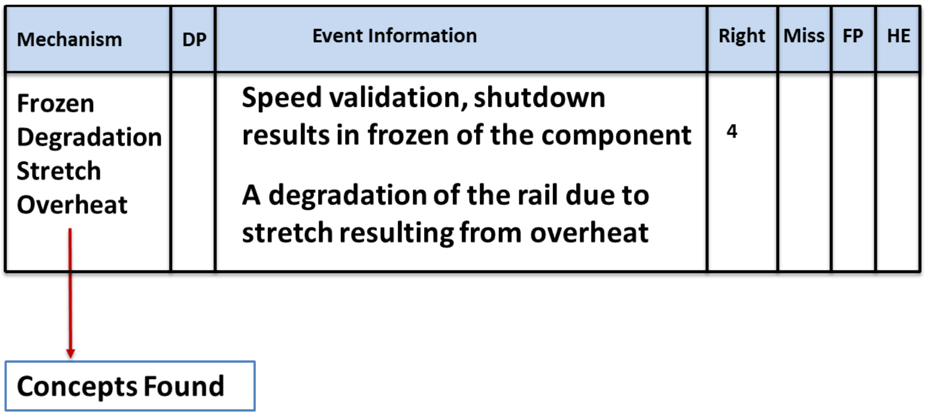
i. *True Positive (TP)* – when the extracted concepts from the event information are correct. An example includes “fret”.
ii. *True Negative (TN)* – concepts not captured by the recognition tool but are correct. The concepts are identified from events report and fixed by adding the same to the ontology e.g. “frozen”.
iii. *False Positive (FP)* – extraction of an incorrect concept in the events information (see Figure 4-7). A fix for FP is removal of concepts in the taxonomy e.g. “close”.
iv. *False Negative (FN)* – attributed to human error – misspelling actual concepts. The recognition tool will not identify and capture relevant knowledge. For instance, “luse” instead of “lose”, to fix this, the word “luse” is added as a taxonomy in the ontology. The reason for this is because service representatives’ report events from different locations around the world and typographic errors are bound to occur. However, it is advisable to train the tool to extract the knowledge “luse”.

A reality check conducted uses new keywords captured to confirm outcomes as shown in Figures 4-7 and 4-8.



*FP: False Positive; HE Human Error; DP: Deterioration Process

Figure 4-7 Samples of relevant concepts analysis (“4” indicates missed keywords)



*FP: False Positive; HE Human Error; DP: Deterioration Process

Figure 4-8 Identification of relevant concepts (“4” means right keywords found)

(g) Result – anticipate and plan the process to know exactly what to extract and how it is conducted. Comparing both current and future states of the ontology of degradation mechanisms to gain insights. Act to agree and implement pruning and refining techniques refer to appendix G.

(h) Test – tests are based on historical information and domain experts' knowledge

(i) Applying results – outcomes are applicable to other domains requiring ontology for documents processing.

The study provides knowledge discoveries, which examines failure mechanisms observed during maintenance repair and overhaul of gas turbines for wide body aircrafts. The events and maintenance information are stored in databases. The databases contain history of issues reported and documented by service engineers. The events information (service data) examined include a collection of engine IDs and names, components' events or problems encountered, engine types, year of manufacture and date of entry into service and the kind of deterioration experienced by engines' components during operations.

4.4.1 Index representation of products, components, features and mechanisms

The outcome from the textual analysis is the Master Index Representation (MIR). The MIR categorises taxonomy of degradation mechanisms which affect features of a component. The component is related to the system or product or engine. The study examines relationship associated with this knowledge representation. The process for conducting this exercise is using a recognition tool to extract concepts from a sentence. The sentence is part of a textual data in a report which follows the 'subject- verb-object'. Table 4-3 contains data with relationships.

Table 4-3 Extraction of concepts from relationships

Components	**Relationships**
Seal&&Spacer&& Ring	Adjusting-hasMechanism-damage
Seal&&Spacer&& Ring	Adjusting-hasMechanism-NICK
Seal&&Spacer&& Ring	Seating-hasMechanism-Damage
Seal&&Spacer&& Ring	Seating-hasMechanism-NICK

In the analysis, recognition of terms as subject and object, verb and noun, and interpreted by extracting the specific taxonomic concept matching the ontology and the text. Future ontology module could be made more robust with standard specific names (concepts) based on an agreed policy. These names can range from single to triple words, separated by a space to ease analysis. In the analysis, hyphenation of concepts in the taxonomy and the report could be avoided, however, they are extracted. For example, the term ‘feature-Hasmechanism-deterioration process’ is used to identify and extract both feature and mechanism with true and untrue relationships. The final master index representation for the analysis shows the name and number of products, the components, features and mechanisms in a hierarchical order (see appendix G).

4.5 Key observations

Comparisons are made between industry practice and academic research based on the industry collaboration and literature review. The outcomes indicate the need for further research in the area of predictive maintenance for assessment of through-life performance prediction of component degradation. Furthermore, maintenance database is required to gain background understanding of the AS-IS practice and come up with a better means of establishing the research aim. Challenges include systematically storing data, identification and classification of the level and nature of component degradation. Due to the limited time, analysing processes are conducted in a traditional way when all data is available. Insufficient time for analysis may hinder expected outcomes. However, the rationale for conducting this industry study relates to the need to understand the challenges of conventional and preventive maintenance from a through-life engineering perspective. The study captures the understanding of through-life performance of component degradation relating to maintenance strategies. The findings from the interactions with stakeholders provided background knowledge about component degradation, through-life engineering services, maintenance strategies, the Weibull distribution, diagnostics and prognostics.

At design stage, all information for constructing component scheme, detail and specification relates to durability. Viswanathan (1989) argues that component life at design stage can be determined by material composition and parameters by considering creep-rupture properties regarding stresses at different temperatures, and crack/fracture hardiness properties. It relates to inspection requirements and procedures for start and stop operation, and resistance to hot operating conditions. Components without data for RUL prediction at component level include turbine blade and fan blade. Assemblies with failure data include rotor and stator, which operate multi-component servicing.

Through-life performance prediction relates to component degradation in an assembly with insufficient data recorded for individual components at assembly level. Failure data are often associated with an assembly as a whole. Therefore, issues involved:-

i. Predicting long-term sustainability of spare parts for inventory management to support operators; providing designers and manufacturers with the information to reduce downtime and save cost.
ii. Predicting time remaining of run-to-failure samples to ensure early maintenance, thereby avoiding unexpected / catastrophic events and providing ample opportunity to schedule maintenance.
iii. Proffering designers and manufacturers better estimate of components' failure to enhance future products. However, the methodology for calculating the number of components expected to degrade, thereby applying a predictive strategy for remaining useful life prediction will be discussed in chapter 6 as well as gaps identified focusing on the research activities.

4.6 Summary

This chapter presented investigation and interviews conducted in the industry to capture an AS-IS practice. The practice is a corrective and preventive maintenance in the aerospace sector from a through-life performance perspective. The capture of the current practice aids assessment and analysis of degradation data. The AS-IS practice was conducted and captured through face-to-face semi-structured interviews with relevant outcomes such as data mining of historical data for classification of taxonomy into predominant mechanisms for ontology, a visual analysis of relationship of components, features and mechanisms. A link between component and system is presented. This chapter compares and identifies gaps between academia and industry. The gap illustrates the predictive maintenance strategy for assessment of through-life performance relating to component degradation. The identified gap is expected to be a research contribution and presented in chapter 6.

This chapter aided the delivery of objective two – investigating the level and nature of components degradation as a current AS-IS industry practice, identifying components, features of that component and the damage mechanisms affecting the components. The findings are further applied to the proposed framework in chapter 6 by incorporating the selected variables for specific components (multi-component assembly). The assembly is combination of the same components interlocking one another in circle / ring. The data collected in this study included number of components in the assembly (stator or rotor), flights cycles, numbers of component expected to degrade and the reliability/degradation model – Weibull distribution. The investigation identifies the qualitative and quantitative data required for analysis. The study captures procedures for analysing historical data to generate qualitative and quantitative results. The next chapter delivers an extension of this chapter to investigate and analyse multiple engines maintenance cycles based on events taxonomy from a through-life performance perspective.

5 ANALYSIS OF MAINTENANCE CYCLES

In this chapter, additional investigation and analysis are conducted following the current practice carried out in chapter 4. While chapter 4 focuses on the taxonomy of different damage mechanisms at low-level, this chapter further classifies taxonomy depicting events at high-level, which affect the availability and reliability of an engine. The understanding of high-level events has led to this study, minimising significant periods devoted to searching for relevant information concerning different assets and their histories.

Data analysis on historical maintenance data containing taxonomy of high-level events is conducted in an attempt to analyse through-life maintenance cycles of multiple aero engines and multiple fixed overhauls. The study conducted here serves as a data collection method and proof of data analysis with multiple overhauls through multiple intervals. The investigation of the maintenance histories identifies relevant keywords needed for information visualisation. Information visualisation concentrates on the use of computer-supported tools to derive new insights and knowledge. A combination of information and knowledge visualisation is explored to deliver an interactive application.

The events accumulated over time at a point-in-time or interval-in-time are rendered along a timeline. However, an event can be defined as a point-in-time where a decision to act is made (event decision). The events will be visualised on a timeline for decision making and help navigate summary information about maintenance from a through-life engineering services perspective. The information modelling approach, techniques used to elicit requirements and navigation of the data are discussed. Section 5.1 describes of events taxonomy. Section 5.2 discusses data collection method. Section 5.3 highlights overhaul sequence and activities. Section 5.4 delivers the methodology to visualise summarised maintenance histories on a timeline. Section 5.5 highlights analysis of data collected for the design of summarised maintenance histories on a timeline. Section 5.6 gives evidence of the design of the summarised maintenance histories on a timeline. Section 5.7 relates to the development of the summarised events on a timeline. Section 5.8 summaries the chapter.

5.1 Description of events

An event is an occurrence at a point-in-time where a decision to act is made. Events are occurrences at any point-in-time or any interval-of-time. Engine events result from in-service which become histories stored in a repository. Dunglinson and Lambert (1983) suggest that an event could be initiated causing disturbance in system variables; enabling, permitting and initiating events to cause system failure. However, a fault occurrence which makes a system unstable, resulting in a number of devices operating with a very short period of time (King, 1981). From the sponsor's perspective, an event is a point-in-time when something significant occurs, which can be a point-in-time where the 'state' of a system is measured or confirmed e.g. an observation or inspection event. Furthermore, the author describes an event as a significant expected or unexpected happening at a single point-in-time or an interval-in-time. An event can be defined as the point-in-time where a decision to act is made (event decision). This event can be related to some system of interest crossing or confirmed to have crossed a threshold of significance, e.g. failed (not functioning), about to fail (rejection decision), and has insufficient life to reach the next inspection event without unacceptable risk of failure (repaired/reuse decision). These events can be either major or minor. Events can be interpreted as interventions on an engine.

Furthermore, outcomes from brainstorming sessions are used to create an ontology for engine events based on agreed keywords used to develop events timeline visualisation. The approach for creating the ontology is discussed in Section 5.5.2. The study demonstrates the means to view relevant knowledge about events which an engine experiences during and after in-service. This study identifies and captures events based on routine checks on engines on-wings before taking to the skies. For example, "routine inspection" is classed as a high-level event. This study aims to categorise engine events collected during maintenance, repair and overhaul, and from workshops/brainstorming sessions/interviews with domain experts. The brainstorming sessions were conducted with selected Rolls Royce senior and mid-level personnel.

The categorised events are occurrences which have impacts on engine availability. The categorisation is at different levels for better understanding of the types of events which are termed “worst”, “less severe” and “standard routine”. The levels of events are outcomes from interviews and brainstorming sessions validated by domain experts. The events are also grouped in key colour codes. The taxonomy of events is processed to display or visualise the categorised events on a timeline. The level and group of events are standard keywords with respective colour codes presented on an interface showing engines’ numbers against point or intervals in time. The study aims to provide visualisation toolkit to help improve service knowledge. This investigation validates the importance of studying a component’s remaining useful life based on maintenance data from both high-level and low-level events. Though records are available at the assembly level, it remains difficult to predict remaining useful life.

5.2 Description of data collection method

This case analyses and visualises maintenance information regarding multiple fleets and multiple overhauls states of different events, which are likely to hinder operational services throughout the life of the engine. Gaining understanding of the rationale for conducting this additional case, a couple of groups participated in brainstorming sessions at different dates and times. The brainstorming sessions were facilitated by the author. The author made a presentation of the sample design of a timeline events visualisation and presented participants with questionnaires based of the proposed design. The event categorisation contains different levels: -

i. Level 1 describes events which determine availability of the product for customer service. For example, overhaul, service disruption, delivery of engine

ii. Level 2 relates to non-standard or infrequent events with the potential to modify a product’s availability or functionality. For example, Borescope, oil change
iii. Level 3 relates to standard activities (daily or weekly) of health maintenance status. For example, engine health monitoring data

5.3 Description of overhaul

An engine is taken for overhaul after in-service operations. Rolls Royce (2005) declare that the RB211 has a total of 42,000 hours on wing prior to overhaul, which is equivalent to 4.79 years approximately 5 years. After specified hours of starts and stops engines are overhauled. Engine histories uses Weibull analysis to enhance and support engine removal factors, thereby creating novel engine management practices based on component statistical failure analysis and distribution relative to bathtub review in chapter 2. Rahman *et al* (2015) describe overhaul as a procedure for periodic preservation of an engine to achieve its functional expectation regarding its design life, thereby enhancing an engine's useful life. Engines are expected to be detached, pull apart, make anew, examined, returned and verified relative to the policymakers’ approved procedures. As suggested by Hoddenbach (2014), during overhaul aircraft engines should be carefully inspected at every 100 hours, and in the process snags discovered are repaired in an annual occasion. Furthermore, van Damme and Stolk-Oele (2015) state that after 3000 flight cycles engine overhaul takes place by disassembling, cleaning and servicing.

The gap between two overhauls and total number of overhauls are dependent on the type of engine, operational routes of the engine, whether long haul or short haul and based on the engine health management practice. As indicated above, it could be after an average of every 3000 cycles. On-wing, about 42,000 hours between overhauls is set by the RB211-535e4 in year 2000 (Rolls Royce, 2005) – but this is for old engines. Modern engines are expected to be on-wing 13,000 hours between overhauls (Rolls Royce, 2005) – meaning about four, six or more overhauls are likely through the life of an engine.

Overhaul sequence and activities

Phase 1: On-Wing

Diagnosis with engine health management system notify the policymaker of any issues of abnormalities (Rolls Royce, 2005).

Phase 2: Off-Wing – Engine removal

Stage 1: Work scope definition - arrival of in-service engine at shop floor. When an engine reaches its cycle threshold, the engine is taken off-wing for maintenance. The identity of the engine - serial number is noted with its unique maintenance place and complete history data. The work scope gives a synopsis regarding the required work to be carried out. Log book is checked before commencing overhaul on an engine – important to have an idea of the previous maintenance and repair conducted and causes.

Stage 2: Cleaning and Inspection – Van Damme and Stolk-Oele (2015) note that cleaning and inspection involve washing an engine with various fluids to get rid of any debris and grease ahead of a visual inspection. The use of borescope inspection is the application of camera driven equipment to examine inside of the engine. Borescope is a flexible pipe with micro camera which move freely inside an engine to identify abnormalities such as wear, deformation and tears (Van Damme and Stolk-Oele, 2015). Rahman *et al* (2015) present a methodology for teardown inspection stripped components from within the engine based on approved procedures and cleaned prepared for inspection. During inspection, reliability and airworthiness conditions are considered to determine health status of the engine based on compression tests. Examples of signs of damage on mechanical components include crack and corrosion, mechanical looseness, clutch engagement, lubricant filling, corrosion, foreign object damage, thermal fatigue and leak, which can lead to disruption of service and unavailability of an engines

Stage 3: Disassemble - Van Damme and Stolk-Oele (2015) argue that about 40,000 components are disassembled from within an engine during overhaul, a combination of static and rotating components. Components are inspected and taken for special examination and repaired as per repair policies to return them to their functional state. A root-cause analysis can be carried out to unveil the nature and level of damage using special methods such as NDT and Borescope.

Stage 4: Assembling and testing - Engine components with limited life span are completely replace with pristine ones. Repairable components are repaired using advanced innovative technologies such as ebeam welding and laser-cladding (Van Damme and Stolk-Oele, 2015). Components are carefully collected and assembled for onward subjection to various testing conditions. Installation is done by mounting of engine and connection of required fluid hoses onto the aircraft. Successfully testing an engine guarantees airworthiness approval, the counter is reset to zero and the engine sets for the skies for years (Hoddenbach, 2014).

5.4 Methodology for visualising maintenance cycles

The systematic approach used in addressing this study includes a literature review relative to information modelling, ontology, database development, timeline visualisation of events histories, observation and participation in brainstorming sessions, and interviews with domain experts for elicitation of engine events. Furthermore, analysis of the requirements, design and development, and results are presented. In this context, the software development approaches considered include, prototyping, eXtreme programming in Agile, Test Driven Development (TDD), Rapid Application Development (RAD) and Waterfall Model. However, an Enhanced-Extreme-Waterfall model has been proposed and developed. The proposed model applies to this case due to stakeholders and users' involvement. This model improves the quality of the product and respond promptly to the customers' changing requirements. The modelling of the data will be achieved using Unified Modelling Language (UML) and Microsoft Visio (MS Visio). The model will be implemented using Oracle MySQL database and SQL scripting language for manipulating the database. The frontend interface is implemented in PHP to control the design representation. Other visualisation tools include High-charts and data-driven document (d3.js).

The methodology adopted for this timeline visualisation is SUMEE (Summarisation of Engine Events) which utilises an aggregate visualisation technique (timeline, data map and time series). According to Tufte and Graves-Morris (1983) the use of a 2D graphical plot algorithm provides a summary of events on a timeline. SUMEE observes both scientific, information and knowledge visualisation (Tory and Moller, 2004). The rationale is to create an avenue where users are able to view on a single screen vast amount of information on a limited space in a timely fashion. The outcome is expected to reduce the number of man hours spent investigating and identifying relevant information for decision making. The outcome helps decision makers to deliver quality results and decision within a specified time frame.

The events visualisation on a timeline is a summarised graphical representation of information in a single user interface. The functionalities attributed to visualisation include data rendering, hover to zoom, click to display and drill down based on key group events. The helicopter and fisheye views have been adopted to focus on events.

i. ***Helicopter view:*** A graphical helicopter view is a data map which incorporates a time series statistical method. The data map illustrates the point of the state space with regards to its dependent variable. Its view might look meaningless; however, it was chosen because big datasets can be neatly represented on a page view of a single-squared dot as a point-in-time and collection of squared dots as a stream or continuous data of time intervals. These squared points are colour coded “look and feel”, which makes the graph attractive and draws the user’s attention to want to investigate what is behind them. The interface describes the presentation of information as data points in a single view without any additional information. The helicopter view is an aerial view of the objects.
ii. ***Fisheye view:*** A graphical fisheye view is a focus-based technique which allows concentration of one specific coloured region on the screen whilst

keeping the context visible (Kumar *et al,* 1998). When a user points, hover or click on a point or an interval-in-time, detailed aggregate information is revealed. The fisheye view can be attributed to the bird's eye view. Relevant information is embedded in each data point on the graph. The fisheye view focuses on a specific object while other objects are negligible.

5.5 Analysis of the historical through-life data

In eliciting and analysing requirements, information extracted from the interviewees and brainstorming sessions is presented in Table 5-1. The Unified Modelling Language (UML) technique is used to model and analyse the captured requirements.

Table 5-1 Interview and brainstorming sessions personnel

Expert	Role Space	Experience (years)	Expert	Role Space	Experience (years)
1	Chief Lifecycle Engineer – Trent 900	30	1	Functional System Engineer - Trent 700	25
2	Chief Life Cycle Engineer Future Programmes CSM - Engineering for Services	30	2	System Engineer A	20
3	System Engineer - Trent 900	22	3	System Engineer B	18
4	Reliability Engineer – Trent 900	20	4	System Engineer C	15
5	Life Cycle Engineer – Trent 900	12	5	System Engineer D	12
6	Life Cycle Engineer – Trent 900	10	6	System Engineer E	10
7	Life Cycle Engineer – Trent 900	3	7	System Engineer F	8
8	Life Cycle Engineer – Trent 900	2	8	System Engineer G	8
9	Life Cycle Engineer – Trent 900	3	9	System Engineer H	6
10	Safety and Reliability Engineer - *Individual*	25	10	System Engineer I	6
			11	System Engineer J	4
			12	System Engineer K	3
			13	System Engineer L	1

5.5.1 Criteria to determine levels of events

In this study, events gathered from the sessions are categorised based on the criteria in Table 5-2. The levels are based on the scheduled and unscheduled impact on availability of the engine.

Table 5-2 Criteria for Levels

Level	Criteria	Description
1	Worst	Affect the availability of the engine in terms of downtime based on a point in time or interval of time
2	Severe	Infrequent occurrences that are likely to affect the availability
3	Daily Routine Check	The events which assessing insignificant or no impact on the availability of the engine

The criteria mentioned in Table 5-2 have been used to design a form which the participants (domain experts in different teams) will fill out as regards to their knowledge in the service domain (see appendix H). The events are captured using the form/questionnaire presented in appendix H based on the criteria in Table 5-2 and presented in Table 5-3. Figure 5-1 depicts the criteria and the overhaul cycles whereby regular routine checks can occur daily; severe fault requires maintenance to be conducted in a duration of few months and worst conditions need maintenance to be carried out over a longer period.

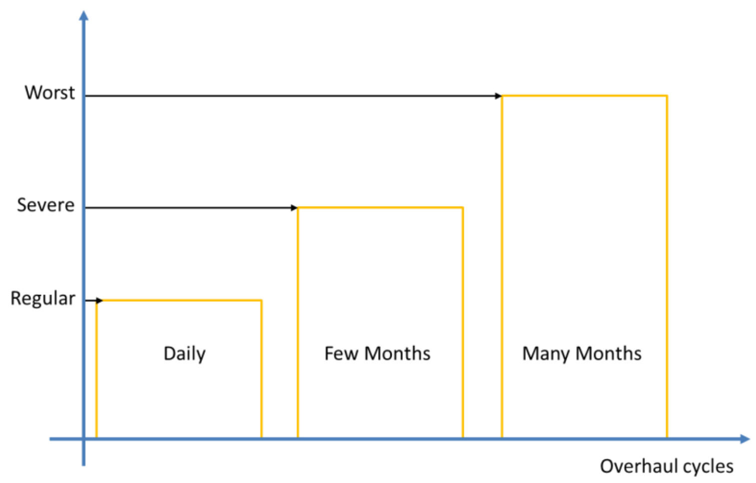


Figure 5-1: Events occurrences and maintenance durations

The research aims to utilise routine check / regular assessment for the prediction of remaining useful of components in an assembly because events happen at random. Furthermore, the criteria applied describe maintenance during engine's service life to ensure a proper, safe, reliable and cost-effective engine operation. Maintenance of an engine is conducted in accordance to full sets of instructions contained in the maintenance manual (Rolls Royce, 2005). The maintenance is based on OEM's recommendations to ensure routine checks are consistent with relevant certification approval. However, maintenance conducted on-wing can be classed as schedule and unscheduled. While schedule maintenance is a vital constituent of gas turbine engine operations, unscheduled maintenance is not considered part of the day-to-day programme of operation which can be initiated by observed symptoms and remote engine monitoring systems. The analysis focuses on schedule maintenance study where routing checks are conducted and analysed for failure effect hidden from human visibility. Examples of common maintenance schedules include cleaning, inspection, lubrication and discard (Rolls Royce, 2005).

5.5.2 Interviews and Brainstorming sessions

In order to understand the rationale for carrying out this study, an individual and two groups participated at different sessions. The first brainstorming session was conducted with T900 Life Cycle Engineering group as shown in Table 5-1. The group is made of nine professionals with various years of experience. After an introduction and a short presentation of the task, individuals in the group engaged in the session by asking several questions amongst themselves based on the questionnaire and to the facilitator such as *"what is the purpose of the events timeline visualisation?"*. The contribution is based on an individual's knowledge with respect to the business from the T900 Life Cycle Engineer perspective. However, only an individual was allowed to document / fill the form as the session progressed. The events translated are shown in Table 5-3. An interview was conducted with a Safety and Reliability Engineer as shown in Table 5-1. The events were presented from the safety and reliability perspective. The individual with a considerable number of years of experience classified different events based on Table 5-2, which are transcribed in Table 5-3 and presented in Table 5-4. Furthermore, another brainstorming session / workshop was conducted with the Functional System Engineering group. It was another interactive session made up of thirteen individuals with different years of experience as shown in Table 5-1. Then, the facilitator introduced and presented the task and the goal as well as what is required by the group. The idea of the task was welcomed by the group and suggested that the facilitator contacts the right individuals responsible for access to a MAXIMO system, which contains most events. Additional definitions were captured. Different ideas and names of events were presented with common ones being repeated.

The data extracted from the interview and brainstorming sessions have been analysed and presented in Table 5-3. The colour codes represent information gathered from different participating groups. Information highlighted in "Yellow" is an individual, "Blue" is also provided by one person, "Green" given by groups and the researcher.

Table 5-3 Extracted events from brainstorming workshop

Level	Description	Event
1	Events that determine the availability of the product for customer service Events that results in a disruptive index	Engine installation
		Engine removal
		Aircraft downtime
		Unplanned engine removals
		Planned engine removals
		In-flight shutdown
		Aborted take-off
		Diversion
		Cancellations
		Delays
		Engine Swap
		Shop visit
		Engine pass-off – Certification test
		Service Disruption
		Delivery
		Engine overhaul
		Fire
		Shaft failure
		Blade-off
		Crack in the disc

Level	Description	Event
2	Non-standard or infrequent events with the potential to modify the products availability or functionality	Service Bulletin
	Trouble shooting performed on engine	Non-mode service bulletin Controlled service introduction Bulk data download Technical variance Immediate operational request Diagnostic magnetic chip detection use On-wing repair Air craft de-icing Maintenance message LRU replacement On Wing compressor washing Module swap EHM Alert Follow up analysis SB incorporation Foreign Object Damage Bird strike Ramp strike Engine start failure Part replacement Borescope Inspection Oil Change Rejection
3	Standard daily or weekly activities that maintain health status	Core washing
		Oil level check (starter and Tank) Walk round checks (pre-flight) Scheduled Borescope LLP remaining life records Flight profile monitoring Maintenance Planning Document tasks Fan Blade maintenance Dry film lubrication reapplication Leading Edge Erosion monitoring Oil top up Trend alerts Operational data Engine health monitoring data Oil Consumption Thermal Couple front Thermal Couple Rear

Grouped events

The various events are grouped based on the following criteria and colour codes as key indicated in Table 5-4. This grouping is done to combine related events to different levels. The groups are classed in terms of delivery, installed maintenance, inspection, instruction manual, overhaul, disruption and engine pass off.

Table 5-4 Grouped events and colour names

No	Key Group	Criteria	Colour name
1	Delivery	Activities which illustrate supply	Green
2	Installed Maintenance	Activities that happen on-wing	Black
3	Inspection	Activities regarding manual or automatic checking	Blue
4	Instruction Manual	Activities referencing manuals	Grey
5	Overhaul	Activities of major engine disassembly	Yellow
6	Disruption	Activities stopping operation for an interval of time	Red
7	Pass Off	Activities requiring successful test	Brown

Partly grouped events as shown in Figure 5-2 with regards to specific keys with reference to Table 5-2. The extracted knowledge is categorised and developed into a list of terms/events taxonomy.

Delivery	Installed Maintenance	Inspection	Disruption	Overhaul	Pass-Off
Delivery	LLP remaining life records	Scheduled boroscopes	Foriegn Object Damage	Engine start failure	Engine pass-off
Engine Swap	Flight profile monitoring	Walk round checks (pre-flight)	Bird strike	Part replacement	
Engine installation	Maintenance Planning Document tasks	Boroscope	Ramp strike	Module swap	
	Fan Blade maintenance	Leading Edge Erosion monitoring	Fire	LRU replacement	
	Dry film lubrication reapplication	Trend alerts	Shaft failure	Rejection	
	Oil top up	Operational data	Blade-off	Planned Engine Removals	
	Oil Consumption	Engine health monitoring data	Crack in the disc	Shop visit	
	Thermal Couple front	EHM Alert	Aircraft downtime		
	Thermal Couple Rear	Diagnostic magnetic chip detection use	Unplanned engine removals		
	Core washing	Maintenance message	Inflight shutdown		
	Oil level check (starter and Tank)		Aborted take-off		
	On Wing compressor washing		Diversion		
	TGT Trimmer Change		Cancellations		
	On-wing repair		Delays		
	Air craft deicing		Compressor Failure		
	Oil Change				
	Controlled service introduction				
	Bulk data download				
	Immediate operational request				

Figure 5-2: Events classified based on key groups

5.5.3 Requirement analysis for the maintenance cycles design

The requirements presented in this section are analysed using object-oriented analysis and design technique. Techniques for analysing requirements include user stories (Breitman and Leite, 2002; Cohn, 2004), rich picture, mind map and UML use case (Avison and Fitzgerald, 2006).

User Stories

It is part of an agile approach that helps users discuss requirements. The user stories have been adopted in this study because it very well supports elicitation of requirements quickly in a concise manner. It requires constant communication with users and stakeholders. The user stories as shown in Figure 5-3 is made up of a series of conversation about desired functionalities, which users would prefer to see in a design.

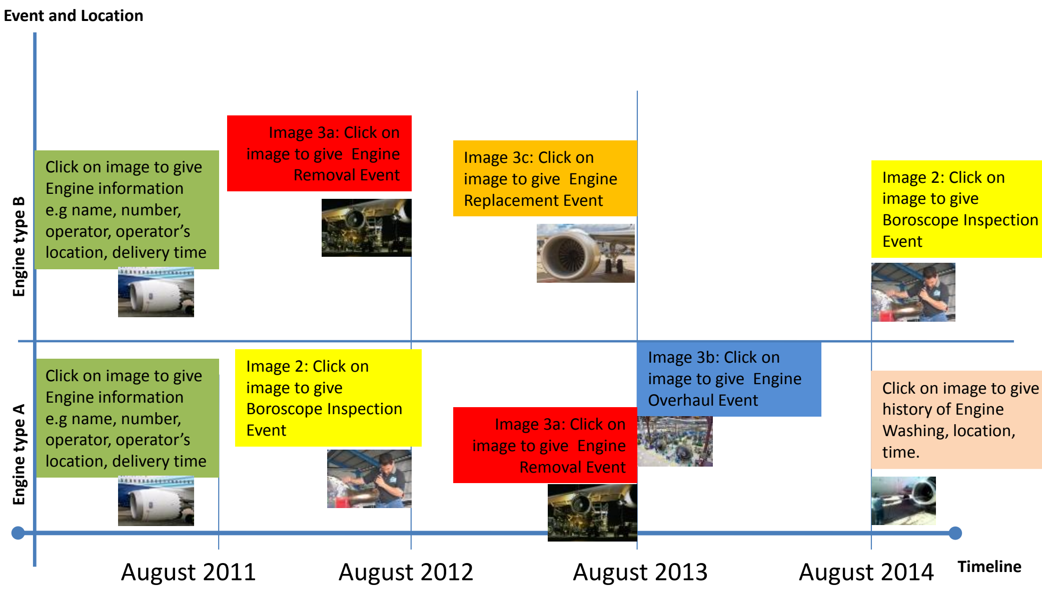


Figure 5-3: Events timeline user stories presented at the brainstorming sessions

Use Case

A UML representation which has been selected to show interactions of the user with the application. The use case as shown in Figure 5-4 focuses on the user's goal. The actor is end user as a role, the line connecting the role and functions is the association, the oval shape is the use case which are functions to be performed by the actor and the rectangle relates to the system/application where the entire operation occurs. It is a graphic representation of the actor's (end user role) association and operation of the proposed events timeline visualisation solution.

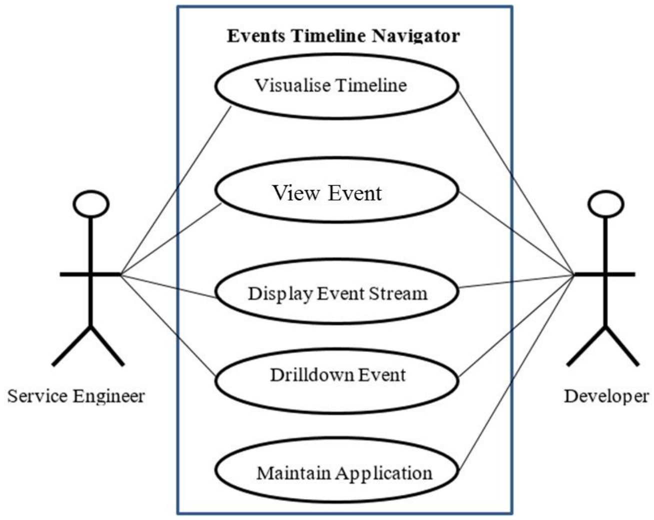


Figure 5-4: Event visualisation use case diagram

The ***service engineer*** (end user) is an actor who uses the event timeline application. The end user can perform only four operations. The use case consists of the ***visualise timeline*** which is when the application starts. The ***view event*** functionality is when a mouse is pointing or hovered on a data point in the timeline to show relevant information, while the ***display event stream*** is when a user initiates a click to reveal stream of information. The ***drill down*** function is when a user selects a key group event from the drop-down menu. The **developer** is an actor who modifies the application. The developer can perform all five operations, hence the introduction of 'maintain application' use case.

5.6 Design of maintenance cycle event visualisation

The conceptual data model represents the data model for information required to develop the database of the historical events.

5.6.1 Entity relationship diagram

The Entity Relationship Diagram (ERD) graphically represents an understanding and capturing of business information requirements (Connolly and Begg, 2005). This technique shows the relationship between each entity, which can be represented as an ontology. The ERD shown in Figure 5-5 is designed using Microsoft Visio in the perspective of using UML.

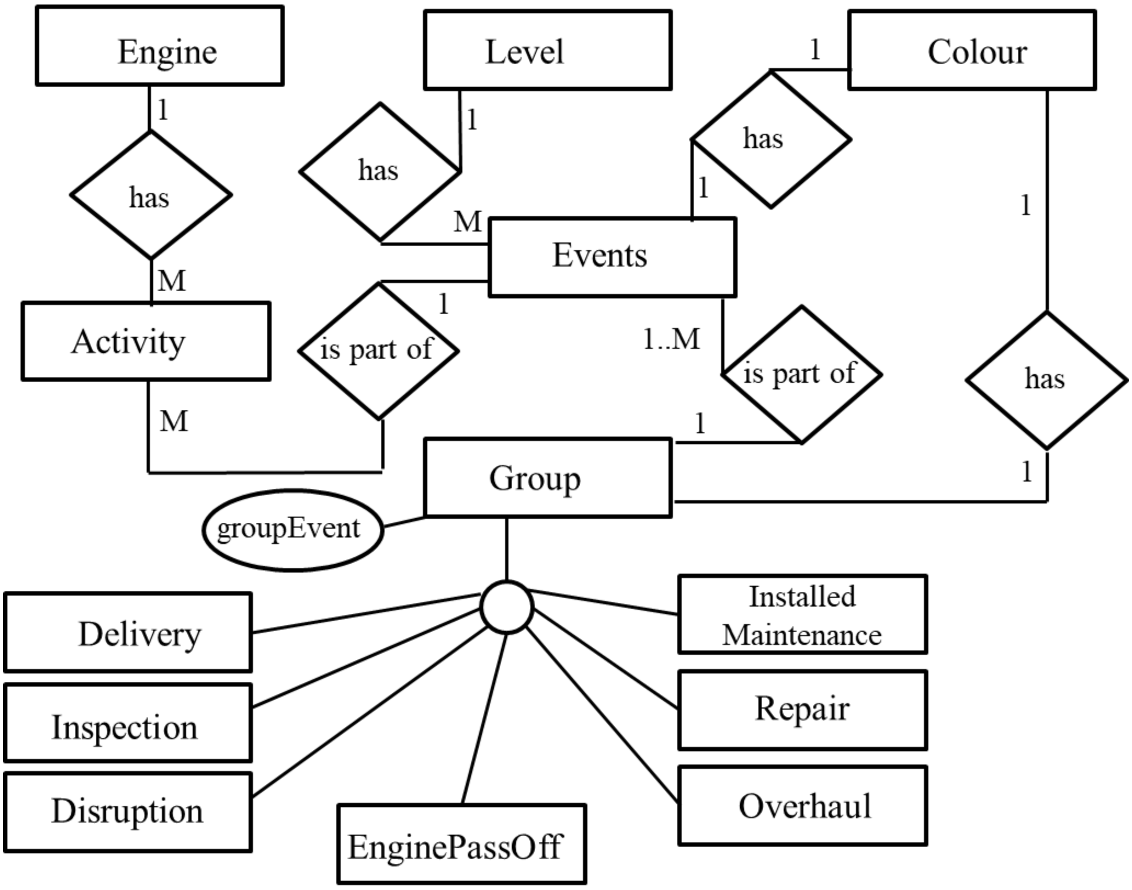


Figure 5-5: Entity Relationship Diagram (“1” means one and “M” signifies many)

The ERD is a specialised graphic for illustrating the relationships between entities in creating a good database design. The rectangle represents an entity, the diamond shape is for relationship, the oval is attribute (primary key shown), and a 1-to- M (means one-to-many) as cardinality. This gives an overview of how the data would be represented and stored in the database. The data dictionary for named variables is available in appendix I.

The ERD is developed using the description of the entities presented below as their relationships from the investigation and brainstorming sessions;

i. Engine relates to attributes, e.g. engine number, model and name

ii. Activity relates to location, point or interval-in-time such as start and end dates events occurred. It shows relationships of repetitive engines and events as well as comments.
iii. Event entity – attributes of different events and relationship to level, colour and group.
iv. Level describes the attribute of the categorised event as numeric values and description in text with named caption.
v. Group entity is the classification of events as key and the representation of the criteria with respect to colour codes.
vi. Colour used to differentiate groups, e.g. blue, green.

5.6.2 Database logical schema

The logical schema gives an overview of the variable names used for the application. The schema represents entities as tables with integrity constraints, primary and foreign key attributes presented in Figure 5-6. This schema extends current industry practice but not state-of-the-art.

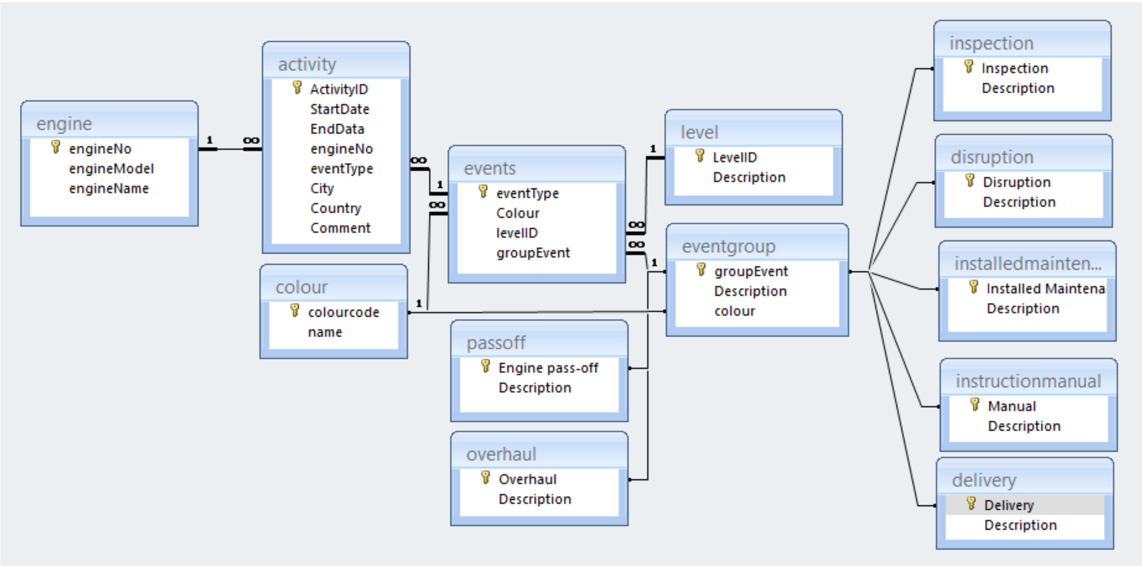


Figure 5-6: Database Logical Schema

The illustration in Figure 5-6 is created with MS Access, the individual square boxes are the tables referred to as relations. The entire picture is designed with relationship functions. The engine and activity relations are connected with a one-to-many relationship meaning a unique engineNo is primary key in the engine table, and cannot be duplicated, however, in activity table, engineNo is a foreign key. The logical schema supports the retrieval of data from a database management system based on Atomicity, Consistency, Isolation and Durability (ACID).

5.6.3 Class diagram

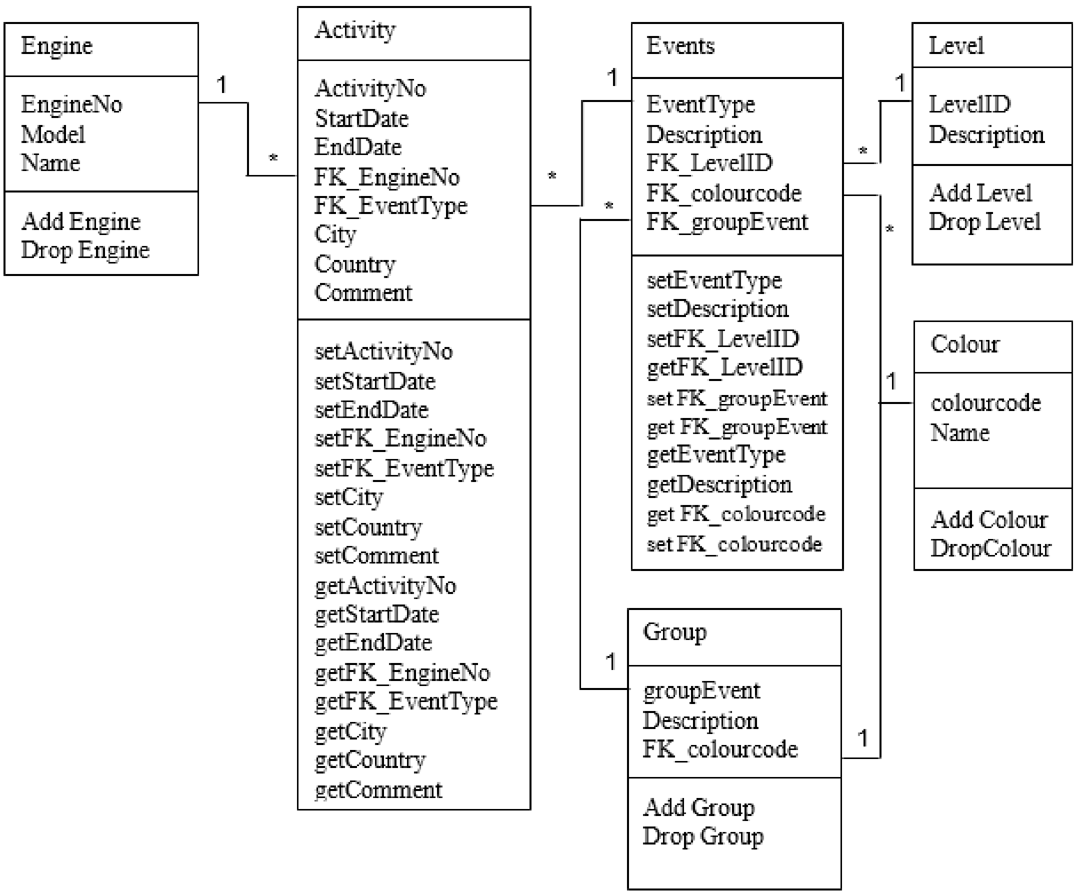


Figure 5-7: Conceptual Class Diagram ("*" signifies many by connecting two table with primary and foreign key attribute)

The class diagram shows functionalities of the application. Figure 5-7 describes the attribute and operation to be performance when the database and the application are developed. The significance is to create a smooth sync or communication between both parties to talk each other when there is a flow of data. Figure 5-8 illustrates an extension of the class diagram in Figure 5-7, which is the representation of grouped events.

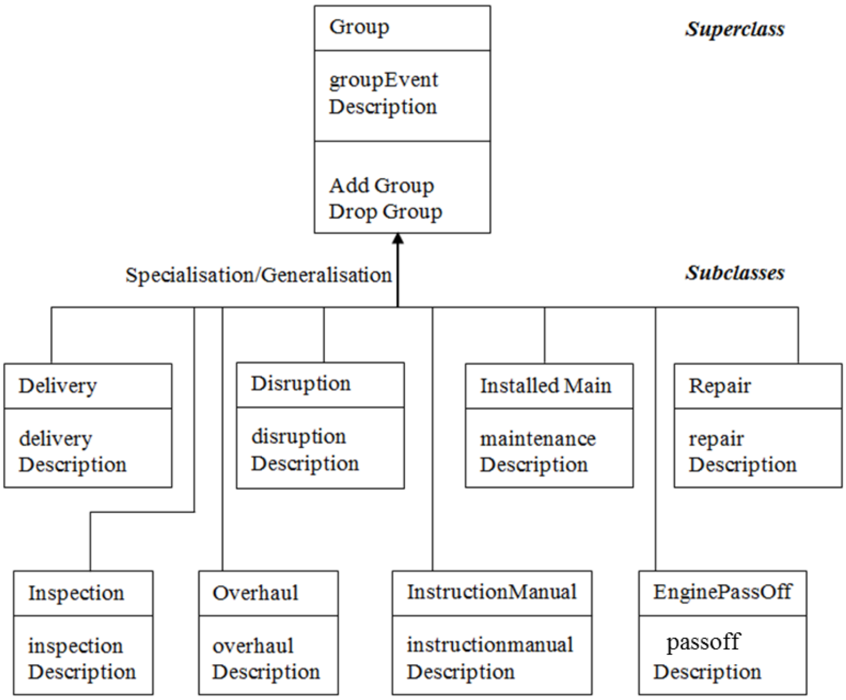


Figure 5-8: Conceptual Class Diagram (Group Entity) with subclass and superclass

In the class diagram in Figure 5-8, group of events distinguishes one group from another. Generalisation and specialisation rule is a one-to-one relationship of superclass and subclass. A specialisation rule utilises differences between members of an entity by identifying distinguishing characteristics, while generalisation uses differences between entities by identifying common characteristics. The participation constraint and disjoint have been used in modelling of the information (many tables – one table for the superclass and one table for each subclass).

5.6.4 Initial interface design

The visualisation technique for the interface design is a timeline. It represents knowledge and information in a clear and concise manner. It entails techniques applied in presenting interactive display of documents. Each technique alters spatial presentation of documents. A user can experiment with these techniques on electronic documents until he/she finds a display that best conveys documents semantics. Aggregate visualisation technique – categorising events into key groups using colour codes differentiates and classifies events into levels. The engine events are represented on data map, timeline, time series and a 2D graphical plot. The proposed application interface visualises occurrences of events over time by an engine in a timeline using summarisation in helicopter and fisheye views. An initial idea of the event timeline application is illustrated in Figure 5-3 as a user story. A reviewed of the proposed idea based on discussions with stakeholders and users is presented in Figure 5-9. This representation serves as a guide for the researcher.

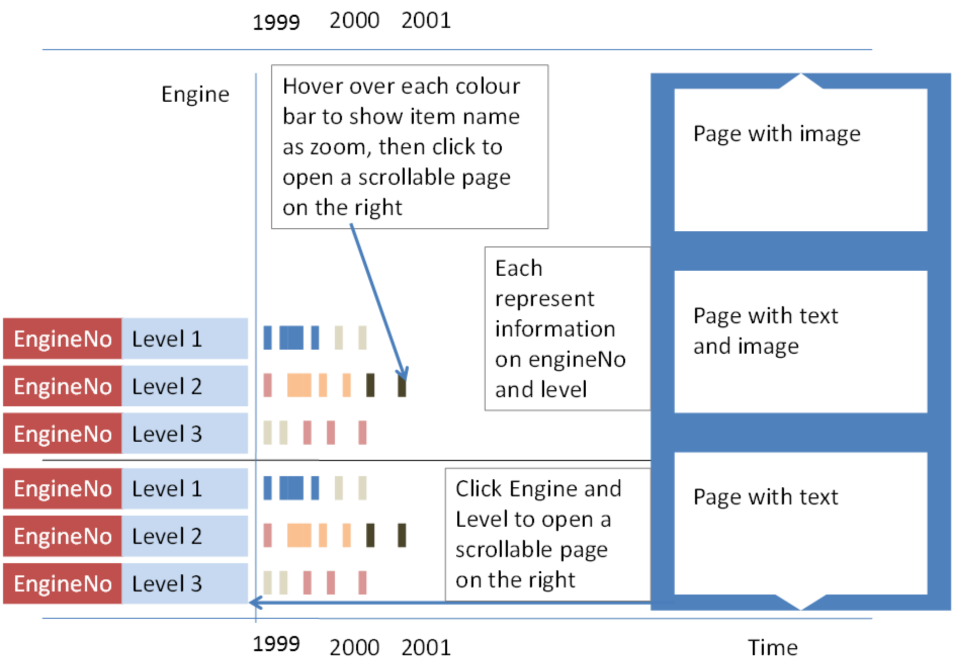


Figure 5-9: Initial interface design with Engine number, levels and year of service

5.7 Development of the interface design

The implementation represents a 2D plot, hover and zoom, click and display, and drill down algorithms developed using tools such as NetBeans IDE, Apache Web server, PHP programming language, HTML, JavaScript with MySQL for the database based on object-oriented programming. It is a graphical display interface resulting from the information modelling. The design patterns was initially implemented as a working prototype.

System Architecture

Figure 5-10 shows a system architecture connecting the user interface, business layer and data layer.

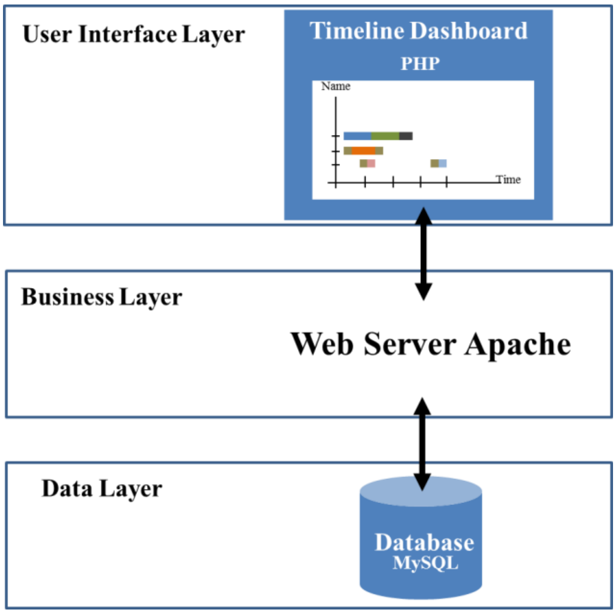


Figure 5-10: Architecture of the events timeline visualisation

User interface: The user interface is attributed to application layer with the main aim of translating tasks into results, which an end user can understand to make better maintenance decisions.

Business layer: The business layer coordinates the application interface layer, which processes the commands for manipulating maintenance records to make logical business assessments and decisions. The layer performs calculations and processes data when transferred between user interfaces and data layers. The apache web server plays a key role connected the application to the internet, so that, the application can be accessed. It communicates with the database and helps render Web pages served over Hypertext Transfer Protocol (HTTP).

Data layer: The data layer stores and retrieves maintenance information from a database. The information is passed on to the business layer for processing and displays it to the end user.

The implementation of events visualisation of maintenance cycles displays objects, attributes and their relationships. The implementation strategy is the system architecture for the design. The visual display of quantitative information on the graphical excellence shows how complex big datasets can be communicated with clarity, precision and efficiency. The graphical design excellence displays data, induce users to think about the substance and not the methodology or graphic design, make large data sets coherent and present much information in a short space, reveal data at several and reasonable level of detail relevant to users for decision making. This study supports and demonstrates a substantive maintenance content. It displays big datasets with real variability of multivariate data.

Interactive user-interface attributes

The single-phase view of a timeline visualisation improves the means of condensing a vast amount of information to unveil relevant data when a mouse hovers on a point or an interval of a state space (time). The timeline visualisation functionalities include: -

a. **Drilldown functionality:** The drill down functionality is a collection of events grouped into specific categories. The categories are colour coded to differentiate the various data points on the graph when a user clicks the drop-down menu.
b. **Key Colour Coding (KCC):** Key colour coding indicates group events (aggregate) referencing irrespective of levels to show severity e.g. red means disruption, green relates to delivery.
c. **Levels of events:** The levels of events refer to classification of events based on certain criteria defined by a domain expert e.g. Events>>Level 1>Delivery, Disruption; Level 2>Repair, Overhaul. The level can be called facet.

d. **State space (time) Axis:** Indicates horizontal representation of the latitude in terms of time e.g. year 2011
e. **Engine Axis:** This shows the engine number as an attribute, which is dependent on the state space. It is the vertical representation of the longitudinal line to demonstrate the location of the point of occurrence
f. **Events:** The event attribute is the various terms which a domain expert would use to describe the impact of the availability of an engine to be in-service e.g. overhaul. Examples of terms which can lead to an overhaul include bird strike, foreign object damage, crack, wear, corrosion and deformation described as low-level events.
g. **Mouse hover:** When there is a mouse hovers on a data point, the information pops up to give relevant on-demand detail
h. **Mouse click:** A mouse click on an engine number reveals a stream of data relating to a specific level of an engine
i. **On-demand information:** These are the relevant information which the user would require for decision making. The on-demand information includes engine number, the level of the event, duration, start and end dates, image, and comments which are revealed when a user does mouse hovers or click.
j. **Relationships:** This represents mapping of the latitude of time to longitudinal events. The events ontology and description are available information for creating a database.

2D graphical plot algorithm

Given a dataset “D” of “M” member of data elements, “D” is classified into groups to illustrate that a member “M” (engine events) is in the same group (Kocherlakota and Healey, 2005). This method is applicable to the different levels created. The levels contain related classified engine events. The group of related events is classified under a different colour coding scheme as key. Apart from enhancing flexibility of information modelling technique, clustering shows a timeline plot as a powerful function to help users to quickly, easily and accurately make decisions. Therefore, it simplifies means through which information is fused to display multivariate data. A 2D graphical plot method introduced on the grounds that visualised information is temporal. Since time is an independent entity, object used is completely dependent on the state (time) space, a mathematical index was implemented to plot a squared dot or rectangular range of the data on a vertical and horizontal axis of events and year of occurrences.

Snapshots of development codes are illustrated to demonstrate how the interface is developed. The codes include structured query language (SQL) scripts to retrieve data from MySQL database, HTML codes to structure the horizontal and vertical lines, fit and format the graphical presentation. The JavaScript codes powers the dynamic nature of the timeline visualisation application, while the PHP code supports alignment of the format and interactivity of events timeline visualisation. However, NetBeans IDE allows fusion of codes for making meaningful outcomes for decision making. The snapshot codes in Figure 5-11 fetch and display engine axis, year, engine numbers and various maintenance cycles histories of activities on the timeline application.

```
//Fetching data from the engine table
$query_engineRS = "SELECT * FROM engine";
$engineRS = mysql_query($query_engineRS, $engineConn) or die(mysql_error());

//Fetching the event levels - RS - resultset
$query_engine1RS = "SELECT COUNT(DISTINCT(engineNo)) AS total FROM engine";
$engine1RS = mysql_query($query_engine1RS, $engineConn) or die(mysql_error());
$row_engine1RS = mysql_fetch_array($engine1RS);
$totalRows_engineRS=$row_engine1RS['total'];

//Get the Minimum year
$query_MinRS = "SELECT MIN(YEAR(StartDate)) AS MinYear FROM activity";
$engineMinRS = mysql_query($query_MinRS, $engineConn) or die(mysql_error());
$row_engineMinRS = mysql_fetch_array($engineMinRS); //fetch minimum date array
$min_year = $row_engineMinRS['MinYear'];

//get the Maximum Year
$query_MaxRS = "SELECT MAX(YEAR(EndDate)) AS MaxYear FROM activity";
$engineMaxRS = mysql_query($query_MaxRS, $engineConn) or die(mysql_error());
$row_engineMaxRS = mysql_fetch_array($engineMaxRS); //fetch maximum date array
$max_year = $row_engineMaxRS['MaxYear'];

$timeline_len = (($max_year-$min_year)+1)*13; //timeline length (columns)
$span = ($timeline_len*16)+120;//timeline length grows just lines)
$height_all = $totalRows_engineRS * 102.0; //timeline height grows)
```

Figure 5-11: A snapshot of the SQL script to return maintenance activities

The snapshot codes retrieves data from database, the scripts produce a record sets and the events are positioned on the timeline, create and adjust vertical lines, engine number and iterate through event levels, display drill down menu to select key events group. The selected key displays data points as events attributed to a specific group and reveal detailed information when mouse-over on a data point.

The validation of the timeline visualisation interface for engine events has been developed to demonstrate past occurrences. The representation contains events in a timeline, which impacts on the engine. The results show summarisation in helicopter and fisheye views. The visualisation is a data-rich illustration based on available information. The key for the event timeline is presented in Table 5.5

Table 5-5 Key: Colour and meanings

Meanings	Colour
Delivery	Green
Installed Maintenance	Black
Inspection	Blue
Instruction Manual	Grey
Overhaul	Yellow
Disruption	Red
Pass Off	Brown

The functionalities implemented in the application illustrate the history of events as shown in Figure 5-12. The summarisation of events renders output in a helicopter view mode.

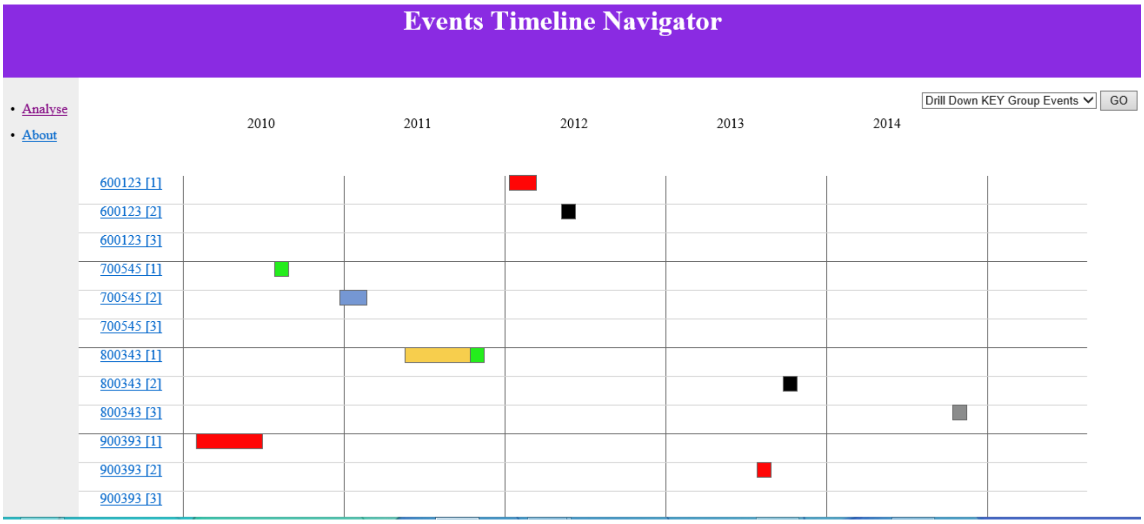


Figure 5-12: Summarisation of Helicopter view events

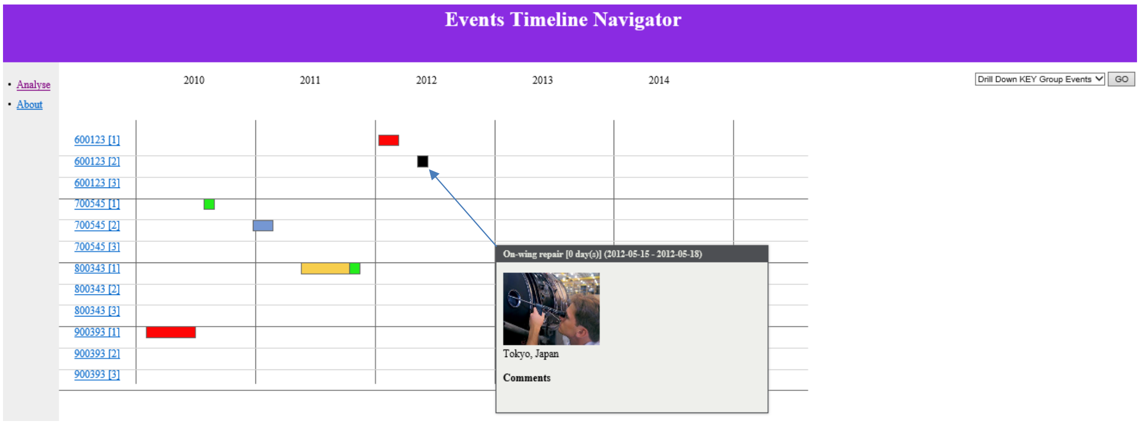


Figure 5-13: Summarisation Fisheye view with hover and zoom

The visualisation of the events in a timeline rendered in fisheye view uses hover and zoom functionalities (see Figure 5-13). With mouse hover on a data point, information behind the point pops up and reveals relevant information. The information beneath the summarised data point include event type, duration, start and end dates, image of events, locations and comments.

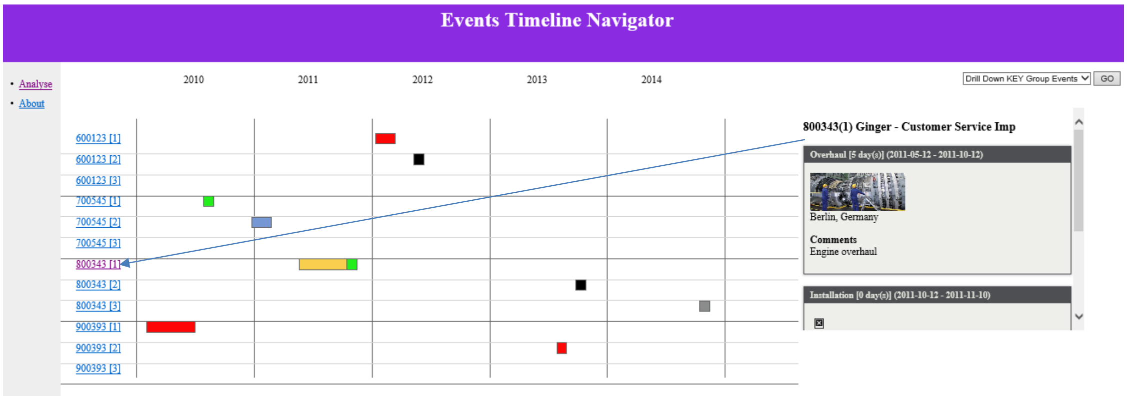


Figure 5-14: Fisheye view with click and display entire events stream

The visualisation of the event histories in a timeline renders Fisheye view using click and display functionalities as shown in Figure 5-14. A click on an engine number on the left axes opens a page on the right to show the entire maintenance information stream.

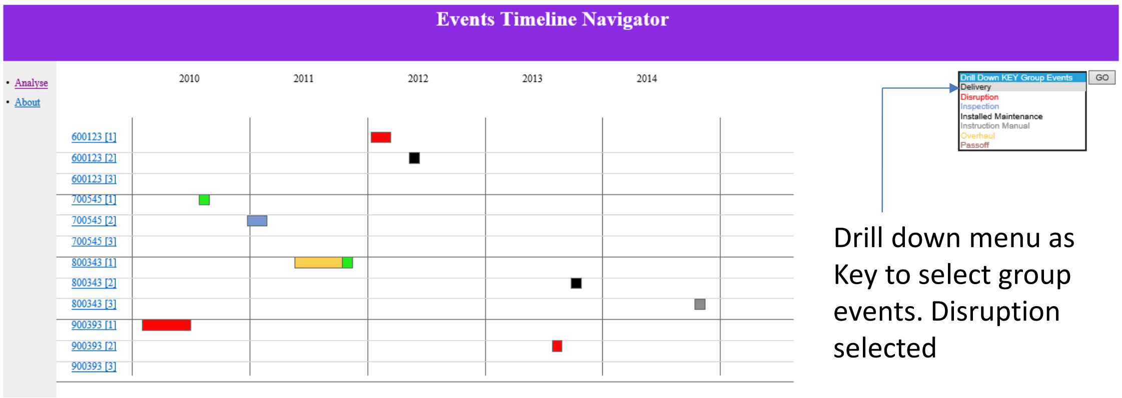


Figure 5-15: Selection of disruption from the drop down menu

The drill down functionality enhances the power of the timeline application. It displays only events in the selected group. This functionality is useful to users who decide to analyse specific events attributed to one or more engines as indicated in Figure 5-15.

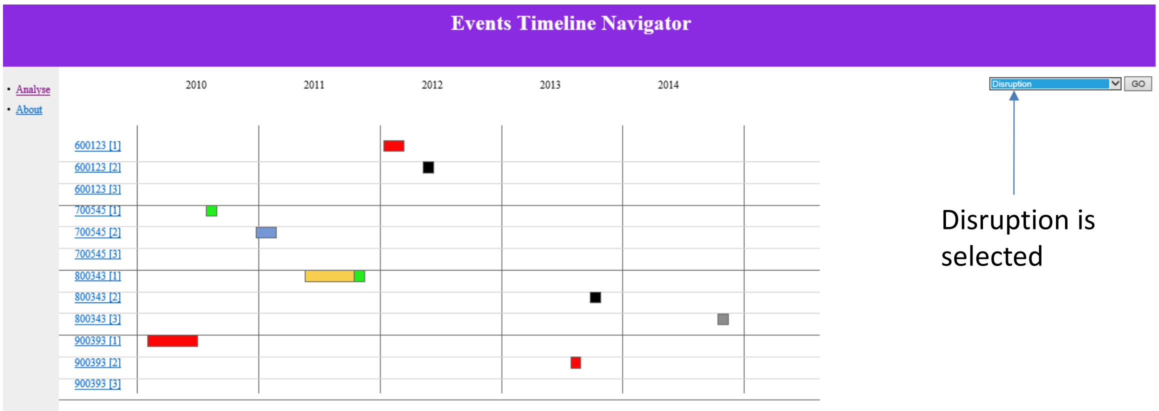


Figure 5-16: Drill down of disruption

Figure 5-16 demonstrates a drill down of disruption. When disruption is selected Figure 5-17 renders.

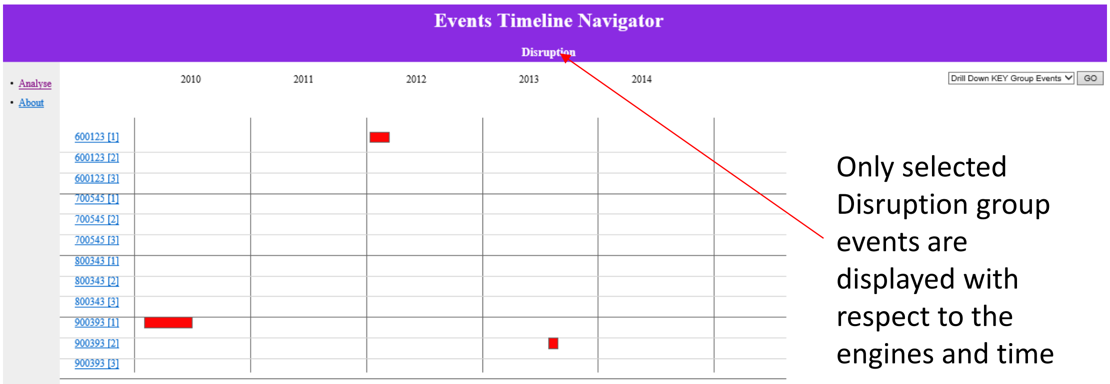


Figure 5-17: Display of only selected disruption events

Figure 5-17 illustrates only disruption grouped events are colour coded in red.

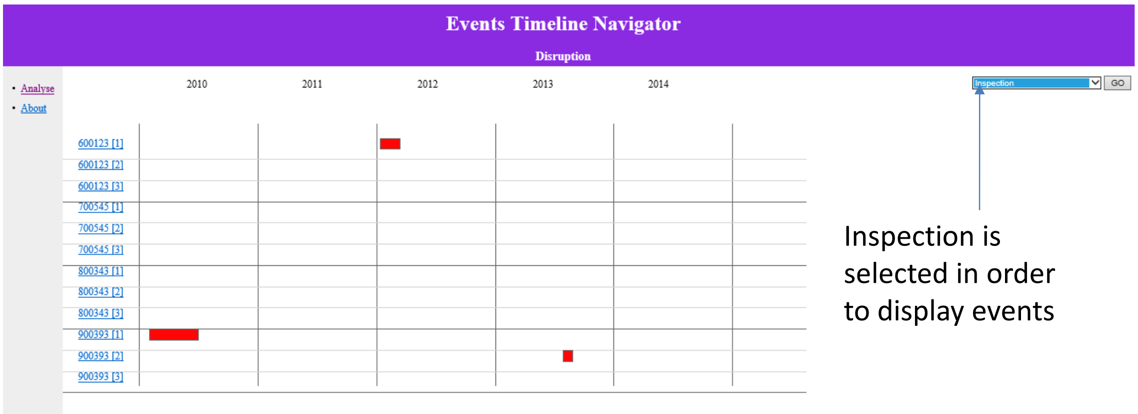


Figure 5-18: Inspection key selected

As indicated in Figure 5-18, the inspection key group is selected whilst still in the disruption selection window. When ‘GO’ button is pressed, the result changes as shown in Figure 5-19. The inspection view reveals events grouped in this category with blue colour code.

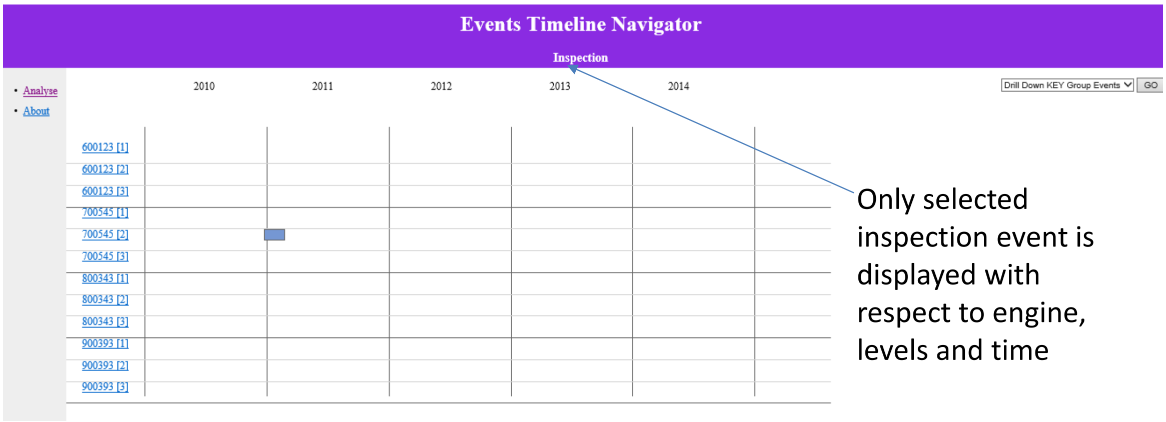


Figure 5-19: Inspection group event

5.8 Summary

This chapter is an extension of the investigation conducted in chapter 4. Whilst chapter 4 focuses on current industry practice relating to taxonomy of degradation mechanisms, chapter 5 emphasises various events taxonomy which can disrupt engine availability. The events taxonomy in relation to maintenance cycles based on through-life performance historical data are collected via brainstorming. Analysis and categorisation of events levels and criteria are presented, whereby events occur randomly across life of components are difficult to predict. This analysis further suggests regular overhauls cycles as a process for predicting remaining useful life for components in an assembly. The design and development of the through-life maintenance cycles for multiple engines and overhauls are visualised in a timeline for quick identification of root causes from system to component levels. The outcomes from this analysis created new knowledge about different high-level events found in a gas turbine engine in the aerospace industry. Furthermore, a developed web-based user interface illustrates a single-screen view of in-service information presented in a timeline. Hovering on a data point provides more details; key colour code illustrates grouped events; click on an engine number reveals complete information on a specific level. The next chapter discusses generic framework development.

6 THROUGH-LIFE PERFORMANCE FOR REMAINING USEFUL LIFE PREDICTION

The findings from previous chapters provided the variables for modelling a proposed novel framework – the Weibull Through-life Performance Prediction Model (WTPPM). The framework uses data-driven prognostic methodology, a statistical technique and the Weibull method to evaluate through-life performance of components degradation in a complex engineering system. This generic framework aims to predict the remaining useful life (RUL) of components in an assembly using only assembly level data. No evidence of predicting remaining useful life of components in an assembly, based on only assembly level data was observed in reviewed literatures. The study is motivated by this gap and a quest to understand the relevance of through-life performance in components degradation. This chapter aims to improve the comprehension of the through-life performance RUL prediction which influences service delivery of spare parts availability, proper maintenance planning and cost analysis. The approach for developing the proposed WTPPM framework is presented.

6.1 Methodology for the proposed framework

The methodology for the proposed WTPPM fulfils the fourth objective and comprises:-

i. Estimation of the Weibull parameters using statistical technique to analyse historical data of observed rejections and flight clyces to interpret the behaviour of the data
ii. Modelling different overhaul states to estimate rejection rates in each state and calculate the effect of prior and next overhaul activities based on renewal theory – whereby components are susceptible to failure at specified overhaul inspection intervals
iii. Fuse observed rejection data with predicted rejection data to conduct performance prediction accuracy to determine deviation/error for back-

fitting, thereby predicting the remaining useful life of a component in an assembly

iv. Estimation of the time to scrap using a novel cost-benefit analysis with cost variable to create a threshold of when renewals on the assembly should cease

v. Separate data employed in the development of this framework

Assumptions and limitations considered in developing the framework are:-

Assumptions

i. A single failure mode

ii. All engines analysed must be of the same model at any one time, e.g. Trent 900 and operate in the same way, (e.g. regions or routes)

iii. All data are clean and complete

iv. There should be only six overhaul states, the model could accept less than six overhaul states

v. Consideration of variability linked to interdepencies between sub-assemblies

Limitations

i. Applies to only components in an assembly

ii. Only the Weibull distribution applies since it assumes some typical distributions as special cases (Abernethy 2006). It is the most often used distribution in the context of reliability and RUL estimation (Abernethy 2006). Weibull plotting to assess the validity of the Weibull assumptions

iii. Fragmented data, that is, missing data concerning failure or engine number or rejected parts for any overhaul was not considered

The assumptions can positively influence the framework development, while the limitations may help control the framework functionality. The choice of a single failure mode enables a systematic application of the Weibull function. Clean and complete data in the specified format enhances robustness of the framework including data relating to six or less overhaul states.

Implications of the WTTPM framework beyond the gas turbine (NGVs)

The WTTPM framework can be deployed in the following industries: -

i. Rail transport (train wheels)
ii. Air transport (fan and turbine blades)
iii. Renewable energy (wind turbine blades)
iv. Healthcare (drug manufacturing machines)
v. Manufacturing (robots for manufacturing of cars at industrial scale)
vi. Robotics (animatronics) and
vii. Marine (fan and turbine blades)

The framework assesses performance of the multi-component to improve design and enhance future component manufacture. This exploratory and explanatory research can be validated with multi-component and multi-connected systems such as the Internet of Things.

6.2 A framework for WTPPM

The framework is developed by through-life performance modelling to:

i. Numerically illustrate the rejection rate at assembly level, the overhaul times, the replacement and reuse values through their life
ii. Get better insights of the data to make realistic decisions based on assessments of the components in an assembly

The framework development started with a direct case which then evolved into a complex model from stages 1 to 4. Stage 1 initially accepts two input parameters, processes the parameters through the four overhaul states and later six overhaul states and produces different results including the number of rejected, replaced and reused components. Stage 2 of the development process introduces observed rejection data, which is compared with the predicted rejection data in Stage 1. In this Stage 2, different error minimisation equations are tested and one is selected. Stage 3 is the back-fitting of the estimated parameters with resulting error values presented in matrix for performance metric and enumeration. The matrix is presented in a 21 x 21 dimension inclusive of the first row representing a range of η parameter, the first column shows a range of β parameter and the remaining 20 x 20 contain the indicative error values for the respective parameters. However, 20 x 20 is suitable dimension for a single page view. Furthermore, an approach to identify optimised parameters from a selected region with minimum error values is incorporated into the modelling. The identified optimised parameters are applied to the Weibull function to estimate the probability of failure for components in an assembly over time. Stage 4 delivers the final framework as shown in Figure 6-1 by incorporating the datasets with specified format and transforming the probability of failure into remaining useful life. The probability failure and the remaining useful life are calculated during the model evaluation. The proposed Weibull Through-life Performance Prediction Model is a non-parametric prediction technique.

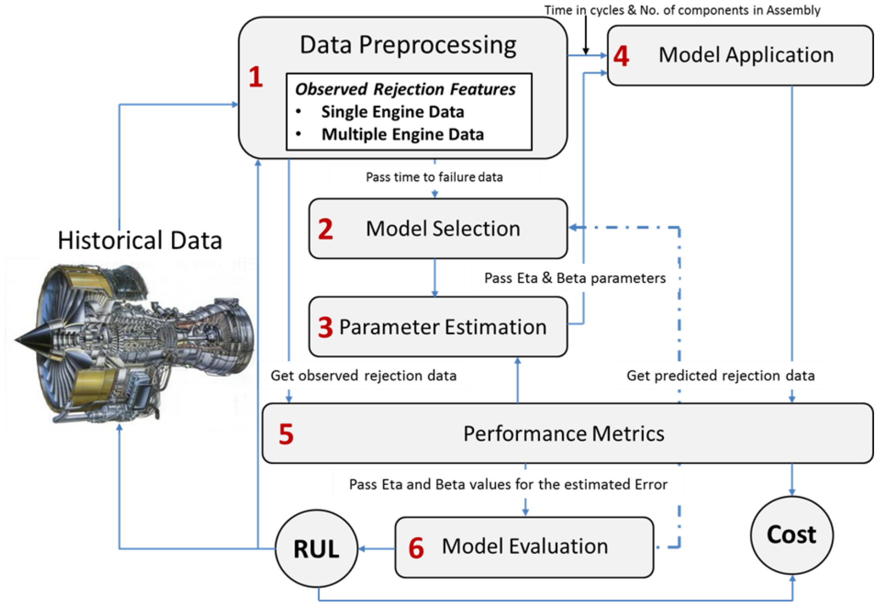


Figure 6-1: Fundamental through-life performance approach to RUL estimation

6.2.1 Prepared data

Data cleansing – also called pre-processing – is a statistical analysis requiring the collection of historical time-to-failure, run-to-failure data and operational data from the operating system. Time-to-failure data are time in cycles, while run-to-failure data relate to observed components. Failure data should be pre-processed to guarantee accuracy and consistency. Data cleansing ensures validation and supports modifications. Application based tools are used to pre-process failure data for a quick and better analysis. A database that stores historical operational time and run-to-failure can expedite data cleansing and sieving.

The initially available data used in this Thesis are observed data provided and assessed by domain experts as shown in Table 6-1. The degradation assessment conducted during maintenance, repair and overhaul of the system assists with identifying rejections. The data requirements include a system’s identity, current inspection time and the number of rejections. Whereas components with defects are rejected and replaced with new components, components without faults are reused. The historical and current health data can be used to assess the through-life performance of a subsystem. However, with semantic knowledge of failure modes and degradation mechanisms, domain experts interpret reasons for rebuffing the predicted components. The types of mechanisms affecting mechanical components can be found in (Okoh *et al,* 2014).

Data generation

The sample data presented in Table 6-1 were derived and formulated from the understanding of the failure modes commonly found in aero mechanical components.

Table 6-1 Sample of pre-processed data (model-building data)

System No	**Failure times x 6 (Hours)**	**Failure times ($t_{Inspect(i)}$ - Cycles)**	**Failure rate=f/100*36**	**Quantity**
10012	6000	1000	5/100*36 = 1.8	2
10012	15000	2500	10/100*36 = 3.6	4
10012	19200	3200	25/100*36 = 9	9
10012	36000	6000	30/100*36 = 10.8	11
10012	48000	8000	40/100*36 = 14.4	14
10012	66000	11000	55/100*36 = 19.8	20

The degradation data generated were based on the service knowledge from the AS-IS industry practice and maintenance cycles analysis. With this same understanding, the nature of the data and the quantity of the rejections or scrap were created and modelled as shown in Figure 6-2. Figure 6-2 gives a conceptual through-life performance prediction model to demonstrated components degradation within an assembly. The numbers represent components in “black = new”, “blue = reused”, and “red = degraded”. The reused components are expected to have different failure rates than the new ones.

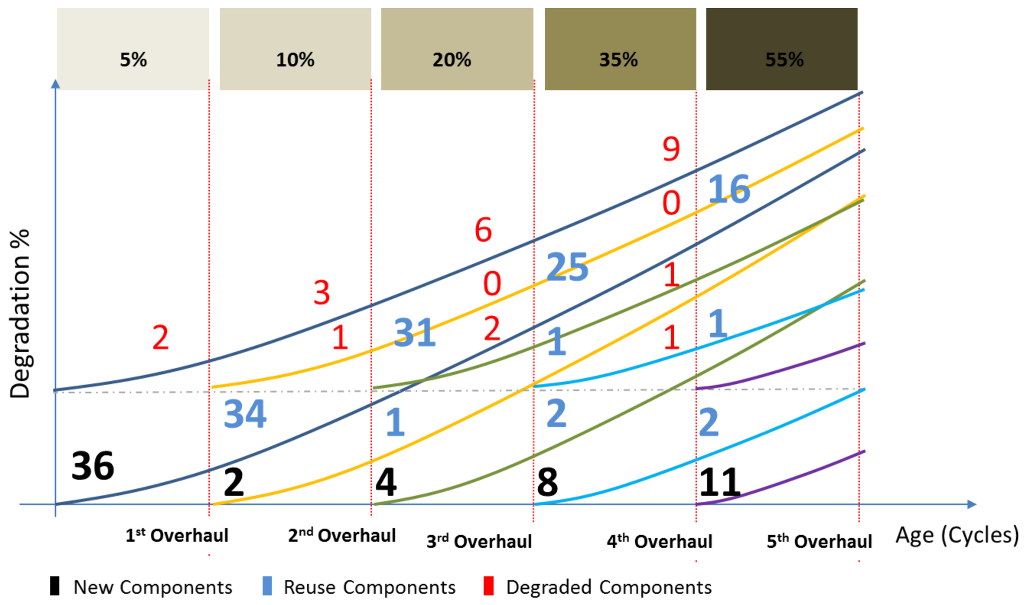


Figure 6-2: Conceptual modelling of through-life performance of components for data generation

In Figure 6-2, the curved lines with different colours illustrate the quantity of components beginning its run at each overhaul state to show a clear distinction of the regression. The red vertical lines represent demarcation of individual overhaul states. The percentage presented in the coloured boxes at the top depicts the failure rate at each overhaul state. Based on the study, where only assembly level data are available, the author attempted to model the through-life performance of different overhaul states, an assumption relating to the expected rate of rejection was taken at “5%”, “10%”, “25%”, “30%”, and “40%”. In the course of developing the framework a 6th state with 55% degradation rate was included.

The quantities rejected are solved using the above stated percentages (see Table 6-1). However, the generated data are created and validated in conjunction with experts.

6.2.2 Model selection

The model equation selected for this statistical analysis is the Weibull reliability function. The Weibull reliability function is most appropriate for degradation and maintenance problems as indicated in chapter 2. A more detail segment of the framework is presented in Figure 6-3 to give a better insight of the variables required for the WTPPM.

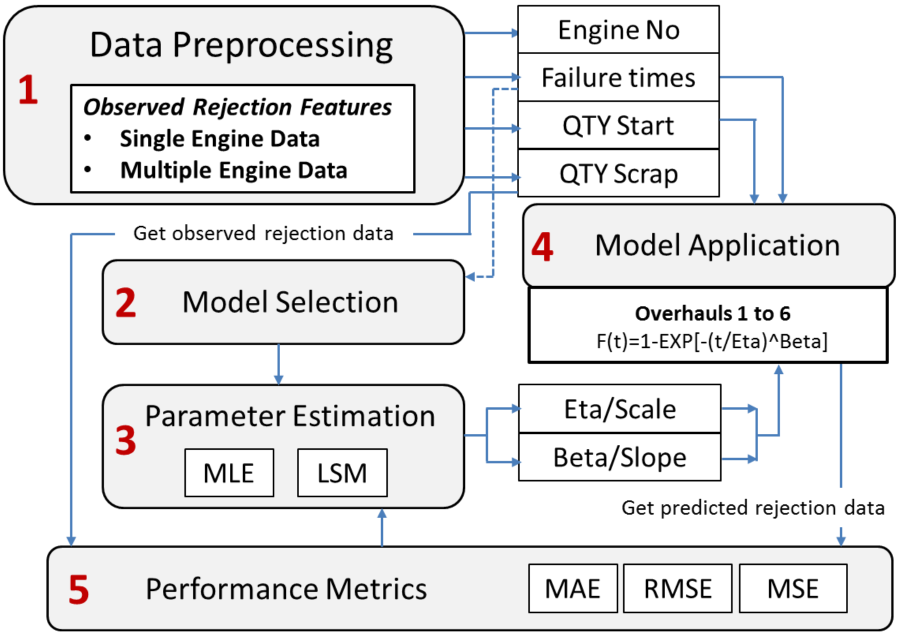


Figure 6-3: Detailed model of through-life performance

Statistical analysis is conducted on the time-to-failure data with analytical methods to calculate and describe the data in terms of mean, standard deviation, coefficient of variance and confidence level of 95%. The time-to-failure in cycles is denoted with $t_{Inspect(i)}$. The time-to-failure $t_{Inspect(i)},\ldots,\ t_{Inspect(n)}$ are statistically analysed to get the moments that describe the data. The first moment calculates the mean of the time-to-failure data with Equation (6-1).

$$\bar{t} = \frac{1}{n}\sum_{i=0}^{n} t_{Inspect(i)} \tag{6-1}$$

where $\bar{t}$ denotes the mean and n denotes the number of cycles $t_{Inspect(i)}, \ldots, t_{Inspect(n)}$. The standard deviation (σ) is solved with Equation 6-2.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(t_{Inspect(i)} - \bar{t})^2} \tag{6-2}$$

The coefficient of variance (CoV) measures variability in absolute term using Equation (6-3). An increase in *n* can lead to a rise in coefficient of variance.

$$CoV = \frac{\sigma}{\bar{t}} \tag{6-3}$$

The confidence level ($L_{Confidence}$) Equation (6-4) assesses the level of assurance of the failure data. The confidence level of 95% describes the Mean with a confidence coefficient of 1.96 (Rumsey, 2016). A confidence level of 95% has been selected with a significance level of 0.05 (Field, 2009).

$$L_{Confidence} = \bar{t} \pm Z_{\alpha/2}\frac{\sigma}{\sqrt{n}} \tag{6-4}$$

where $Z_{a/2}$ denotes a confidence coefficient, the standard error of the mean is the standard deviation of the sampling distribution represented as $\frac{\sigma}{\sqrt{n}}$. The margin of error is the product of the multiplier and the standard error, which is added to and subtracted from the mean to get the interval endpoints. The sample mean is the best point estimate and the centre of the confidence level. The minimum and maximum values for a chosen confidence level are statistically generated to fall between the through-life bounds of the failure times. The next section describes the methods of estimating two parameters of the Weibull function.

6.2.3 Weibull Parameter estimation

Analytical techniques for estimating the two-parameter Weibull function include Least Square Estimate (LSE) and Maximum Likelihood Estimator (MLE). Based on the time-to-failure sample data the η and β parameters are calculated (Abernethy, 2006).

$$F(t) = 1 - \exp\left[-\left(\frac{t_{\text{Inspect(i)}}}{\eta}\right)^{\beta}\right] \tag{6-5}$$

where F(t) is the probability of failure, $t_{\text{Inspect(i)}}$ is the failure times, η represents characteristic life measured by cycles and β is slope for determining failure rate.

Least square method

The least square method as an analytical method estimates the Weibull parameters needed as input into the WTPPM. This method is applied best where data sets are complete with an assumed single failure. The preferred estimating method is the median rank (see Equation 6-14) (Bernard's Approximation), a statistical regression approach for fitting data as a standard method and best practice (Abernethy, 2006). The objective of the LSM is to estimate the parameters based on best fit lines solved by the LSM to minimise the sum of squared errors (E).

$$E = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{6-6}$$

where y_i denotes probability of failure and $\hat{y}_i$ denotes estimated probability of failure. Using the well-known Weibull distribution in Equation (6-5). The two-parameter unreliability Weibull CDF is transformed into the natural (base e) logarithm of the failure times (Abernethy, 2006).

$$\ln(1 - F(t)) = \ln\left(e^{-\left(\frac{t_{\text{Inspect(i)}}}{\eta}\right)^{\beta}}\right) \tag{6-7}$$

$$\ln(1 - F(t)) = -\left(\frac{t_{Inspect(i)}}{\eta}\right)^{\beta} \tag{6-8}$$

$$\ln(-\ln(1 - F(t))) = \beta\ln\left(\frac{t_{Inspect(i)}}{\eta}\right) \tag{6-9}$$

$$\ln\left(\ln\left(\frac{1}{1 - F(t)}\right)\right) = \beta\ln\left(t_{Inspect(i)}\right) - \beta\ln(\eta) \tag{6-10}$$

Setting the value

$$x = \ln(T_{Inspect(i)}) \tag{6-11}$$

and

$$y = \ln\left(\ln\left(\frac{1}{1 - F(t)}\right)\right) \tag{6-12}$$

The cumulative distribution function equation is rewritten as

$$y = \beta x - \beta\ln(\eta) \tag{6-13}$$

This CDF equation becomes a linear equation, with slope of β and an intercept of $\beta\ln(\eta)$. The procedure to perform parameter estimation is as follows:-

Step 1: Calculate median rank using Bernard's approximation estimates failure times using Equation (6-16), where i denotes incremental rank order and n denotes number of items (Abernethy, 2006).

$$MR = \left[\frac{i - 0.3}{n + 0.4}\right] \tag{6-14}$$

The median rank, calculated with Equation (6-14) is used in Equation (6-15) to determine the values for the y-axis.

Step 2: Calculate the natural (base e) logarithm of the time by calling

$$Y = \ln\left[\ln\left[\frac{1}{1 - MR}\right]\right] \quad (6\text{-}15)$$

$$X = \ln\left[t_{Inspect(i)}\right] \quad (6\text{-}16)$$

Step 3: Calculate the least square estimates of A and B of A (intercept) and B (slope) in Equation (6-17)

$$Y = A + BX \quad (6\text{-}17)$$

Where $\overline{Y}$ is the average of the Ys and $\overline{X}$ is the average of the Xs

$$\widehat{A} = \overline{Y} - \widehat{B}\overline{X} \quad (6\text{-}18)$$

$$\widehat{B} = \frac{\sum_{i=1}^{n} x_i y_i - \frac{\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n}}{\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}} \quad (6\text{-}19)$$

However, the correlation coefficient calculates proportion of variation in the data.

$$cc = \frac{\sum_{i=1}^{n} x_i y_i - \frac{\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n}}{\sqrt{\left(\sum_{i=1}^{n} x_i^2 \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}\right)\left(\sum_{i=1}^{n} y_i^2 \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}\right)}} \quad (6\text{-}20)$$

where cc denote correlation coefficient and calculated as cc^2.

Step 4: Calculate the median rank regression estimates of the first parameter β

$$\hat{\beta} = \frac{1}{\widehat{B}} \quad (6\text{-}21)$$

$\hat{\eta}$ can be solved since $\hat{\beta}$ has been estimated. To calculate the median rank regression estimates of the second parameter η, e denotes exponential

$$\hat{\eta} = e^{\frac{\widehat{A}}{\hat{\beta}}} \quad (6\text{-}22)$$

Maximum likelihood estimate

The MLE is another analytical method for parameter estimation. The MLE commonly used due to its desirable properties. Let (t_1, t_2, …, t_n) be a random sample of size n from a probability distribution function. The maximum likelihood Weibull analysis method comprises finding the η and β parameters, which maximises the "likelihood" of getting the and parameters of a given observed data (Abernethy, 2006). The objective is to estimate the probability of η and β using a statistical expression of the likelihood function, given the observed data. When the samples are complete (all units are run to failure), the likelihood function L becomes Equation (6-23);

$$L = \prod_{i=1}^{n} F(t_i) = F(t_1)F(t_2) \ldots F(t_n) \qquad (6\text{-}23)$$

where n denotes the sample size.

The MLE of t maximises F(t) is equivalently, the logarithm of F(t). The MLE of t is a subject to:

$$\frac{dL}{dt} = 0 \qquad (6\text{-}24)$$

The MLE solution is: $\hat{\theta} = \arg_{\theta \in \vartheta}$max(L) where θ = {β,η}, ϑ is the whole parameter space of β,η. The solution space follows the Weibull distribution using Equation (6-5). Regarding reliability, F(t) is the probability that components will fail by time t. F(t) represents the unreliability at time $t_{Inspect(i)}$.

The Weibull probability density function (PDF) gives

$$f(t) = \frac{\beta}{\eta}\left(\frac{t_{Inspect\,(I}}{\eta}\right)^{\beta-1} e^{-\left(t_{Inspect(i)}/\eta\right)^{\beta}} \qquad (6\text{-}25)$$

Apply MLE to estimate η and β parameters by considering the Weibull probability density function. This MLE application to Weibull probability density function becomes Weibull likelihood function in Equation (6-26).

$$L(t_1, \dots, t_n; \eta, \beta) \;=\; \prod_{i=1}^{n} \left(\frac{\beta}{\eta}\right) \left(\frac{t_{\mathrm{Inspect(i)}}}{\eta}\right)^{\beta-1} e^{-(\frac{t_{\mathrm{Inspect(i)}}}{\eta})^{\beta}} \tag{6-26}$$

$$\ln L \;=\; \sum_{i=1}^{n} \ln \left(\frac{\beta}{\eta}\right) \left(\frac{t_{\mathrm{Inspect(i)}}}{\eta}\right)^{\beta-1} e^{-(\frac{t_{\mathrm{Inspect(i)}}}{\eta})^{\beta}} \tag{6-27}$$

The likelihood of the sample failure data is a function of the Weibull parameters η and β. Taking the logarithm of Equation (6-27), differentiating based on parameters η and β which equates to zero. The maximum likelihood estimate of β is subject to: (the $\hat{\beta}$ signifies maximum likelihood). From Equation (6-23), the Equation (6-28) holds.

$$\frac{\sum_{i=1}^{n} t_i^{\hat{\beta}} \ln(t_{\mathrm{Inspect(i)}})}{\sum_{i=1}^{n} t_{\mathrm{Inspect(i)}}{}^{\hat{\beta}}} - \frac{1}{n} \sum_{i=1}^{n} \ln(t_{\mathrm{Inspect(i)}}) - \frac{1}{\hat{\beta}} = 0 \tag{6-28}$$

In Equation (6-28) η has been eliminated. However, when $\hat{\beta}$ is solved, the η can be determined by the MLE using Equation (6-29). The $\hat{\eta}$ denotes maximum likelihood.

$$\hat{\eta} = \left(\frac{\sum_{i=1}^{n} t_{\mathrm{Inspect(i)}}{}^{\hat{\beta}}}{n}\right)^{\frac{1}{\hat{\beta}}} \tag{6-29}$$

The MLE of β is solved using an iterative process (i.e., Newton-Raphson method) (Abernethy, 2006). The estimated parameters are for the Weibull reliability function. Once the estimated parameters were established, the parameters are then introduced to the prognostics modelling discussed in the next section.

6.2.4 Through-life performance modelling

Through-life performance modelling (TPM) is a data-driven predictive approach used in Stage 1 of the initial framework development. The TPM visualises and represents estimated η and β parameters, total number of components in an assembly, number of components rejected, replaced and reused, different overhaul states, times and subsequent population to be replaced either brand new and/or repaired components as well as the varying repair condition. The TPM facilitates components renewal / replacement in an assembly as independently and identically distributed (Rausand and Høyland, 2004). The objective of TPM is to model R-Cube components in an assembly to assess degradation at each overhaul state and through their life cycle. The purpose of TPM provides an understanding of the through-life performance assessment at design stage to recognise number of degrading components before failure occurs. The TPM incorporates renewal modelling process of replacing components in a multi-component assembly to demonstrate the effect of changes to the system (Maria, 1997). The through-life observation ensures accuracy of the outcome from TPM. The use of input plus model application gives outputs which visually represents rejected, replaced and reused components. The contribution is the application of the Weibull cumulative distribution function to a renewal process in TPM to

i. model and estimate prior inspection to estimate R-Cube,
ii. determine when to scrap the entire multi-component in an assembly and
iii. predict the remaining useful life of components.

The goal of through-life performance modelling is to estimate the rejection rate and calculate number of component rejections based on probability theory. The TPM is developed to estimate the expected number of rejected components at the next inspection; converts rate of rejections; converts designed model into statistical model; verifies and validates expected outcome with an expert. A systematic approach solves for the population of components starting at an initial zero value. The new population of components continues with existing reused components. In this research, the requirements for TPM include: -

i. Factors are input from historical and current health data including mock-up numbers for a specified domain. These are called uncertain variables
ii. Process are in-between deterministic computations on the inputs in (i)
iii. Responses are output which depends on computing the input based on selected functions

The flowchart presented in Figure 6-4 is used to visually depict the prognostics modelling operations.

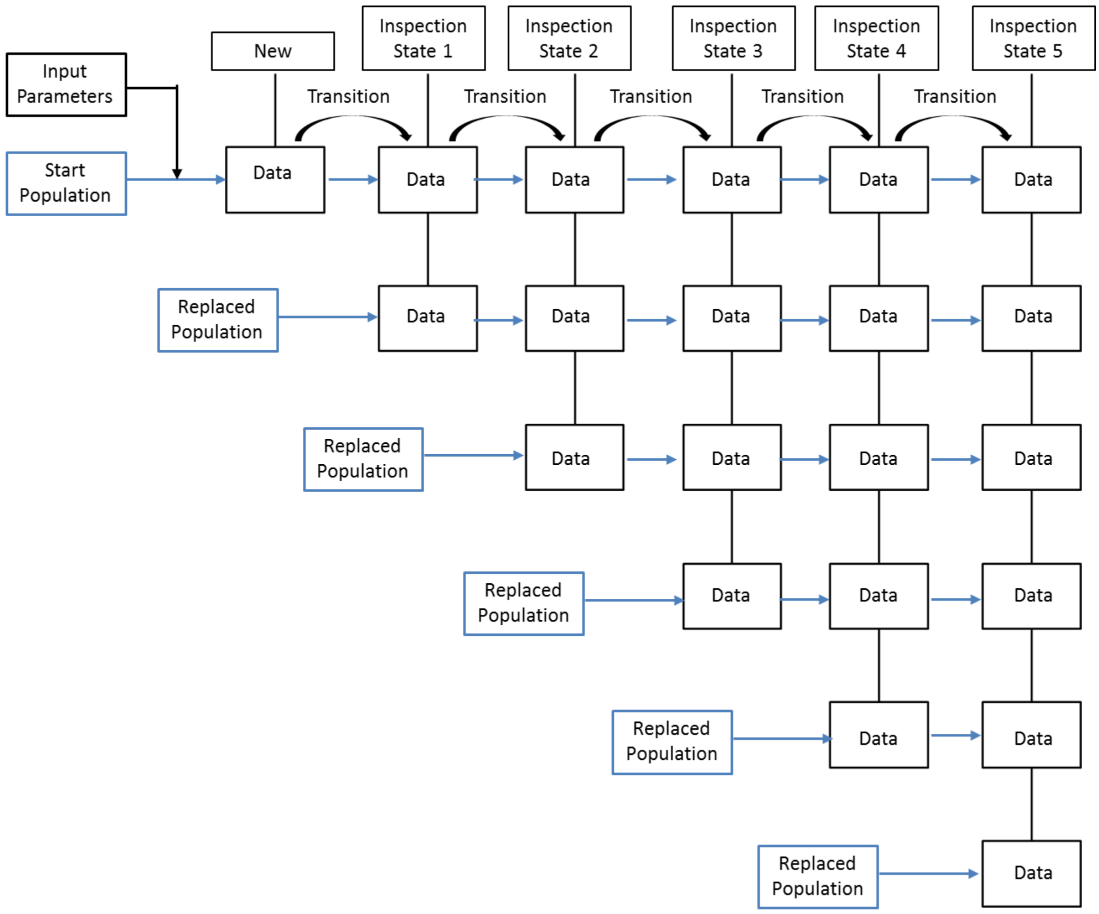


Figure 6-4: An outline of a modelled TPM for through-life performance operation

The Microsoft Office (MS) Excel and Visual Basic for Application (VBA) modelling of the through-life performance of components in an assembly. The modelling establishes the use of recursive process based on a population and overhaul inspection times. The flowchart presented in Figure 6-5 shows a step by step processing through the chart shown in Figure 6-4.

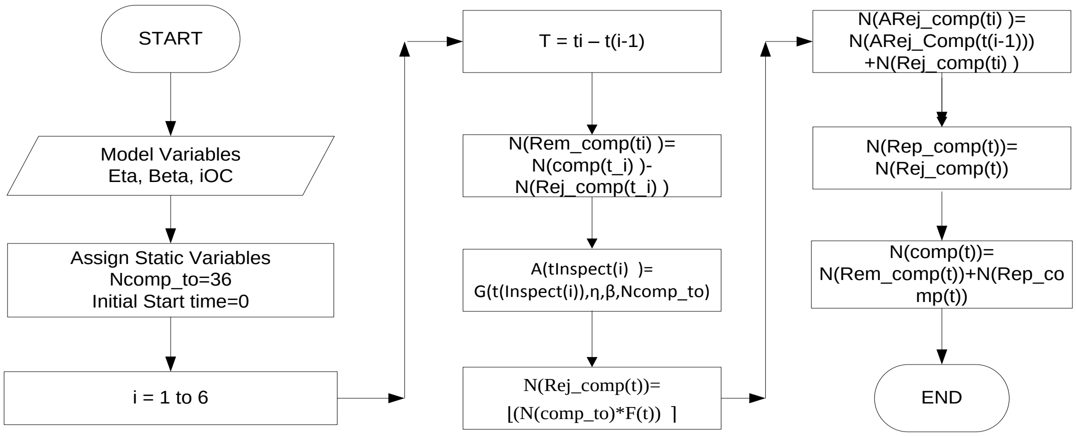


Figure 6-5: The flowchart to modelling each segment of TPM

The TPM is transformed into the Weibull Through-life Performance Prediction Model (WTPPM) with specified data format. The renewal modelling consists of *n* inspection overhaul states ($s_1, s_2, \ldots, s_n$) starting with the first inspection overhaul state. The population of component at the inspection ($p_1, p_2 \ldots, p_n$) represents replacement and recursion. For every item of population p, p=1,2,3,…n_p, there are a series of overhauls states s, s=1,2,3,…max_s. The data can be summarised in a matrix A, where $A(t_{Inspect(i)})$ is number of rejections on N_{comp_to} at $t_{Inspect(i)}$. While the $A(t_{Inspect(i)})$ is output of the function for the input, the input includes overhaul inspection time, number of component at the start, characteristic life and slope parameter. The mathematical model for $A(t_{Inspect(i)})$ for the through-life predictive model is given as

$$A\left(t_{Inspect(i)}\right) = G(t_{Inspect(i)}, \eta, \beta, N_{comp\_to}) \quad (6\text{-}30)$$

where $A\left(t_{Inspect(i)}\right)$ is rate of expected degrading component, $t_{(i)}$ represents failure time in cycles at various overhaul stages (1, 2,…, n), N_{comp_to} is total number of components (e.g. 36). The Equation (6-30) determines outcome of components expected to fail at each inspection overhaul time. The mathematical model uses the two-parameter Weibull cumulative distribution function by incorporating N_{comp_to} as seen in Equation (6-30). Equation (6-30) is necessary for the process flow of the population and overhaul inspection times. It calculates the rate of rejections based on the overhaul inspection time and population. The matrix formation in horizontal and vertical directions – horizontal formation relates to population, while vertical formation is top-down showing the overhaul inspection states and the number of components expected to fail. At every state inspection space, the data box / block reuses Equation (6-30). The total number of both the reused and replaced population of components are kept for the next overhaul. The through-life performance model, which is prognostics modelling limited to *n* inspection states with *n* iterations of the population.

The Population Group and Overhaul State/Point at time $t_{(i)}$

Equation (6-31) provides a current inspection time of the system from a start time. This equation describes the differences between overhauls and the initial start time = 0.

$$\mathrm{T_{inspect(i)}} = \mathrm{t_{inspect(i)}} - \mathrm{t_{inspect(i-1)}} \tag{6-31}$$

where $t_{inspect(i)}$ denotes current inspection overhaul time, $t_{inspect(i-1)}$ denotes previous time and $T_{inspect(i)}$ denotes total inspection overhaul time by time $t_{(i)}$.

Call the result of Equation (6-31) as input to calculate failure rate for each inspection overhaul time. The predicted rate of unreliability uses Equation (6-5).

The calculated failure rate is a cumulative function. Conversion to number of rejections from cumulative rate of rejection uses Equation (6-32) to round to the nearest value. The symbol ⌊ ⌉ represents round-up and round-down. Examples are a value 6.56 is rounded up to 7, and a value 6.46 is rounded down to 6 a single figure. The rationale is to get a discrete whole number.

$$\mathrm{N_{Rej\_comp(t)}} = \lfloor \left(\mathrm{N_{comp\_to}} * \mathrm{F(t)}\right) \rceil \tag{6-32}$$

where $N_{Rej\_comp(t)}$ denotes number of cumulative rejected components, N_{comp_to} represents total number of components at start. An exact number of rejections at each inspection uses Equation (6-33) which is same as cumulative number of rejections for the first inspection.

$$N_{Rep\_comp(t)} = N_{Rej\_comp(t)} \quad (6\text{-}33)$$

where $N_{Rep\_comp(t)}$ denotes number replaced at this overhaul

Get total number of components at each inspection and population of component which will transit until next inspection by calling Equation (6-34). The total number of components after replacement $N_{comp(t)}$ and number of reused components $N_{Rem\_comp(t)}$ plus number of replaced components :

$$N_{comp(t)} = N_{Rem\_comp(t)} + N_{Rep\_comp(t)} \quad (6\text{-}34)$$

where $N_{comp(t)}$ denotes total number of components after replacement and N_{Rem-_comp} denotes number of reused components.

Next Overhaul Point

In the next overhaul, the Population Group One and Overhaul Point Two starts with using

i. Equation (6-31) to give the time $t_{inspect(i)}$, $t_{inspect(i+1)}, \ldots,$ $t_{inspect(n)}$ n represents overhauls
ii. Equation (6-5) uses the outcome from Equation (6-31) to produce the failure rate
iii. Equation (6-33) applies results from Equation (6-5) and converted failure rate into cumulative number of rejections
iv. Equation (6-35) is called to calculate exact number of rejections for that population and overhaul inspection time.

$$N_{ARej\_comp(t_i)} = N_{ARej\_Comp(t_{i-1})} + N_{Rej\_comp(t_i)} \quad (6\text{-}35)$$

where $N_{Rej\_comp}(t_i)$ denotes exact number of rejections for that population and overhaul inspection time and $N_{ARej\_comp}(t_i)$ denotes cumulative number of rejections.

Equation (6-36) calculates remaining replacement after the rejected components through the lifecycle of the replacements and overhaul states.

$$N_{Rem\_comp(t_i)} = N_{comp(t_i)} - N_{Rej\_comp(t_i)} \quad (6\text{-}36)$$

In order to validate the installed components after overhaul, use Equation (6-34) to check that the number of parts and replacements at n inspection stages equal number of components at start, the outlined equations have been utilised to successfully model through-life performance component degradation as shown in Figure 6-5.

The population block in Figure 6.6 contains inspection time, the Weibull estimated rejection rate, cumulative and explicit component rejections. Each block contains recursively reused formulae. The block at subsequent inspections include calculations of cumulative number of rejections throughout the life cycle and number of rejections at each inspection by adding rejections minus cumulative number of rejections. The result on the first population gives an underlying distribution rejection rate. The capability of the data-driven prognostics methodology estimates expected rejections before failure occurrence. The prognostics approach supports maintenance scheduling and reduction of unnecessary maintenance actions in spare parts manufacturing and maintenance management. Refer to appendix J for model class diagram and appendix K for through-life model flowchart. The next section focuses on error minimisation calculations for back-fitting using performance metric evaluation.

6.2.5 Performance metric evaluation

The MAE calculation minimises error for back-fitting of the initial estimated Weibull parameters. The predicted outcome from the through-life performance predictive model and the observed real-world values are evaluated. The difference between predicted and observed rejection rate is evaluated using Equation (6-39) to calculate for absolute error.

$$\overline{E} = \frac{1}{n}\sum_{i=1}^{n}\left|\widehat{V}_i - V_i\right| \quad (6\text{-}39)$$

where $\widehat{V}_i$ denotes predicted values from the through-life performance prediction model and V_i denotes observed values. The error values reflect the two parameters, which are initially predicted in the parameter estimation and performance evaluation for the back-fitting (enumeration / matrix), the process to select optimal η and β parameters for probability of failure and RUL prediction is presented. Figure 6-6 illustrates an enumeration of the η and β parameters to produce resulting error values. The optimised error values, η and β parameters are transformed into probability distribution and RUL. The enumeration is a complete and ordered listing of estimated parameters and error values (Thomas, 2002). The enumeration presents a matching error values to both η and β parameters as back-fitting.

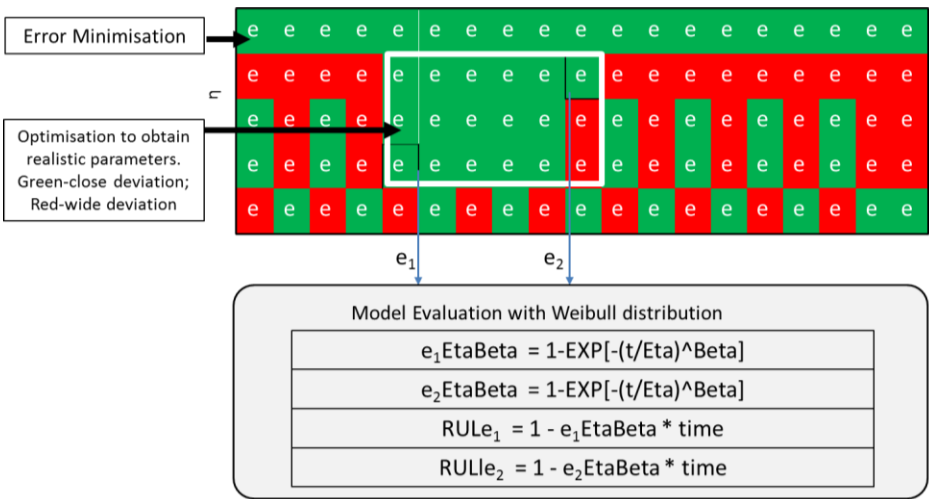


Figure 6-6: Approach to calculate probability distribution and RUL; ‘e in green’ means acceptable and ‘e in red’ is unacceptable error values

The back-fitting displays error values with a range of η and β. The colour code is introduced to differentiate high and low error values. The back-fitting process is a Generic Enumeration Technique (GET) as shown in Figure 6-6 and in Figure 6.7 as an outcome, and the procedures outlined below. The rationale ensures error values and estimated parameters match. The enumeration relates to a 20 x 20 dimensional array based on a visual acuity that a person can see detail from a specified distance (Kirschen and Laby, 2006; NDT Resource Center, 2014).

β

η	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6
-646.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
-146.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
353.8	-131	-139	-144	-146	-149	-150	-151	-152	-153	-154	-154	-155	-155	-155	-155	-155	-156	-156	-156	-156	-156
853.8	-94	-101	-109	-115	-118	-120	-123	-123	-126	-126	-127	-126	-127	-128	-128	-128	-128	-127	-128	-128	-128
1353.8	-65	-75	-81	-86	-91	-93	-95	-96	-98	-99	-100	-100	-102	-102	-101	-101	-100	-100	-100	-100	-100
1853.8	-50	-55	-59	-65	-68	-70	-72	-73	-74	-77	-77	-77	-78	-78	-77	-77	-79	-79	-79	-82	-81
2353.8	-38	-41	-44	-46	-51	-53	-56	-55	-57	-58	-59	-59	-59	-61	-59	-60	-61	-60	-60	-60	-60
2853.8	-31	-34	-34	-37	-39	-42	-42	-44	-42	-44	-46	-47	-45	-44	-44	-45	-46	-46	-46	-45	-44
3353.8	-31	-33	-30	-29	-32	-35	-33	-35	-36	-35	-36	-35	-36	-36	-34	-37	-35	-33	-33	-33	-30
3853.8	-30	-30	-26	-26	-28	-24	-27	-29	-27	-30	-28	-28	-28	-27	-26	-27	-27	-29	-28	-28	-28
4353.8	-28	-29	-26	-26	-25	-24	-22	-21	-21	-23	-24	-22	-19	-21	-23	-23	-26	-27	-24	-23	-23
4853.8	-34	-32	-27	-25	-27	-24	-19	-20	-22	-20	-20	-20	-17	-20	-18	-22	-20	-22	-22	-19	-24
5353.8	-33	-29	-27	-23	-24	-22	-23	-21	-19	-20	-19	-19	-17	-24	-20	-21	-19	-22	-19	-19	-24
5853.8	-34	-28	-27	-27	-25	-24	-21	-21	-15	-21	-19	-19	-22	-19	-23	-19	-20	-21	-20	-20	-20
6353.8	-34	-30	-30	-26	-25	-22	-25	-20	-21	-21	-21	-20	-17	-18	-19	-18	-18	-18	-21	-21	-22
6853.8	-33	-31	-29	-23	-26	-23	-20	-21	-21	-21	-18	-19	-19	-18	-19	-18	-20	-22	-24	-22	-19
7353.8	-35	-28	-30	-26	-23	-25	-23	-22	-19	-19	-20	-18	-19	-18	-20	-20	-22	-21	-21	-20	-20
7853.8	-34	-30	-28	-26	-26	-27	-24	-21	-20	-20	-18	-19	-23	-20	-21	-23	-21	-22	-22	-22	-21
8353.8	-36	-34	-30	-28	-27	-24	-24	-24	-21	-20	-21	-22	-23	-24	-23	-23	-24	-24	-23	-24	-24
8853.8	-37	-33	-31	-29	-27	-25	-24	-24	-23	-24	-25	-24	-24	-25	-26	-26	-26	-26	-26	-25	-26
9353.8	-36	-35	-32	-29	-27	-26	-27	-25	-26	-26	-26	-26	-27	-27	-28	-28	-29	-28	-28	-29	-30

Figure 6-7: Enumeration of error values, estimated η and β parameters

Step 1: Define the η and β parameters; calculate change in maximum and minimum η and β parameters: the maximum minus minimum η and β parameters, are used to generate an enumeration of a range of the η and β parameters with calculated error values.

Step 2: Display the η and β parameters on horizontal and vertical axis with the error values in the matrix as an enumeration. The matrix is a 20x20 – a single view area of focus.

Step 3: For each η and β values, calculate the rejection rate by calling Equation (6-30) and subsequent equations. The equations are repeated through the life cycle.

Step 4: Define performance metric variables and call Equation (6-39). The equation calculates error values based on the inspection overhaul state with outcomes from Equation (6-30) in Step 3 for single and multiple engines.

Step 5: For every minimised error value calculated, estimated η and β parameters are shown in matrix. This matrix illustrates a total of 400 varying error values resulting from the range of η and β parameters.

Colours green and red in gradient form applied shows region of data sensitivity. The green region indicates closeness to the actual data – components can still be in good condition and fit for reuse, while red region indicates distant deviation from real data – components are likely to be significantly unfit for reuse.

6.2.6 The process to select optimal η and β parameters

A Generic Optimisation Technique (GOT) is a zoom-in functionality applied in the GET to identify and optimise for realistic parameters. The procedures for conducting the GOT are

Step 1: Display error value for every η and β across the matrix for every result element of η and β, then use the lower and upper η and β parameters based on the error values to do a recalculation into the 20 x 20 matrix.

Step 2: Draw a borderline to highlight the region of green with low error values as shown in Figure 6-8. The selected region with the lowest error values is defined as a pattern, which is search by the GOT algorithm.

β

η	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6
-646.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
-146.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
353.8	-131	-139	-144	-146	-149	-150	-151	-152	-153	-154	-154	-155	-155	-155	-155	-155	-156	-156	-156	-156	-156
853.8	-94	-101	-109	-115	-118	-120	-123	-123	-126	-126	-127	-126	-127	-128	-128	-128	-128	-127	-128	-128	-128
1353.8	-65	-75	-81	-86	-91	-93	-95	-96	-98	-99	-100	-100	-102	-102	-101	-101	-100	-100	-100	-100	-100
1853.8	-50	-55	-59	-65	-68	-70	-72	-73	-74	-77	-77	-77	-78	-78	-77	-77	-79	-79	-79	-82	-81
2353.8	-38	-41	-44	-46	-51	-53	-56	-55	-57	-58	-59	-59	-59	-61	-59	-60	-61	-60	-60	-60	-60
2853.8	-31	-34	-34	-37	-39	-42	-42	-44	-42	-44	-46	-47	-45	-44	-44	-45	-46	-46	-46	-45	-44
3353.8	-31	-33	-30	-29	-32	-35	-33	-35	-36	-35	-36	-35	-36	-36	-34	-37	-35	-33	-33	-33	-30
3853.8	-30	-30	-26	-26	-28	-24	-27	-29	-27	-30	-28	-28	-28	-27	-26	-27	-27	-29	-28	-28	-28
4353.8	-28	-29	-26	-26	-25	-24	-22	-21	-21	-23	-24	-22	-19	-21	-23	-23	-26	-27	-24	-23	-23
4853.8	-34	-32	-27	-25	-27	-24	-19	-20	-22	-20	-20	-20	-17	-20	-18	-22	-20	-22	-22	-19	-24
5353.8	-33	-29	-27	-23	-24	-22	-23	-21	-19	-20	-19	-19	-17	-24	-20	-21	-19	-22	-19	-19	-24
5853.8	-34	-28	-27	-27	-25	-24	-21	-21	-15	-21	-19	-19	-22	-19	-23	-19	-20	-21	-20	-20	-20
6353.8	-34	-30	-30	-26	-25	-22	-25	-20	-21	-21	-21	-20	-17	-18	-19	-18	-18	-18	-21	-21	-22
6853.8	-33	-31	-29	-23	-26	-23	-20	-21	-21	-21	-18	-19	-19	-18	-19	-18	-20	-22	-24	-22	-19
7353.8	-35	-28	-30	-26	-23	-25	-23	-22	-19	-19	-20	-18	-19	-18	-20	-20	-22	-21	-21	-20	-20
7853.8	-34	-30	-28	-26	-26	-27	-24	-21	-20	-20	-18	-19	-23	-20	-21	-23	-21	-22	-22	-22	-21
8353.8	-36	-34	-30	-28	-27	-24	-24	-24	-21	-20	-21	-22	-23	-24	-23	-23	-24	-24	-23	-24	-24
8853.8	-37	-33	-31	-29	-27	-25	-24	-24	-23	-24	-25	-24	-24	-25	-26	-26	-26	-26	-26	-25	-26
9353.8	-36	-35	-32	-29	-27	-26	-27	-25	-26	-26	-26	-26	-27	-27	-28	-28	-29	-28	-28	-29	-30

Figure 6-8: Borderline for the selection of low error values

Step 3: Use zoom-in (GOT) functionality to further recalculate for error minimisation highlighting region in relation to the η and β parameters. The output of the GOT from Figure 6-8 is presented in Figure 6-9.

β

η	1.27	1.3225	1.375	1.4275	1.48	1.5325	1.585	1.6375	1.69	1.7425	1.795	1.8475	1.9	1.9525	2.005	2.0575	2.11	2.1625	2.215	2.2675	2.32
4686.3	-17	-24	-20	-20	-20	-21	-21	-20	-20	-18	-18	-19	-19	-18	-19	-21	-21	-19	-22	-24	-19
4796.55	-19	-21	-21	-21	-20	-20	-20	-19	-20	-20	-18	-17	-18	-17	-17	-21	-23	-23	-23	-18	-18
4906.8	-20	-20	-21	-23	-21	-20	-20	-20	-17	-17	-18	-20	-20	-15	-23	-22	-22	-17	-17	-22	-22
5017.05	-20	-22	-22	-21	-21	-19	-18	-19	-20	-19	-19	-18	-16	-16	-21	-22	-17	-21	-21	-21	-19
5127.3	-20	-19	-20	-22	-20	-19	-19	-20	-19	-19	-18	-17	-17	-20	-21	-20	-20	-20	-20	-20	-20
5237.55	-20	-18	-20	-19	-19	-20	-20	-19	-19	-21	-18	-17	-16	-24	-18	-19	-19	-22	-21	-22	-21
5347.8	-20	-20	-19	-19	-20	-20	-19	-18	-19	-17	-17	-18	-24	-21	-20	-19	-21	-19	-19	-19	-22
5458.05	-19	-19	-19	-20	-21	-18	-19	-22	-17	-17	-19	-19	-21	-21	-22	-21	-18	-18	-20	-23	-19
5568.3	-19	-21	-21	-21	-17	-15	-20	-20	-17	-17	-19	-21	-21	-22	-22	-21	-21	-21	-22	-19	-19
5678.55	-22	-20	-21	-21	-17	-21	-21	-17	-20	-20	-18	-20	-21	-21	-20	-20	-21	-19	-17	-18	-20
5788.8	-20	-20	-20	-15	-18	-20	-18	-21	-21	-19	-19	-22	-22	-20	-23	-21	-22	-20	-21	-20	-20
5899.05	-23	-21	-20	-19	-18	-17	-19	-19	-20	-20	-22	-22	-19	-23	-21	-21	-17	-20	-20	-19	-17
6009.3	-24	-21	-19	-19	-21	-21	-21	-21	-21	-21	-23	-21	-24	-21	-19	-17	-21	-20	-20	-17	-20
6119.55	-20	-19	-19	-19	-19	-19	-20	-17	-19	-19	-22	-19	-19	-19	-18	-19	-19	-19	-18	-20	-20
6229.8	-22	-19	-19	-19	-20	-19	-20	-21	-21	-21	-19	-19	-19	-19	-20	-19	-20	-18	-20	-20	-20
6340.05	-25	-20	-19	-20	-21	-21	-21	-21	-21	-18	-17	-17	-18	-19	-19	-19	-17	-18	-18	-18	-19
6450.3	-21	-19	-20	-19	-20	-20	-21	-20	-18	-18	-18	-17	-19	-19	-19	-18	-19	-19	-18	-19	-21
6560.55	-19	-19	-19	-20	-20	-21	-21	-20	-18	-20	-20	-21	-19	-18	-16	-18	-19	-19	-19	-19	-20
6670.8	-20	-22	-19	-21	-21	-21	-21	-18	-18	-18	-18	-19	-19	-19	-19	-19	-19	-19	-21	-21	-20
6781.05	-20	-19	-22	-21	-20	-19	-18	-19	-19	-19	-19	-19	-19	-20	-20	-18	-18	-20	-20	-20	-21
6891.3	-21	-18	-21	-21	-21	-19	-18	-19	-19	-20	-18	-17	-19	-19	-19	-19	-20	-20	-21	-22	-22

Figure 6-9: Optimised estimated η and β parameters with error values

6.2.7 Through-life performance model evaluation

As stated in Section 6.2.6, the optimised η and β parameters are achieved by drawing a borderline focusing on a region of interest (green region) based on the selected error values. The highlighted region is assumed best area with good data for analysis. However, the rationale for selecting error values on the border is to get optimised required values based on the cells of the first row with last column and the last row with the first column. The GET represents the entire stream of error values and the parameters in the matrix. The GOT capability minimises error values until the coverage of the entire matrix (three times – the maximum zoom-in recalculation) is rendered. A Weibull distribution resulting from Equation (6-5), the estimated parameters and the interval time/age in cycles step are passed as input to graph the probability of failure in Figure 6-10.

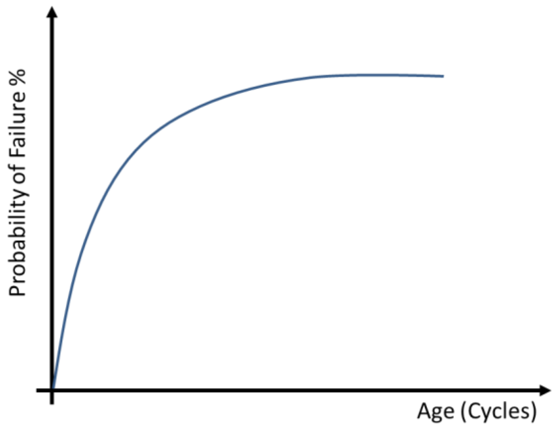


Figure 6-10: A Probability of failure distribution

In this Thesis, remaining useful life of individual components in an assembly is time left for each component to perform its defined function. The estimated parameters for the error values are transformed into the Weibull distribution probability of failure and remaining useful life of the components. The outcomes give realistic η and β parameters for the error values. The probability of failure becomes an input into Equation (6-40) by incorporating the values of $t \in \{t_i, ..., t_n.\}$ to calculate the remaining useful life (T_{RUL}). Figure 6-11 illustrates the RUL distribution from a Weibull perspective.

$$T_{RUL} = (1 - F(t)) * t \qquad (6\text{-}40)$$

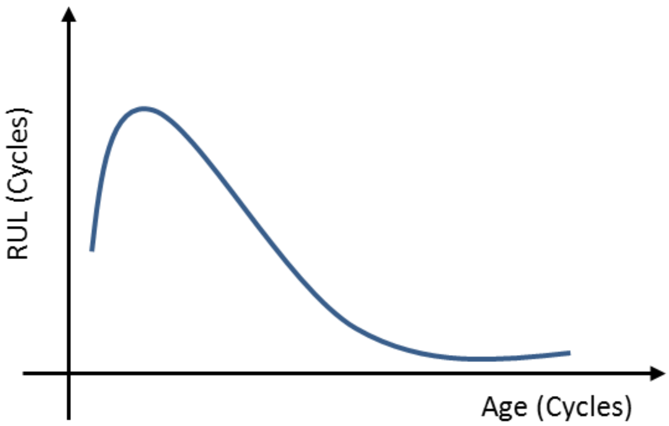


Figure 6-11: A Weibull representation of the RUL

Considering a maintenance situation where renewals are component rejections, the distribution is the remaining useful life of components at time t (Rausand and Høyland, 2004).

The confidence level ($L_{Confidence}$), the Weibull MTTF and Variance (second moments) were calculated by calling Equations (6-29) and (6-30). The confidence coefficient and significance level is 0.05 as a 95% confidence level.

$$L_{Confidence} = MTTF \pm Z\alpha\sqrt{Var} \qquad (6\text{-}41)$$

6.2.8 Cost-benefit analysis

A safety factor of 50% of the original cost of new components within the entire assembly replacement for a single system. The end of economic life is determined by the Weibull mean-time-to-failure as seen in Equation (6-41). The decision to replace entire multi-component in an assembly depends on overall cost at each overhaul state. The replacement cost is applied to make better maintenance decision to know when to scrap or replace a whole component in an assembly. Other applicable costs were assumed to be included in the cost per item and replacement cost. In this case, where $R_{cost} = T_{cost}$ the entire components in the assembly are expected to be replaced with new components.

$$\mathrm{T}_{\mathrm{Cost}} = 50\% * \mathrm{A}_{\mathrm{Cost}} \tag{6-42}$$

where A_{Cost} denotes cost per component in an assembly, T_{Cost} denotes threshold cost

$$\mathrm{R}_{\mathrm{Cost}} = \mathrm{C}_{\mathrm{Replaced}} * \mathrm{I}_{\mathrm{ComponentCost}} \tag{6-43}$$

where $C_{Replaced}$ denotes number of components replaced, R_{Cost} denotes replacement cost, and $I_{ComponentCost}$ denotes cost of replacing individual components. The class diagram is in appendix J. The flowcharts for these sections relating to the through-life performance approach is presented in appendix K.

6.3 Summary

The overall through-life performance prediction framework presented in this chapter presents a theoretical description of a predictive modelling tool capability. In this research, the proposed framework developed addresses the knowledge gap identified in literature and AS-IS industry practice from a Through-life Engineering Services perspective. The MS Excel software was used to develop the component deterioration and remaining useful life tool for through-life performance assessment. The gap has led to the development of a Weibull Through-life Performance Prediction Model – a prognostics tool for decision making. The application of the approach assesses components in an assembly to enhance prediction accuracy and robustness in estimating the number of R-Cube components. The framework applies to assessing through-life performance of components in an assembly for Through-life Engineering Services.

The data provide sufficient indication showing minimum and maximum components rejected would fall into a region of certainty. The framework contains parameter estimation of the Weibull function based on failure data, modelling of the Weibull through-life performance prediction model, back-calculation using performance metric and enumeration, and introduction of the model evaluation with interval time step and remaining useful life prediction. The next chapter presents an application of the framework to case study scenarios.

7 CASE STUDY SCENARIOS AND RESULTS

The previous chapter presented a framework describing component degradation and remaining useful life prediction of components within an assembly using only assembly level data. During the implementation of the methodology for the framework, different data were used. This chapter presents the application of the WTPPM framework to a relevant case study with three different scenarios and their results presented.

In the framework, a partitioning cross-validation approach is applied in the performance assessment, whereby model-building and validation data sets were introduced. In the evaluation of the model, MAE and RMSE were tested. The MAE gives low error values, while the RMSE provides large error values.

Initial results from the WTPPM framework

The initial results from this framework uses the model-building data sets (see Table 6-1, page 137). The data applied to the model and analysed produces results presented in Tables 7-1 to 7-2 and Figures 7-1 to 7-5.

Table 7-1 The **η** and β outcomes of the LSM and MLE

Estimation Method	η	β	Optimised η	Optimised β
MLE	5881	1.5	6156	1.46
			5481	1.70
LSM	6073	1.2	6523	1.09
			5873	1.28

Table 7-2 The number of rejected components, η and β outcomes of the LSM and MLE

Methods	η	β	OS1	OS2	OS3	OS4	OS5	OS6	Total
LSM	6073	1.2	4	7	4	14	10	14	53
MLE	5881	1.5	2	7	3	16	11	16	55

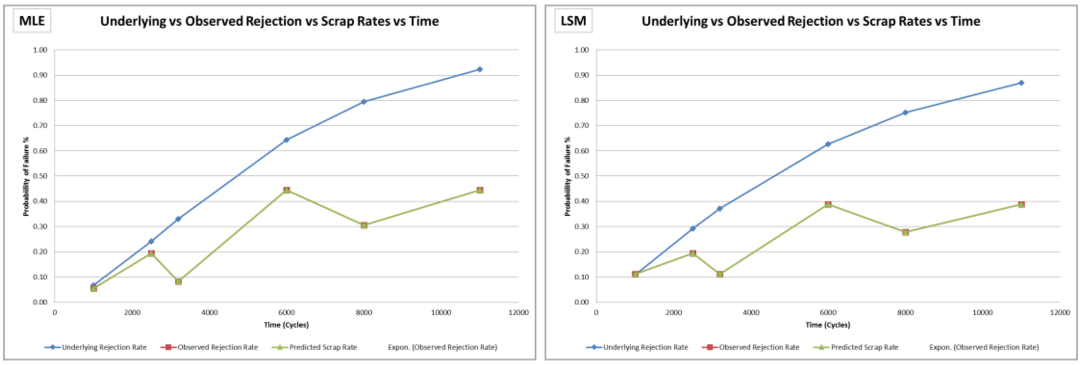


Figure 7-1 Graph with same observed and predicted rejection rates and time

Normal MLE β

η	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5
881	-82	-97	-103	-112	-118	-119	-122	-127	-128	-128	-130	-130	-131	-131	-131	-131	-131	-131	-132	-131	-131
1381	-62	-71	-78	-85	-90	-94	-95	-100	-99	-101	-103	-102	-103	-104	-105	-106	-105	-104	-105	-104	-103
1881	-46	-54	-59	-64	-70	-71	-73	-75	-78	-79	-80	-80	-81	-82	-83	-82	-81	-82	-84	-82	-82
2381	-37	-40	-45	-49	-50	-55	-58	-59	-60	-60	-62	-63	-62	-62	-63	-64	-64	-64	-64	-63	-64
2881	-28	-32	-35	-37	-40	-42	-43	-46	-47	-46	-46	-48	-47	-46	-47	-49	-49	-48	-48	-48	-47
3381	-29	-25	-25	-27	-29	-31	-31	-33	-36	-36	-36	-36	-37	-36	-36	-36	-35	-35	-35	-36	-35
3881	-25	-26	-22	-21	-21	-23	-23	-24	-26	-26	-27	-27	-26	-26	-25	-26	-27	-25	-26	-27	-27
4381	-28	-21	-20	-15	-16	-16	-16	-17	-17	-15	-18	-17	-18	-18	-17	-17	-18	-19	-19	-19	-18
4881	-26	-23	-17	-16	-11	-12	-11	-11	-11	-10	-11	-9	-10	-11	-11	-13	-13	-14	-13	-13	-15
5381	-29	-26	-18	-14	-12	-9	-11	-9	-7	-6	-5	-4	-6	-6	-7	-9	-10	-11	-11	-12	-12
5881	-28	-25	-19	-16	-12	-12	-9	-10	-4	-8	0	-2	-6	-5	-6	-5	-6	-7	-6	-8	-8
6381	-28	-23	-21	-17	-13	-10	-9	-8	-7	-6	-6	-5	-5	-7	-5	-6	-9	-7	-7	-8	-6
6881	-28	-26	-20	-16	-14	-11	-12	-11	-11	-8	-8	-8	-8	-9	-10	-10	-9	-10	-11	-12	-13
7381	-28	-24	-19	-17	-15	-16	-14	-12	-14	-10	-10	-11	-11	-12	-11	-13	-13	-14	-14	-14	-13
7881	-29	-25	-21	-19	-15	-15	-17	-15	-14	-13	-14	-14	-14	-15	-15	-16	-16	-16	-17	-17	-17
8381	-30	-25	-23	-23	-19	-18	-19	-17	-17	-16	-15	-16	-17	-18	-19	-18	-18	-19	-20	-18	-19
8881	-29	-26	-22	-24	-20	-18	-18	-19	-19	-18	-19	-20	-20	-20	-20	-21	-22	-21	-21	-21	-21
9381	-30	-27	-24	-23	-19	-20	-20	-20	-21	-21	-21	-21	-21	-23	-22	-23	-23	-24	-24	-23	-25
9881	-32	-26	-25	-22	-21	-21	-23	-23	-22	-22	-22	-23	-24	-25	-25	-24	-25	-27	-26	-27	-28
10381	-31	-29	-27	-25	-24	-22	-23	-23	-23	-25	-24	-25	-25	-26	-26	-29	-29	-29	-29	-29	-29
10881	-30	-31	-25	-25	-25	-24	-25	-25	-25	-25	-27	-26	-27	-28	-30	-30	-30	-31	-31	-31	-31

Optimised MLE β

η	1.462	1.47415	1.4863	1.49845	1.5106	1.52275	1.534899	1.547049	1.559199	1.571349	1.583499	1.595649	1.607799	1.619949	1.632099	1.644249	1.656399	1.668549	1.680699	1.692849	1.704998
5481	-6	-6	-6	-6	-7	-7	-6	-4	-4	-4	-3	-2	-2	-2	-2	-2	-3	-5	-6	-6	-6
5514.75	-4	-4	-4	-6	-6	-8	-8	-3	-3	-3	-2	-2	-2	-2	-2	-2	-2	-5	-6	-6	-6
5548.5	-5	-4	-6	-6	-8	-8	-8	-3	-3	-3	-3	-3	-3	-3	-3	-3	-4	-4	-4	-6	-6
5582.25	-5	-6	-6	-8	-8	-8	-3	-3	-3	-3	-3	-3	-3	-3	-3	-4	-4	-4	-4	-4	-5
5616	-6	-6	-8	-8	-8	-5	-3	-3	-3	-3	-3	-3	-3	-3	-4	-4	-4	-4	-4	-4	-4
5649.75	-5	-7	-7	-7	-5	-4	-2	-3	-3	-3	-3	-3	-3	-4	-4	-4	-4	-4	-5	-5	-5
5683.5	-6	-6	-5	-5	-4	-4	-4	-4	-4	-1	-2	-2	-4	-4	-4	-4	-4	-5	-5	-5	-5
5717.25	-6	-4	-4	-3	-3	-3	-3	-3	-3	-3	-3	-3	-4	-4	-4	-4	-5	-5	-5	-5	-5
5751	-4	-4	-3	-3	-2	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-4	-4	-5	-5	-5	-5
5784.75	-5	-5	-5	-5	0	0	-1	-3	-3	-3	-3	-3	-3	-2	-2	-2	-2	-4	-4	-4	-4
5818.5	-5	-5	-5	0	0	0	0	-1	-5	-5	-5	-4	-2	-2	-2	-2	-2	-2	-2	-2	-2
5852.25	-5	-5	-5	0	0	0	0	-4	-5	-5	-3	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2
5886	-4	-5	0	0	0	0	-4	-4	-4	-3	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-5
5919.75	-4	-4	-2	0	0	-4	-4	-4	-2	-3	-2	-2	-2	-2	-2	-1	-1	-1	-1	-5	-5
5953.5	-4	-4	-2	-2	-2	-3	-4	-2	-3	-3	-3	-4	-3	-3	-1	-1	-1	-1	-5	-5	-5
5987.25	-4	-2	-2	-2	-3	-3	-1	-2	-4	-2	-2	-2	-2	-3	-3	-3	-3	-5	-5	-5	-6
6021	-4	-2	-2	-5	-5	-2	-2	-2	-2	-2	-2	-2	-2	-3	-4	-4	-5	-5	-5	-6	-6
6054.75	-1	-1	-5	-2	-2	-2	-2	-2	-2	-2	-4	-4	-5	-3	-3	-5	-5	-5	-6	-6	-6
6088.5	-1	-6	-2	-2	-2	-2	-4	-6	-6	-6	-6	-5	-5	-5	-5	-6	-3	-4	-4	-4	-4
6122.25	-2	-2	-2	-2	-4	-6	-6	-6	-6	-6	-5	-5	-5	-5	-6	-4	-4	-4	-5	-4	-4
6156	-2	-4	-4	-4	-4	-6	-6	-6	-6	-5	-5	-5	-5	-6	-4	-4	-4	-4	-4	-5	-5

Figure 7-2 MLE: Normal and optimised error values of η and β parameters to check the approach returns the expected outcome

Normal LSM β

η

	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2
1073	-45	-47	-62	-77	-85	-97	-101	-109	-112	-115	-117	-117	-121	-121	-121	-121	-121	-123	-122	-122	-122
1573	-39	-39	-47	-55	-63	-71	-80	-83	-86	-89	-92	-93	-96	-94	-94	-96	-98	-96	-97	-98	-99
2073	-38	-34	-36	-43	-50	-55	-60	-64	-68	-70	-70	-71	-75	-76	-75	-76	-75	-76	-77	-77	-78
2573	-38	-34	-30	-35	-39	-44	-46	-49	-51	-53	-56	-56	-57	-56	-57	-60	-60	-59	-59	-59	-59
3073	-40	-32	-28	-28	-31	-33	-35	-38	-40	-41	-42	-43	-46	-46	-45	-44	-45	-46	-45	-46	-47
3573	-38	-32	-29	-22	-25	-25	-27	-28	-28	-30	-31	-33	-34	-35	-33	-33	-36	-36	-36	-37	-38
4073	-40	-33	-26	-22	-19	-20	-22	-20	-23	-23	-23	-24	-23	-25	-26	-28	-26	-29	-29	-28	-29
4573	-40	-32	-27	-20	-18	-14	-15	-15	-15	-15	-16	-16	-18	-18	-18	-20	-22	-21	-20	-22	-21
5073	-41	-32	-26	-19	-15	-13	-10	-11	-10	-11	-10	-11	-11	-12	-12	-12	-14	-17	-17	-17	-18
5573	-38	-32	-26	-20	-18	-12	-11	-9	-6	-6	-4	-6	-6	-10	-11	-10	-14	-12	-15	-14	-17
6073	-40	-31	-24	-20	-16	-12	-7	-4	-5	-2	0	-6	-5	-8	-11	-10	-9	-10	-11	-12	-12
6573	-39	-32	-27	-20	-16	-13	-9	-6	-4	-6	-4	-6	-8	-7	-8	-9	-7	-8	-11	-10	-10
7073	-41	-32	-26	-20	-18	-12	-13	-8	-7	-5	-7	-5	-7	-9	-9	-10	-8	-11	-12	-11	-10
7573	-38	-32	-26	-20	-16	-12	-10	-9	-7	-9	-9	-10	-11	-9	-12	-10	-13	-12	-12	-15	-13
8073	-38	-32	-28	-21	-19	-15	-12	-10	-9	-11	-11	-13	-13	-13	-13	-15	-13	-14	-19	-17	-17
8573	-38	-32	-26	-21	-20	-16	-16	-13	-12	-13	-13	-15	-15	-14	-15	-17	-17	-17	-17	-17	-18
9073	-39	-32	-25	-21	-18	-16	-16	-15	-14	-14	-17	-17	-18	-18	-18	-18	-19	-20	-19	-20	-20
9573	-38	-33	-27	-23	-19	-18	-16	-14	-16	-17	-18	-19	-20	-20	-19	-21	-21	-22	-22	-22	-22
10073	-38	-31	-26	-24	-21	-17	-18	-15	-17	-19	-21	-21	-21	-22	-21	-22	-23	-23	-24	-25	-26
10573	-38	-32	-27	-23	-21	-19	-19	-18	-20	-21	-22	-22	-23	-22	-23	-24	-24	-25	-27	-27	-27
11073	-37	-32	-24	-24	-23	-20	-20	-19	-20	-22	-23	-23	-24	-25	-25	-25	-27	-28	-28	-28	-29

Optimised LSM β

η

	1.09	1.099625	1.10925	1.118876	1.128501	1.138126	1.147751	1.157376	1.167001	1.176626	1.186251	1.195876	1.205501	1.215126	1.224751	1.234376	1.244002	1.253627	1.263252	1.272877	1.282502
5873	-4	-5	-5	-2	-2	-3	-3	-3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5905.5	-4	-5	-5	-2	-2	-3	-3	-3	-3	-3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5938	-4	-4	-2	-2	-2	-3	-3	-3	-3	-3	-3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5970.5	-4	-2	-2	-2	-3	-3	-3	-3	-3	-3	-3	-3	-4	-4	-3	-3	-3	-3	-4	-4	-4
6003	-4	-2	-2	-2	-3	-3	-3	-3	-3	-3	-3	-3	-3	-4	-2	-2	-3	-3	-3	-6	-4
6035.5	-2	-2	-2	-2	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-2	-2	-2	-2	-3	-6	-6
6068	-2	-2	-2	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-3	-2	-2	-2	-2	-5	-6
6100.5	-2	-2	-2	-3	-3	-3	-3	-3	-5	-6	-6	-2	-2	-2	-2	-2	-3	-3	-3	-3	-3
6133	-3	-3	-3	-5	-5	-5	-5	-5	-6	-6	-6	-2	-2	-2	-2	-2	-2	-3	-3	-3	-3
6165.5	-4	-4	-5	-5	-5	-5	-5	-6	-6	-6	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2
6198	-3	-4	-5	-5	-5	-5	-6	-6	-6	-2	-2	-2	-2	-2	-2	-3	-3	-1	-1	-1	-2
6230.5	-3	-3	-4	-5	-4	-4	-6	-6	-2	-2	-2	-2	-3	-3	-3	-3	-3	-1	-1	-1	-3
6263	-3	-4	-5	-5	-4	-4	-4	-4	-1	-2	-2	-3	-3	-3	-3	-3	-2	-1	-1	-3	-3
6295.5	-3	-5	-5	-5	-5	-4	-4	-1	-1	-1	-2	-2	-3	-3	-3	-3	-2	-2	-3	-3	-3
6328	-3	-5	-5	-5	-5	-5	-1	-1	-1	-1	-2	-2	-2	-2	-3	-3	-2	-4	-4	-4	-3
6360.5	-5	-5	-5	-5	-5	-5	-2	-1	-1	-1	-2	-2	-2	-2	-2	-2	-4	-4	-4	-2	-2
6393	-5	-5	-5	-5	-5	-2	-2	-2	-1	-2	-2	-2	-2	-2	-2	-4	-4	-4	-4	-4	-2
6425.5	-5	-5	-5	-5	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-4	-4	-4	-4	-4	-4	-4
6458	-5	-5	-5	-5	-2	-2	-2	-2	-2	-3	-2	-2	-2	-4	-4	-4	-6	-4	-4	-4	-4
6490.5	-5	-5	-5	-2	-2	-2	-2	-2	-2	-3	-3	-2	-4	-3	-3	-3	-4	-4	-4	-4	-4
6523	-5	-5	-5	-2	-2	-4	-4	-4	-4	-4	-4	-3	-4	-3	-3	-4	-4	-4	-4	-4	-4

Figure 7-3 LSM: Normal and optimised error values of η and β parameters to check the approach returns the expected outcome

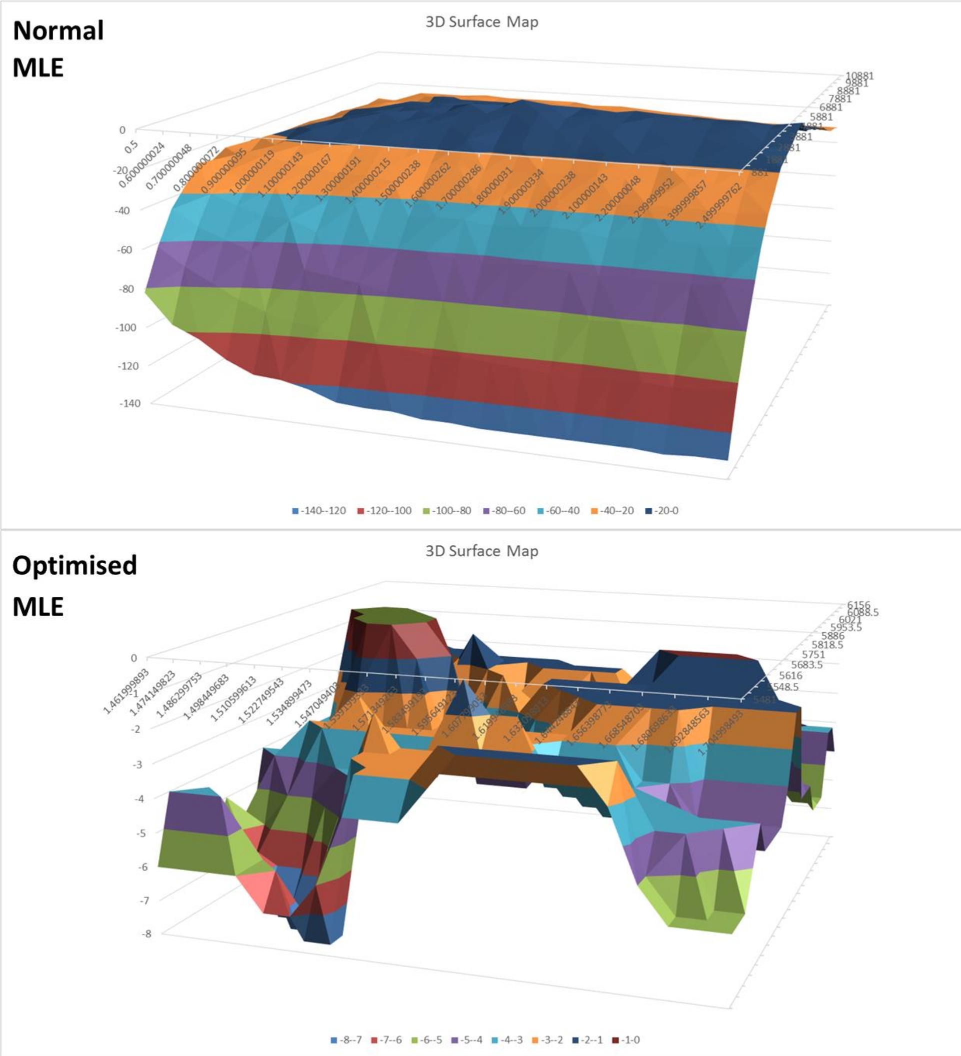


Figure 7-4 MLE: 3D visualisation of normal and optimised error values with η and β parameters

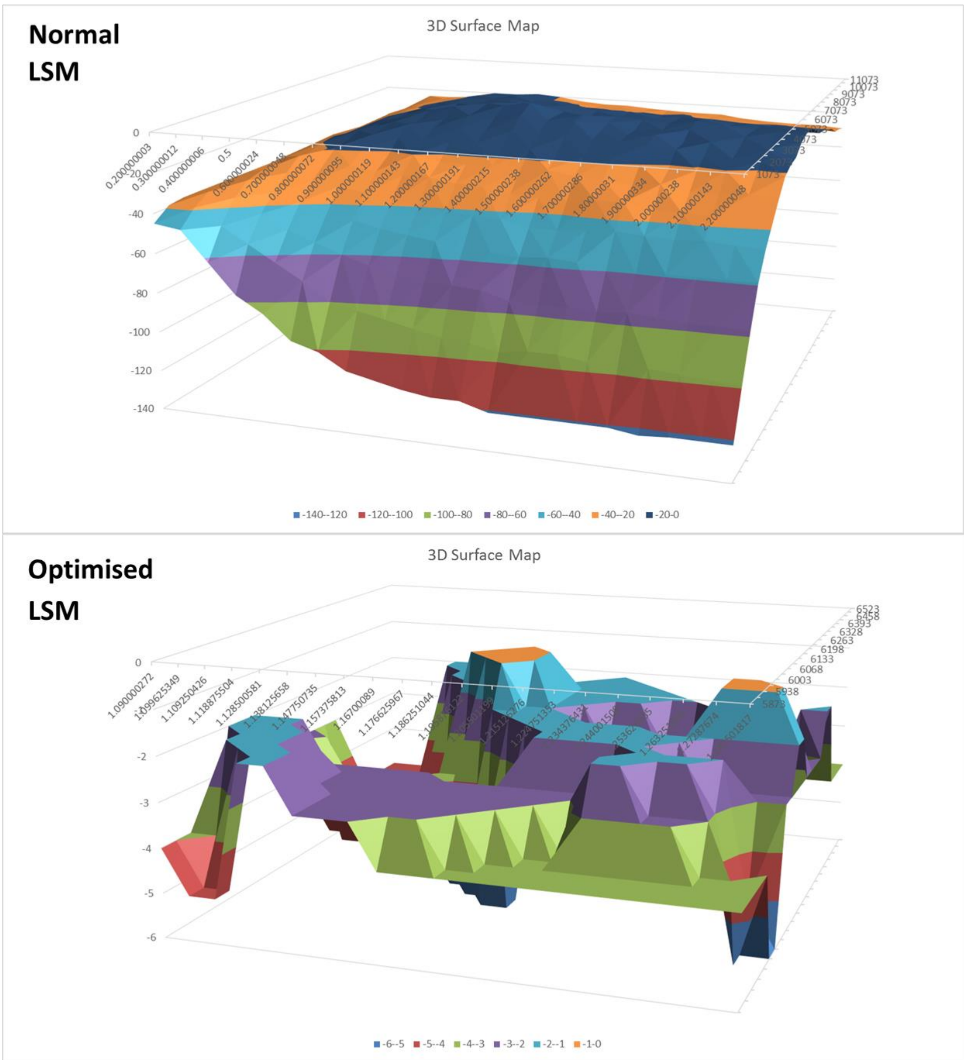


Figure 7-5 LSM: 3D visualisation of normal and optimised error values with η and β parameters

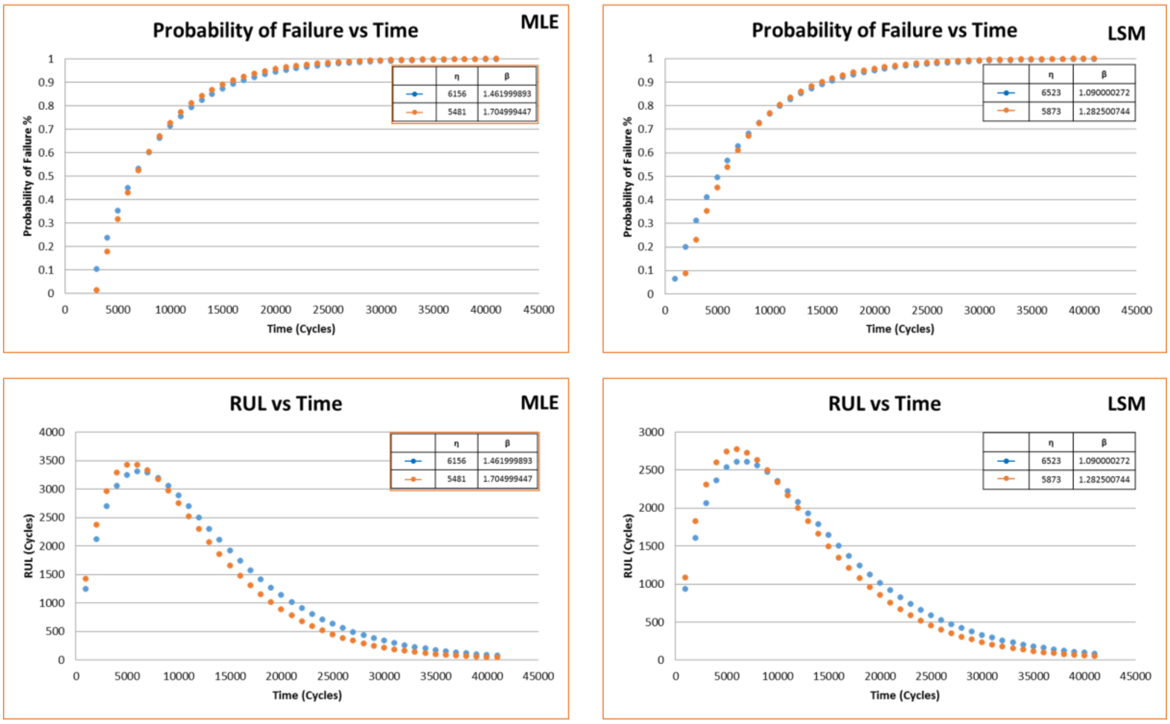


Figure 7-6 Probability of failure and RUL of optimised η and β parameters

Further results are analysed and discussed for components of complex engineering systems. Figure 7-7 shows a complete framework of the research with different scenarios of the case study: -

i. Single stage turbine (Nozzle Guide Vanes) for an Aero engine
ii. Applying repaired components of the single stage turbine
iii. Multiple of four stage turbine (Blade) for Steam Turbine

The Weibull analysis estimates η and β parameters from the data using LSM and MLE parameter estimation methods to show the robustness of the developed WTPPM framework. This section presents the application of the Weibull through-life performance prediction model framework to three scenarios for the case study.

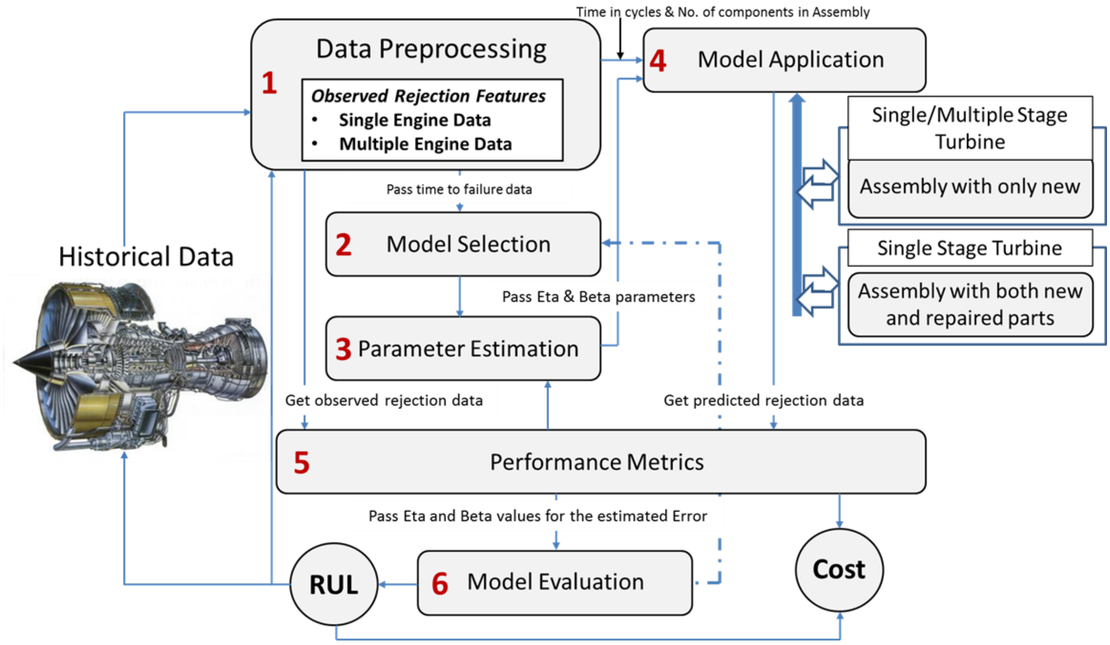


Figure 7-7 Framework with different scenarios

7.1 Scenario one - Single stage turbine

In the first scenario, multiple engines with different overhaul times are analysed using the developed framework in chapter 6. The framework can be applied to the two aero engines (a two-shaft and a three-shaft). Both aero engines are subject to same problem. The following technical configurations for a three-shaft High Bypass Ratio engine are Fan Diameter - 97.4 inches, Eight-stage intermediate pressure (IP) compressor, Six-stage high pressure (HP) compressor, Single Combustor with 24 fuel injectors, Single-stage HP turbine, Single-stage IP turbine and Four-stage low pressure (LP) turbine. A two-shaft technical configuration includes low-bypass turbofan engine with a mixed exhaust, low-pressure and high-pressure spools. The fan and booster stages are powered by low-pressure turbine, high-pressure compressor is driven by high-pressure turbine.

This scenario of the case study focuses on a single-stage turbine nozzle guide vanes (NGV) of a gas turbine. The data presented in Table 7-3 were developed in conjunction with industry partners and presented as a representative of real data.

Table 7-3 Data with multiple engines and overhaul state used for the analysis (validation data)

Engine No	Time (hrs)	Time (Cycles)	Scrapped Quantity
10010	6000	1000	2
10010	12000	2000	4
10010	18000	3000	9
10011	6000	1000	2
10011	15000	2500	4
10011	19800	3300	9
10012	6000	1000	2
10012	19200	3200	4
10012	36000	6000	9
10012	48000	8000	11
10012	66000	11000	14
10013	12000	2000	2
10013	21000	3500	4
10013	36000	6000	9
10013	60600	10100	11
10014	6000	1000	2
10014	15000	2500	4
10014	36000	6000	9
10014	48000	8000	11
10015	6000	1000	2
10015	15000	2500	4
10015	19200	3200	9
10015	36000	6000	11
10015	48000	8000	14
10015	66000	11000	20
10016	5880	980	2
10016	13200	2200	4
10016	21600	3600	9
10016	36000	6000	11
10017	5520	920	2
10017	8400	1400	4
10017	15000	2500	9
10017	33000	5500	11
10017	48000	8000	14
10019	6000	1000	2
10019	12000	2000	4
10019	18000	3000	9
10019	24000	4000	11
10019	30000	5000	14

The OS represents an overhaul state described in chapter 6, this case analyses a single engine (10015) from the multiple engines data in Table 7-3 using same η and β parameters. In Table 7-4, comparison of results from the historical failure data are analysed using LSM and MLE methods. The outcomes of data analysis using the two methods varied slightly. While LSM gives high β, MLE produces less β. The MLE method has a high η value, and LSM outputs a low η value.

Table 7-4 The rejected components, η and β outcomes for LSM and MLE methods

Methods	**η**	**β**	**OS1**	**OS2**	**OS3**	**OS4**	**OS5**	**OS6**	**Total**
LSM	4353.8	1.6	3	9	5	21	13	23	74
MLE	4523.5	1.5	4	9	5	19	14	19	70

The η value suggests 63.2% of components reflect performance loss. The values show difference between the LSM and MLE. The difference is due to the median rank discussed in chapter 6. The Weibull β of '1.0' indicates an exponential distribution of the data, '2.0' is a Rayleigh distribution and '3.0' is a normal distribution of the data. The β values tend to unity describing the effect of the failure mode, therefore, β range between 1.5 and 1.6 with a difference of 0.1 indicating deviation away from the degradation observed data. As indicated in Table 7-1, this outcome is significant because initially the β of 1.5 will produce high number of rejections, while β of 1.6 give a less number of rejections in the model. However, as replacement continues, high numbers of rejections are observed between OS4 and OS6. As an engine's β increases, estimated rejections decrease. There is bigger variation and sensitivity to variation in each individual component β. The optimised zoom-in capability estimates the most realistic η and β with error values. Hence, if the β value is greater than 2, indicates a small variation in the degradation data.

The results presented in Figure 7-8 show the number of data points and trajectory of non-linearity. The points illustrate a cumulative distribution for a through-life predictive model of a single-stage assembly.

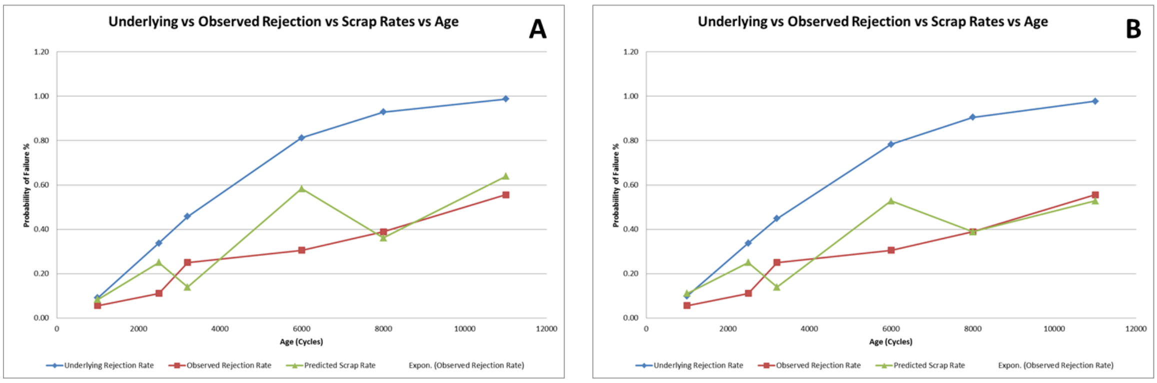


Figure 7-8 Single system (A) LSM β = 1.6 and (B) MLE β = 1.5 with predicted and observed values on Probability of failure

The observation was based on rejection and replacement strategy following the bathtub curve where the failure rate remains constant, decreasing and increasing. The outcome in Table 7-4 illustrates that policymakers, manufacturers, designers and maintenance engineers can make better maintenance decision based on cost as a safety factor and the rate of failure of components. The practitioners can decide at what stage the entire components should be replaced with new components, that is, where the numbers of expected renewal are slightly above half of the total of 36 components.

The life of a population of NGVs can be described as early life, useful life and wear-out or ageing. The values of β in Table 7-4 signify an early wear-out when β value is > 1 and < 2. In the analysis, components in an assembly show a slight wear-out condition because the value of β parameter is greater than 1. The outcome leads to an optimal time of replacement analysis based on total cost of maintenance. Few early ageing failures are observed which increases over time in cycles. The β parameter for all methods gives a better predictability of the scenario with variance showing through-life performance of NGVs in an assembly.

The early wear-out with β is constant for the six overhaul states. In OS1, LSM predicted the rejection of the 3 while MLE estimated 4. For OS2, quantity of NGVs rejected are 9 for both LSM and MLE. This difference resulted from (a) failure modes, and (b) reuse of existing NGVs relative to time interval. In OS3, degraded

NGVs are 5 – this outcome can be attributed to optimum renewal (replacement) of rejected NGVs in OS2. However, in OS4, 21 NGVs are projected to fail using LSM, while 19 NGVs are estimated to reject with the MLE method. This occurrence can be ascribed to minimal renewal in OS3 and the time interval. The reliability of a majority of the NGVs are based on the renewal principles, hence, the high number of rejections in OS4. The same can be said of OS5 and OS6.

The WTPPM predicts the number of rejections and optimal renewal (replacement). LSM has a total number of NGVs renewals at 74 and MLE projected a through-life performance quantity of NGVs rejected as 70. These outcomes can be attributed to β parameters – high β leads to less number of rejections and low β produces a high number of rejections. The outcome can be seen in the first overhaul state, but the reverse is the case for the rejections at subsequent overhauls.

The replacement cost of individual NGV, maintenance, repair, overhaul and logistics can be high regarding the engine for each OS. At each OS, if the cost of replacing the NGVs in an assembly is 50% of the cost of replacing the entire NGVs in an assembly, the expert advice would be to scrap and replace. The LSM and MLE have been described as reliable methods for parameter estimation.

In calculating the minimised error values, η and β parameters are passed through the model. Equation 6-39 (MAE) is called to calculate the outcome from predicted rejection values and observed rejected values as shown in Figure 7-8. The outcome is a single error value based on the estimated Weibull parameters. The error values are presented in a 20 x 20 matrix for back-fitting as shown in Figure 7-9. The matrix representation is a generic enumeration approach, which is calibrated into different shades of green and red. While green colour indicates a region with the closest deviation, red colour specifies a region with the farthest deviation. The effect of the failure modes affects the characteristic life of the population of NGVs. While red region indicates that NGVs cannot be reused, green region illustrates the population of NGVs can be reused.

A

β

η	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6
-646.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
-146.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
353.8	-131	-139	-144	-146	-149	-150	-151	-152	-153	-154	-154	-155	-155	-155	-155	-155	-156	-156	-156	-156	-156
853.8	-94	-101	-109	-115	-118	-120	-123	-123	-126	-126	-127	-126	-127	-128	-128	-128	-128	-127	-128	-128	-128
1353.8	-65	-75	-81	-86	-91	-93	-95	-96	-98	-99	-100	-100	-102	-102	-101	-101	-100	-100	-100	-100	-100
1853.8	-50	-55	-59	-65	-68	-70	-72	-73	-74	-77	-77	-77	-78	-78	-77	-77	-79	-79	-79	-82	-81
2353.8	-38	-41	-44	-46	-51	-53	-56	-55	-57	-58	-59	-59	-59	-61	-59	-60	-61	-60	-60	-60	-60
2853.8	-31	-34	-34	-37	-39	-42	-42	-44	-42	-44	-46	-47	-45	-44	-44	-45	-46	-46	-46	-45	-44
3353.8	-31	-33	-30	-29	-32	-35	-33	-35	-36	-35	-36	-35	-36	-36	-34	-37	-35	-33	-33	-33	-30
3853.8	-30	-30	-26	-26	-28	-24	-27	-29	-27	-30	-28	-28	-28	-27	-26	-27	-27	-29	-28	-28	-28
4353.8	-28	-29	-26	-26	-25	-24	-22	-21	-21	-23	-24	-22	-19	-21	-23	-23	-26	-27	-24	-23	-23
4853.8	-34	-32	-27	-25	-27	-24	-19	-20	-22	-20	-20	-20	-17	-20	-18	-22	-20	-22	-22	-19	-24
5353.8	-33	-29	-27	-23	-24	-22	-23	-21	-19	-20	-19	-19	-17	-24	-20	-21	-19	-22	-19	-19	-24
5853.8	-34	-28	-27	-27	-25	-24	-21	-21	-15	-21	-19	-19	-22	-19	-23	-19	-20	-21	-20	-20	-20
6353.8	-34	-30	-30	-26	-25	-22	-25	-20	-21	-21	-21	-20	-17	-18	-19	-18	-18	-18	-21	-21	-22
6853.8	-33	-31	-29	-23	-26	-23	-20	-21	-21	-21	-18	-19	-19	-18	-19	-18	-20	-22	-24	-22	-19
7353.8	-35	-28	-30	-26	-23	-25	-23	-22	-19	-19	-20	-18	-19	-18	-20	-20	-22	-21	-21	-20	-20
7853.8	-34	-30	-28	-26	-26	-27	-24	-21	-20	-20	-18	-19	-23	-20	-21	-23	-21	-22	-22	-22	-21
8353.8	-36	-34	-30	-28	-27	-24	-24	-24	-21	-20	-21	-22	-23	-24	-23	-23	-24	-24	-23	-24	-24
8853.8	-37	-33	-31	-29	-27	-25	-24	-24	-23	-24	-25	-24	-24	-25	-26	-26	-26	-26	-26	-25	-26
9353.8	-36	-35	-32	-29	-27	-26	-27	-25	-26	-26	-26	-26	-27	-27	-28	-28	-29	-28	-28	-29	-30

B

β

η	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5
-476.5	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
23.5	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156
523.5	-106	-116	-125	-130	-136	-139	-141	-143	-143	-145	-145	-147	-147	-148	-149	-149	-149	-150	-151	-151	-151
1023.5	-71	-80	-93	-96	-104	-106	-110	-111	-115	-116	-116	-116	-116	-118	-118	-117	-117	-118	-118	-117	-117
1523.5	-52	-59	-66	-73	-78	-80	-85	-87	-89	-89	-89	-91	-92	-91	-92	-94	-94	-94	-93	-95	-95
2023.5	-42	-43	-50	-54	-58	-63	-64	-66	-66	-69	-69	-71	-70	-71	-72	-72	-71	-72	-71	-71	-72
2523.5	-35	-35	-38	-42	-43	-46	-49	-51	-53	-51	-55	-52	-55	-56	-54	-53	-54	-54	-55	-55	-54
3023.5	-34	-32	-32	-33	-36	-36	-34	-40	-42	-41	-42	-42	-43	-42	-41	-41	-43	-42	-42	-40	-39
3523.5	-35	-30	-31	-28	-27	-28	-30	-29	-32	-36	-33	-32	-32	-34	-34	-32	-32	-32	-31	-31	-28
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5523.5	-35	-30	-29	-28	-28	-24	-23	-22	-19	-21	-17	-23	-17	-19	-21	-22	-20	-21	-18	-18	-22
6023.5	-35	-35	-30	-30	-24	-23	-23	-24	-21	-20	-18	-21	-21	-23	-21	-19	-21	-20	-20	-20	-19
6523.5	-37	-31	-29	-29	-23	-25	-24	-27	-19	-18	-20	-21	-18	-19	-19	-19	-19	-19	-20	-20	-21
7023.5	-35	-33	-29	-29	-25	-28	-24	-19	-18	-23	-19	-18	-19	-19	-19	-19	-20	-19	-23	-23	-21
7523.5	-37	-35	-29	-27	-26	-25	-24	-19	-23	-22	-18	-20	-18	-18	-21	-21	-19	-22	-19	-22	-22
8023.5	-37	-35	-32	-29	-27	-26	-24	-22	-22	-20	-19	-20	-20	-20	-21	-21	-22	-22	-23	-22	-22
8523.5	-38	-37	-32	-31	-28	-27	-24	-22	-24	-22	-21	-22	-24	-23	-24	-24	-24	-25	-25	-25	-24
9023.5	-38	-35	-33	-31	-30	-29	-25	-26	-24	-24	-25	-25	-25	-26	-26	-26	-27	-27	-26	-26	-27
9523.5	-38	-36	-35	-31	-29	-29	-26	-27	-26	-27	-26	-26	-26	-28	-29	-28	-29	-29	-30	-30	-31

Figure 7-9 Single system (a) LSM β = 1.6 and (b) MLE β = 1.5 with error values, η and β parameters

The representation shows robustness of the WTPPM for reliability purposes. Optimal η and β values based on the residuals can be used for decision making. The region with the closest residuals of observed data is highlighted around the green area. The region indicates optimised fit for predicting values of η and β of the Weibull distribution. The predicted η and β parameters are used to estimate number of future rejections, and when they will occur. The 3D surface map is a representation of maximum and minimum error values seen in the Wireframe contour map is numerically analysed and illustrated in appendix L.

Further analysis shows that the generated parameters from GOT as shown in Figure 7-10 are calculated as failure probability in the Weibull distribution. The failure data are solved to represent RUL of components. Table 7-5 shows the estimated and optimised η and β parameters.

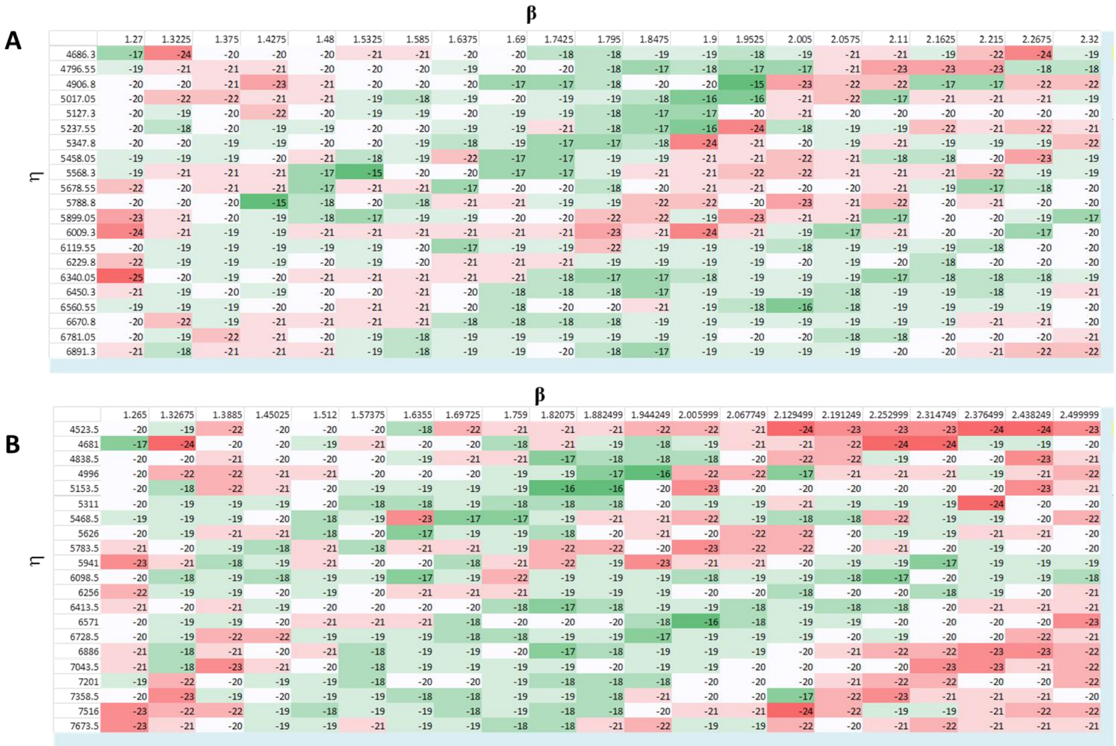

Figure 7-10 Single system (a) LSM β = 1.6 and (b) MLE β = 1.5 with error values and optimised η and β parameters

Table 7-5 Outcomes of the optimised values from LSM and MLE methods

Method	Initial η	Initial β	Zoom-in (optimised)	η	β
LSM	4353.8	1.6	High η and Low β	8103.8	0.98
			Low η and High β	3353.8	2.6
MLE	4523.5	1.5	High η and Low β	8273.5	1.0
			Low η and High β	3523.5	2.5

The RUL results in Figure 7-11 are presented as “RUL with High η Low β” and “RUL with Low η High β” with values in Table 7-5. The distribution can be used to highlight the RUL of components from each data point in the trajectory. RUL distribution is reliable and appropriate because it depicts multiple renewals of multi-component in an assembly.

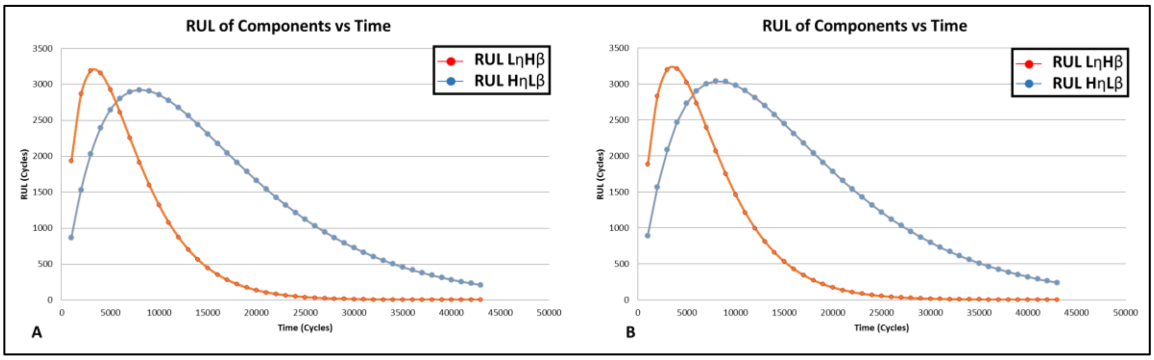

Figure 7-11 RUL for single system (a) LSM β = 1.6 and (b) MLE β = 1.5 for optimised η and β parameters

The results of predicted rejected NGV in an assembly historical data are required for the remaining useful life prediction derived from probability of failure distribution illustrated in Figure 6-7. The data analysed for a single system with an outcome of underlying predicted rejection rate and observed rejection rate with time are based on the historical data.

A cost indicator discussed in chapter 6 creates a known threshold of when it is uneconomically viable to continue replacing components in the assembly. If cost at any overhaul state equals average total cost of an assembly replacement, the assembly should be replaced with new NGVs in the assembly as shown in Figure 7-12.

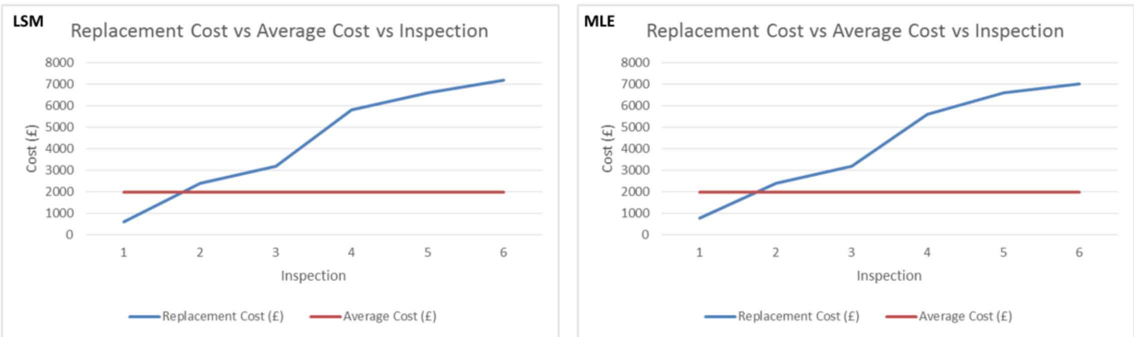

Figure 7-12 Cost threshold for components assembly rejection

Multiple engines and overhauls analysis

The application of multiple engines and overhaul states present the following results. The GOT capability aims to get the most realistic η and β parameters relating to error values (see Figure 7-13). The GOT process is initiated until the function reaches ends of the matrix. The residuals of estimated η and β parameters are recalculated using GOT. The representation shows a variation of residuals /error values with respect to the η and β parameters. The variation of results comes from failure modes which affect NGVs in their environmental operating condition. A representation of the variation of error values is presented in a 3D surface map (see Figure 7-14), which represents a real-world entity behaviour of components in an assembly in service. The variation can be described as noise, which reflects failure modes and the characteristic life of NGVs. Most of the low error values of the estimated η and β parameters have various gradients or shades of green with same error values. Invariably, error values are similar, but appear the same due to approximation problem. The value with the lowest decimal has bright green colour; others have low and high decimal approximate values respectively with different shades of green.

The model evaluation is conducted with selected error values, η and β parameters in green region as outcome from GOT functionality, the Weibull function is then applied to the last selected optimised η and β values to generate a Weibull distribution for probability of failure and converted to remaining useful life. The graphed red distribution results from the minimum η value, while the blue distribution from the maximum η. The outcomes relate to the actual historical data as shown in Figure 7-15.

Normal MLE β

η	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5
-476.5	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9
23.5	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24
523.5	-14	-16	-17	-18	-19	-20	-21	-21	-22	-22	-22	-22	-22	-23	-23	-23	-23	-23	-24	-24	-24
1023.5	-9	-10	-12	-13	-13	-14	-14	-14	-15	-15	-15	-15	-15	-15	-15	-16	-16	-16	-16	-16	-16
1523.5	-7	-8	-8	-9	-9	-10	-10	-10	-10	-10	-10	-10	-10	-10	-10	-11	-10	-10	-10	-10	-10
2023.5	-5	-6	-6	-7	-7	-7	-7	-7	-7	-7	-7	-7	-8	-8	-7	-7	-7	-7	-7	-7	-7
2523.5	-5	-5	-6	-5	-6	-6	-6	-6	-5	-6	-6	-6	-6	-5	-6	-6	-6	-5	-5	-5	-5
3023.5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-4	-5	-5	-5	-4	-5	-4	-4	-4	-4	-4
3523.5	-5	-4	-4	-5	-4	-4	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-3	-4	-4	-4	-4
4023.5	-5	-5	-4	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-3	-4	-4	-4	-4
4523.5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5023.5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5523.5	-5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5
6023.5	-5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5
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7023.5	-5	-6	-4	-4	-4	-4	-3	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-6	-6	-6	-6
7523.5	-6	-5	-5	-5	-4	-3	-3	-4	-4	-4	-4	-4	-5	-5	-5	-5	-6	-5	-6	-6	-6
8023.5	-6	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6
8523.5	-6	-5	-5	-5	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6
9023.5	-6	-6	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6
9523.5	-6	-6	-5	-5	-5	-4	-4	-4	-4	-4	-5	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6

Optimised MLE β

η	1	1.075	1.15	1.225	1.3	1.375	1.45	1.525	1.6	1.674999	1.749999	1.824999	1.899999	1.974999	2.049999	2.124999	2.199999	2.274999	2.349999	2.424999	2.5
3523.5	-4	-4	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-3	-4
3761	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-3	-3	-3	-3	-4	-4
3998.5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-3	-4	-4	-4	-4	-4
4236	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
4473.5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
4711	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
4948.5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5186	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5
5423.5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5
5661	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5
5898.5	-3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6
6136	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6
6373.5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6
6611	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6
6848.5	-4	-3	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6	-6
7086	-4	-3	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6	-5	-5	-6
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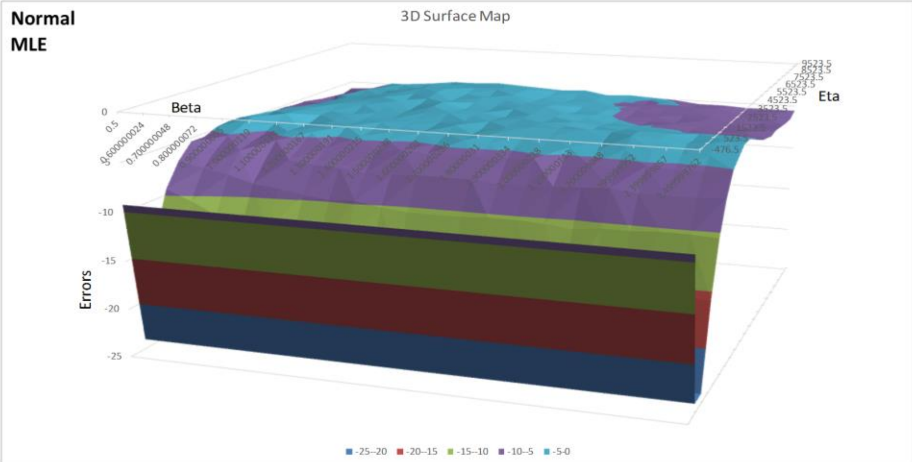
7798.5	-4	-3	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6
8036	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6
8273.5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6

Figure 7-13 MLE multiple systems: β = 1.5 with error values, realistic η and β with



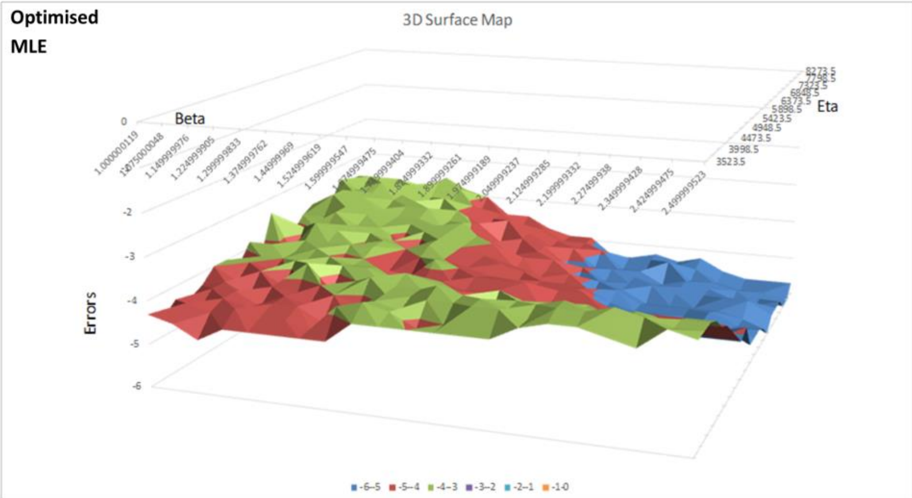
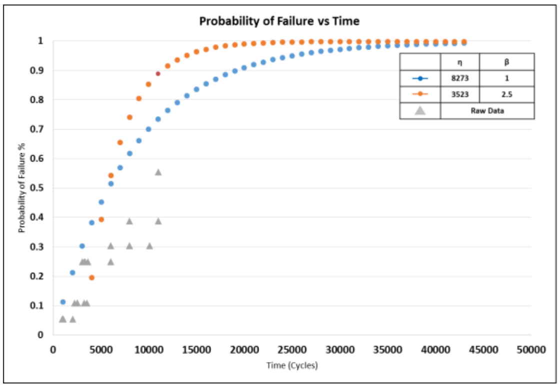


Figure 7-14 3D surface map: β = 1.5 with errors values, realistic η and β



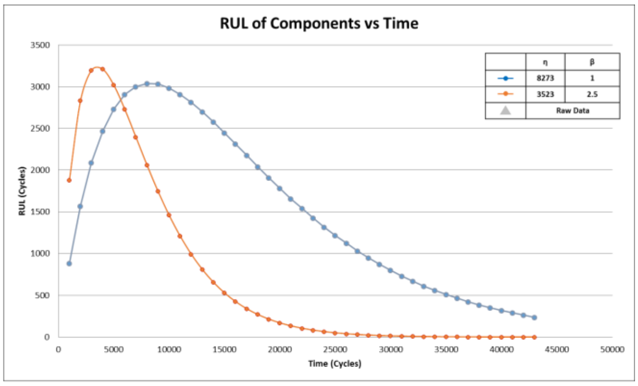


Figure 7-15 RUL: MLE multiple systems: β = 1.5

7.2 Scenario two - Repair of single stage turbine for aero engine

Repair refers to actions taken during the use of a product in order to return it to a working condition after a fault has occurred. In this scenario case, new components failure times are estimated as well as repaired components for further analysis of single stage turbine for an engine as illustrated in Figure 7-16.

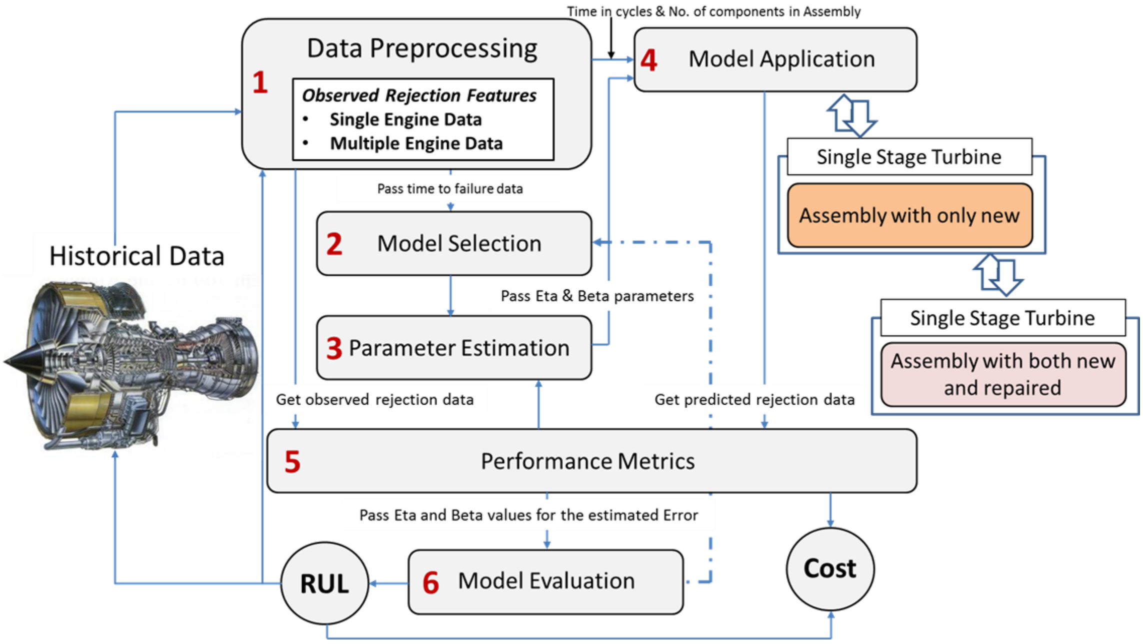


Figure 7-16 Framework for incorporating repair components

7.2.1 Generating repair failure data

The failure data for repair is developed based on the assumption that design life of a new component is not same for a repaired part. If the nominal life of a new component is 100%, the nominal life of a repaired component is assumed to be 90%.

Multiple components of different assembly in a gas turbine have different failure times, hence, failure times for multiple repaired components may vary. The scenario considers same components of a single assembly. The logic is multiplying failure times of repaired components by 90% in the framework to achieve new failure times. The new failure times are aggregated to estimate the Weibull parameters.

The repaired components have a nominal life less than new components; however, Figure 7-17 illustrates a typical new component, rejected and repaired replacement in relation to Figure 6-7. The colour “purple” indicates repaired components.

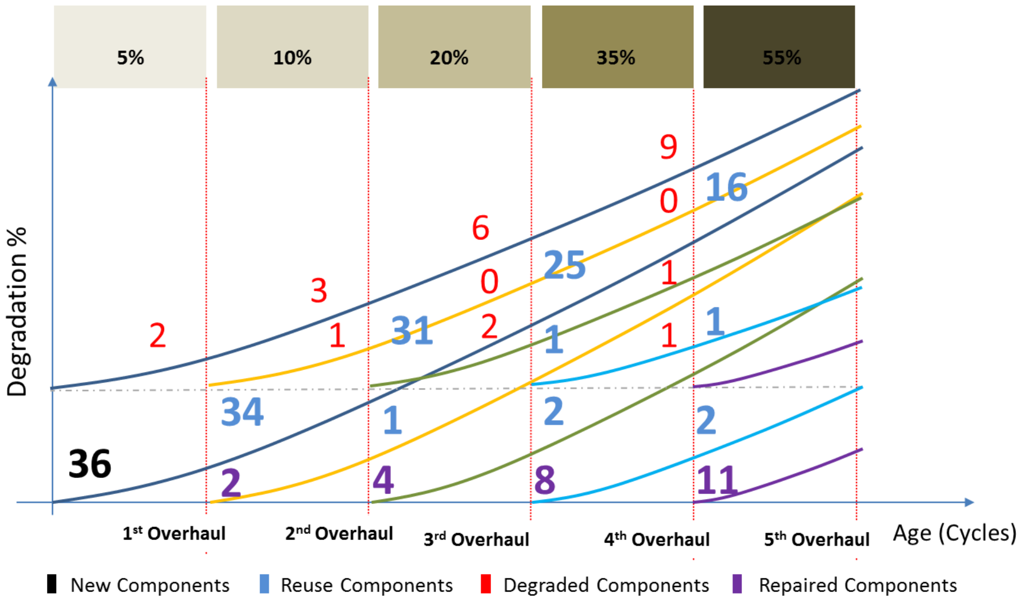


Figure 7-17 A typical trend of new, reused, degraded and repaired components

Repaired replacement is conducted in Through-life Engineering Services to study the behaviour of NGVs within an assembly. The components rejected in the prediction model are replaced with repaired NGVs. The rejected components contain locations of the NGV affected by damage mechanisms in the operating environment, but not investigated in this Thesis.

7.2.2 The procedure for replacement with repaired components

The framework was applied to the second scenario of the case study and results are presented accordingly. The estimated parameters from the LSM method are highlighted in this analysis.

Step 1: Get single engine failure data (overhaul times), then estimate the Weibull parameters with the LSM approach in chapter 6. The new and repaired data used are presented in Table 7-6. The data “New” is representative of real data, while “Repair” is simulated as it difficult to obtain component life. This research is designed to offer engineers and policy makers an approach to identify and predict component RUL in a multi-component assembly which include repaired components.

Table 7-6 Estimated parameters for new and repair data

New	**Repair**
Time (Cycles)	Time (Cycles)
1000	630
2500	1350
3200	1800
6000	1980
8000	2520
11000	2700
	3150
	4320
	4500
	4500
	4950
	6300
	7020
	7650
	9000

The estimated parameters of the new and repaired values are presented in Table 7-7 as outcome from Table 7-6.

Table 7-7 Estimated parameters for new and repair data

Type of component	**η**	**β**
New	6073	1.2
Repaired	4968	1.5

Step 2: Pass the estimate Weibull parameters into the model as well as the overhaul times in step 1 to calculate the number of rejections at any overhaul time.

Step 3: Introducing repaired NGVs to replace the rejected NGVs. Assumed nominal life of repaired NGV is 90%. The 90% nominal life is applied to the repaired NGVs at each overhaul state throughout all populations in the through-life performance model.

Step 4: Get repaired failure times by identifying them individually and perform a Weibull parameter estimation using LSM to predict the characteristic life and the slope. The characteristic life and the slope become η_{repair} and β_{repair}

Step 5: Pass the newly estimated parameters in the model and ascertain the forecast of the rejections

Step 6: Use initial and repaired estimated parameters to generate a distribution of probability of failure

Step 7: Convert outcomes of Step 6 into remaining useful life of NGVs (new and repaired)

Step 8: Get η and β values for total failure times of both new and repaired population to determine probability of failure and RUL

7.2.3 The results of the repaired replacement

The results of the single stage gas turbine engine with known overhaul failure times are presented. Simulated data employed here due to the nature of the analysis, where in real application identifying the underlying time-to-failure for replacement is difficult. This approach provides an insight into the way to achieve it. The prognostics outcome of number of rejections is shown is Table 7-8.

Table 7-8 The **η** and β outcomes of new and repaired rejected components with LSM

	η	**β**	**OS1**	**OS2**	**OS3**	**OS4**	**OS5**	**OS6**
New	6073	1.2	4	7	3	16	11	17
Repair	4968	1.5	4	7	3	15	10	16

The overhaul times are generated to estimate the Weibull parameters and to calculate the number of rejected NGVs at subsequent overhauls. The green region shows error values based on the likelihood of realistic η and β parameters. The outcome shows closeness of predicted values to observed values. The error values of the refined estimated η and β parameters are calculated. The estimated η and β parameters give a variation of the NGVs in the assembly and the most realistic values are those with lowest error. In the repaired, each population and overhaul times are calculated to estimate Weibull parameters for the repaired replacement based on initial outcome. Threshold is calculated by a given assumed design life multiplied by 63.2%. With a shape factor of less than one, the outcome can be attributed to maintenance issues during the putting together of the entire system.

Figure 7-18 shows GET and GOT for the new, repaired and optimised outcomes of the predicted and observed error values based on initially estimated parameters. Figure 7-19 illustrates 3D map representation for the GET and GOT of the new, repaired and optimised outcomes. The results illustrate the numerical analysis for the through-life performance of the components in complex engineering systems (see appendix L). The combination of the new and repaired components produces optimised $\eta_{new+repair}$ and $\beta_{new+repair}$ (see Table 7-9).

Normal LSM β

η	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2
1073	-50	-48	-55	-70	-78	-90	-94	-102	-105	-108	-110	-110	-114	-114	-114	-114	-114	-116	-115	-115	-115
1573	-48	-46	-46	-50	-56	-64	-73	-76	-79	-82	-85	-86	-89	-87	-87	-89	-91	-89	-90	-91	-92
2073	-47	-43	-39	-42	-43	-48	-53	-57	-61	-63	-63	-64	-68	-69	-68	-69	-68	-69	-70	-70	-71
2573	-47	-43	-37	-36	-34	-37	-39	-42	-44	-48	-49	-51	-50	-51	-50	-53	-53	-54	-52	-52	-52
3073	-49	-39	-37	-35	-32	-32	-32	-33	-37	-40	-41	-40	-41	-41	-40	-39	-40	-41	-38	-39	-40
3573	-49	-43	-38	-35	-30	-30	-28	-27	-27	-29	-28	-34	-33	-32	-34	-32	-33	-31	-31	-30	-29
4073	-49	-42	-39	-35	-32	-29	-27	-25	-24	-24	-24	-23	-24	-26	-25	-27	-23	-26	-24	-27	-24
4573	-49	-45	-38	-35	-33	-31	-28	-24	-24	-24	-21	-19	-25	-21	-17	-21	-21	-20	-21	-21	-22
5073	-50	-45	-39	-34	-32	-28	-29	-24	-27	-22	-21	-22	-20	-19	-19	-19	-19	-16	-20	-20	-21
5573	-51	-45	-39	-35	-31	-27	-26	-28	-25	-23	-21	-19	-21	-15	-20	-17	-19	-21	-22	-21	-22
6073	-51	-46	-39	-35	-35	-31	-30	-27	-24	-23	-23	-21	-20	-21	-22	-19	-22	-19	-18	-19	-17
6573	-50	-47	-42	-37	-31	-28	-30	-23	-25	-23	-27	-19	-21	-20	-21	-18	-20	-19	-16	-19	-19
7073	-52	-45	-39	-35	-33	-29	-30	-25	-28	-24	-20	-18	-22	-20	-18	-19	-19	-20	-17	-20	-21
7573	-51	-47	-41	-37	-33	-29	-27	-26	-26	-24	-20	-23	-22	-18	-21	-19	-18	-21	-21	-22	-22
8073	-51	-47	-43	-38	-36	-32	-29	-27	-26	-24	-22	-22	-20	-20	-20	-20	-20	-21	-22	-22	-22
8573	-53	-47	-41	-38	-37	-33	-31	-28	-27	-24	-22	-24	-22	-21	-22	-24	-24	-24	-24	-24	-25
9073	-52	-47	-42	-38	-35	-33	-31	-30	-29	-25	-26	-24	-25	-25	-25	-25	-26	-27	-26	-27	-27
9573	-51	-48	-44	-38	-36	-35	-31	-29	-29	-26	-27	-26	-27	-27	-26	-28	-28	-29	-29	-29	-29
10073	-51	-46	-43	-39	-38	-32	-33	-30	-28	-28	-28	-28	-28	-29	-28	-29	-30	-30	-31	-32	-33
10573	-51	-47	-42	-40	-36	-34	-34	-33	-31	-30	-29	-29	-30	-29	-30	-31	-31	-32	-34	-34	-34
11073	-52	-49	-41	-41	-38	-35	-33	-32	-29	-29	-30	-30	-31	-32	-32	-32	-34	-35	-35	-35	-36

Optimised LSM β

η	1.38775	1.428363	1.468975	1.509588	1.5502	1.590812	1.631425	1.672037	1.71265	1.753262	1.793875	1.834487	1.8751	1.915712	1.956325	1.996937	2.037549	2.078162	2.118774	2.159387	2.199999
4873	-22	-22	-20	-20	-20	-21	-19	-17	-19	-17	-17	-18	-20	-20	-20	-18	-22	-22	-22	-22	-19
4985.5	-22	-21	-20	-21	-20	-20	-20	-18	-20	-19	-19	-18	-17	-14	-16	-22	-22	-21	-17	-21	-21
5098	-21	-22	-22	-19	-19	-19	-19	-19	-19	-18	-19	-22	-17	-16	-20	-20	-21	-20	-20	-20	-20
5210.5	-21	-19	-19	-20	-20	-20	-19	-19	-19	-20	-18	-17	-16	-21	-21	-18	-20	-20	-20	-20	-22
5323	-19	-19	-19	-20	-20	-19	-18	-18	-19	-18	-18	-18	-18	-24	-20	-20	-19	-19	-21	-19	-19
5435.5	-20	-20	-21	-21	-18	-19	-22	-20	-17	-17	-17	-19	-21	-21	-21	-21	-21	-18	-21	-21	-20
5548	-21	-21	-19	-15	-20	-20	-20	-17	-17	-19	-19	-19	-21	-21	-22	-22	-20	-20	-21	-21	-21
5660.5	-21	-21	-17	-18	-21	-20	-17	-17	-20	-19	-18	-20	-21	-21	-21	-20	-20	-21	-21	-19	-17
5773	-19	-15	-20	-23	-22	-18	-21	-21	-20	-19	-18	-22	-22	-22	-20	-20	-23	-22	-22	-20	-20
5885.5	-17	-19	-18	-21	-17	-19	-19	-19	-18	-20	-22	-22	-21	-19	-23	-20	-21	-19	-17	-20	-20
5998	-20	-19	-21	-18	-21	-21	-20	-18	-21	-21	-23	-23	-20	-20	-20	-21	-19	-17	-20	-20	-20
6110.5	-19	-19	-17	-19	-19	-20	-17	-19	-19	-22	-22	-20	-19	-19	-19	-18	-18	-19	-19	-19	-18
6223	-19	-19	-20	-19	-20	-20	-21	-21	-21	-21	-19	-19	-19	-19	-19	-20	-19	-19	-20	-18	-20
6335.5	-19	-20	-20	-21	-21	-21	-21	-21	-22	-18	-17	-17	-17	-18	-19	-19	-19	-19	-17	-18	-18
6448	-18	-19	-20	-20	-21	-20	-20	-20	-18	-18	-18	-18	-18	-19	-19	-19	-19	-19	-19	-19	-18
6560.5	-18	-20	-20	-21	-21	-21	-21	-18	-18	-20	-20	-21	-20	-19	-18	-18	-18	-18	-19	-19	-19
6673	-21	-21	-21	-21	-21	-21	-18	-18	-17	-18	-18	-19	-19	-19	-19	-19	-19	-19	-19	-19	-21
6785.5	-22	-21	-20	-20	-20	-18	-19	-19	-19	-19	-19	-19	-19	-19	-20	-20	-18	-18	-18	-20	-20
6898	-22	-21	-21	-21	-19	-19	-19	-19	-20	-20	-18	-17	-18	-19	-19	-19	-19	-19	-20	-20	-21
7010.5	-23	-21	-21	-20	-20	-20	-18	-18	-19	-18	-19	-19	-20	-19	-19	-19	-19	-22	-20	-20	-19
7123	-23	-22	-18	-19	-18	-18	-19	-20	-19	-19	-19	-20	-20	-18	-17	-17	-20	-20	-20	-20	-21

Repair Optimised LSM β

η	1.17	1.226525	1.28305	1.339575	1.3961	1.452625	1.50915	1.565675	1.6222	1.678725	1.73525	1.791775	1.8483	1.904825	1.96135	2.017875	2.0744	2.130925	2.18745	2.243975	2.3005
4800.5	-17	-19	-20	-21	-20	-21	-20	-20	-20	-20	-20	-18	-17	-18	-17	-18	-21	-23	-23	-20	-18
4902.875	-21	-20	-20	-20	-21	-20	-20	-22	-20	-17	-17	-18	-20	-20	-15	-22	-22	-22	-17	-22	-22
5005.25	-22	-21	-20	-22	-23	-21	-21	-18	-20	-19	-19	-19	-17	-14	-21	-21	-22	-17	-21	-21	-21
5107.625	-21	-21	-19	-20	-21	-22	-19	-19	-20	-19	-18	-19	-17	-16	-20	-21	-20	-20	-20	-20	-23
5210	-19	-20	-20	-18	-19	-19	-20	-20	-19	-19	-19	-18	-17	-16	-23	-18	-20	-20	-22	-22	-20
5312.375	-25	-21	-20	-19	-19	-19	-20	-20	-18	-18	-21	-18	-18	-24	-20	-19	-19	-21	-19	-19	-19
5414.75	-22	-20	-19	-23	-19	-20	-21	-19	-20	-20	-17	-17	-19	-20	-21	-20	-22	-21	-20	-20	-23
5517.125	-24	-19	-19	-19	-21	-19	-17	-20	-23	-17	-17	-19	-19	-21	-22	-22	-20	-18	-21	-22	-18
5619.5	-22	-22	-19	-19	-21	-21	-15	-20	-17	-17	-19	-18	-20	-21	-21	-22	-21	-22	-20	-19	-19
5721.875	-21	-22	-22	-21	-21	-17	-22	-22	-17	-20	-20	-18	-22	-21	-20	-20	-22	-21	-19	-18	-20
5824.25	-21	-21	-23	-20	-20	-18	-21	-16	-19	-19	-17	-22	-21	-24	-22	-23	-22	-20	-20	-21	-20
5926.625	-22	-23	-21	-21	-18	-19	-21	-20	-19	-20	-20	-22	-23	-19	-20	-21	-21	-20	-19	-19	-17
6029	-22	-25	-21	-21	-20	-19	-21	-21	-22	-18	-21	-23	-21	-21	-19	-19	-21	-21	-20	-18	-20
6131.375	-23	-23	-20	-19	-19	-20	-19	-19	-17	-20	-19	-22	-19	-19	-19	-19	-19	-19	-18	-18	-20
6233.75	-21	-24	-24	-19	-19	-20	-19	-20	-21	-21	-21	-19	-19	-19	-19	-20	-19	-18	-20	-20	-20
6336.125	-22	-25	-20	-19	-19	-20	-21	-21	-21	-21	-21	-17	-17	-18	-19	-19	-19	-18	-18	-18	-18
6438.5	-23	-25	-21	-20	-18	-19	-20	-21	-20	-20	-18	-18	-17	-19	-19	-19	-18	-19	-18	-19	-20
6540.875	-23	-24	-19	-22	-18	-20	-20	-21	-21	-19	-18	-20	-20	-19	-19	-16	-18	-19	-19	-17	-20
6643.25	-27	-21	-20	-21	-21	-20	-21	-21	-19	-19	-17	-18	-19	-19	-18	-19	-19	-19	-19	-21	-20
6745.625	-27	-20	-23	-19	-22	-22	-19	-19	-18	-19	-18	-18	-19	-19	-20	-19	-19	-18	-20	-20	-20
6848	-27	-20	-24	-17	-21	-20	-21	-18	-19	-19	-20	-19	-19	-16	-19	-19	-18	-20	-20	-21	-22

Figure 7-18 Normal, optimised and repair optimised for error values, η and β parameters

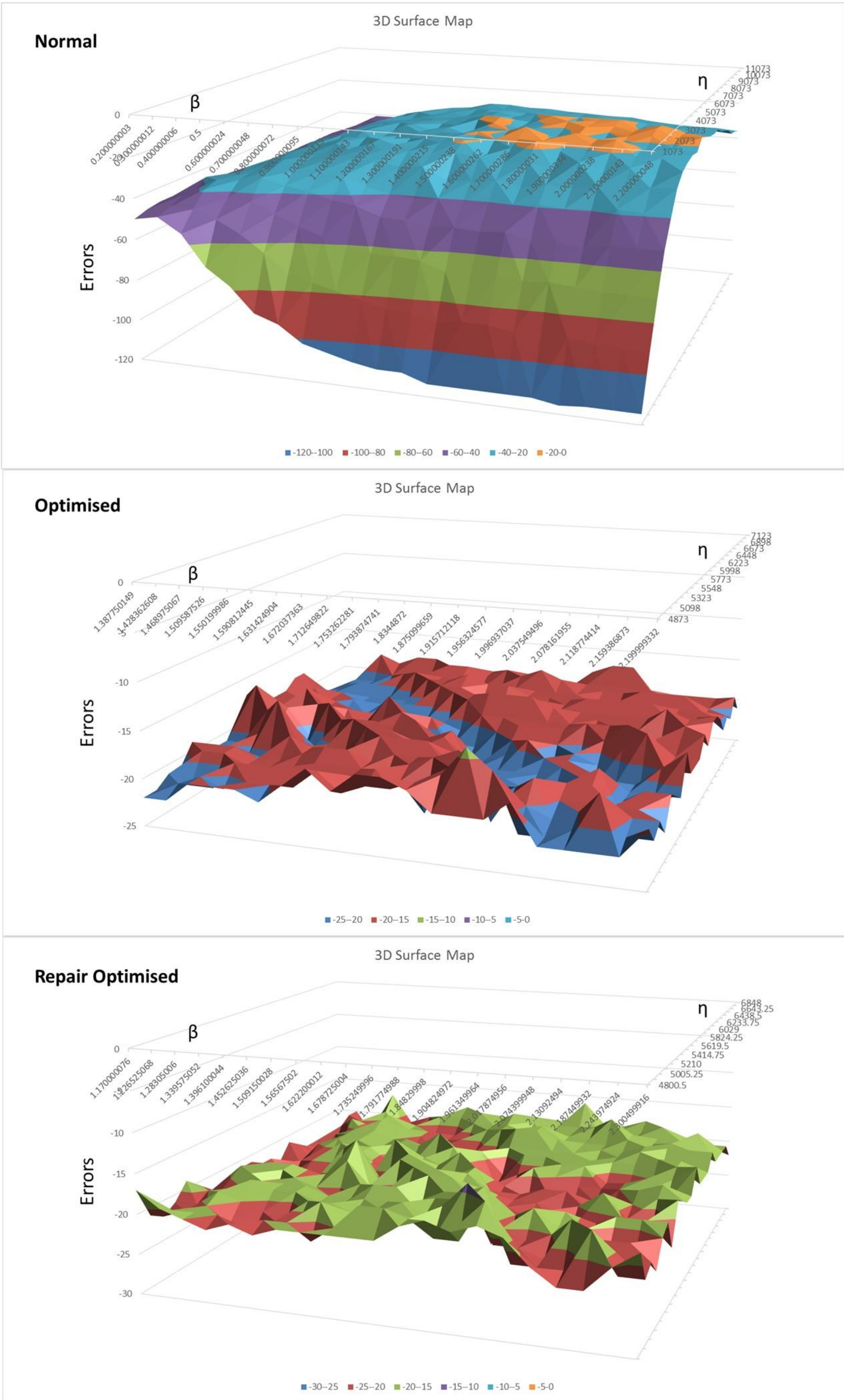


Figure 7-19 3D shape of normal, optimised and repair optimised error values, η and β parameters

Table 7-9 Outcomes of the optimised values from LSM methods

	Initial η	Initial β	zoom-in (optimised)	η	β
New	6073	1.2	High η and Low β	7123	1.4
			Low η and High β	4873	2.2
Repaired	4968	1.5	High η and Low β	6848	1.2
			Low η and High β	4801	2.3

Figure 7-20 displays failure rate and RUL distribution results which are interpreted in statistics and engineering context with only initial new and repaired η and β parameters. In Figure 7-21, η_{new} and β_{new} (6073 and 1.2) – data provided from historical overhaul inspection time for single engine system. The application of repaired components in the model starting with new components are further considered and analysed. The first population contains new components and subsequent population replaced consists of repaired components. The idea suggests repaired components may have less life. The likelihood of less life is included in the individual segment and a recalculation conducted visualises the outcome. The recalculated η and β gives η_{repair} and β_{repair} (4968 and 1.5) – β parameter illustrates an early wear-out showing that the components suffer from either corrosion, erosion or low cycle fatigue. The η_{repair} and β_{repair} (4968 and 1.5) are achieved by taking an aggregate of the failure times in the through-life performance model together with the new population of component. In Figure 7-21, optimised η_{new}; βnew and η_{repair}; βrepair gives final results showing mixture of new and repaired components. The mixture of new and repaired replacement probability of failure and remaining useful life are illustrated in this scenario. The Weibull distribution for RUL prediction shows that observed pattern relates to multi-component renewal. The results appeal to both end-users and experts in relation with the validation and verification conducted. Technically, outcomes of the Weibull distribution resulted from the replacement of a proportion of the components in an assembly. The results suggest that the mixed replacement with repaired components could lead to early maintenance and submit that engines should be assessed more frequently.

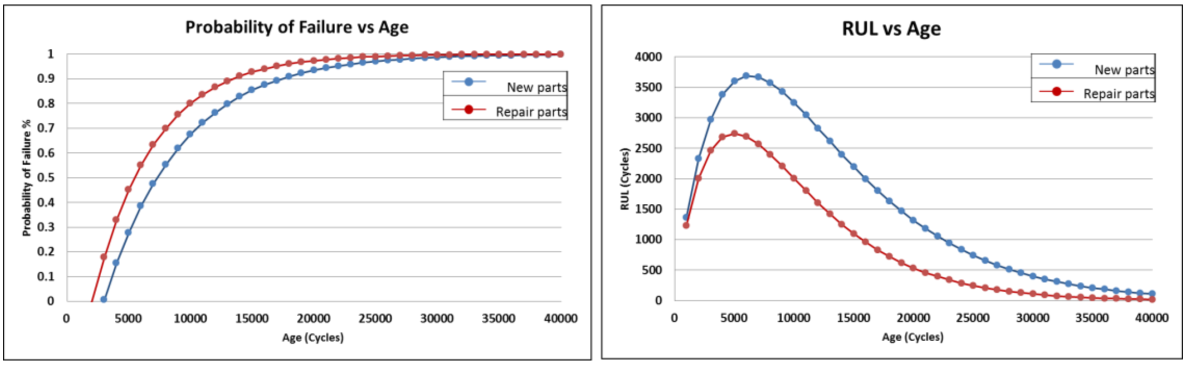


Figure 7-20 RUL for new η,β: 6073,1.2 and repaired η,β: 4968,1.5. The red represents the repair and blue indicates new components.

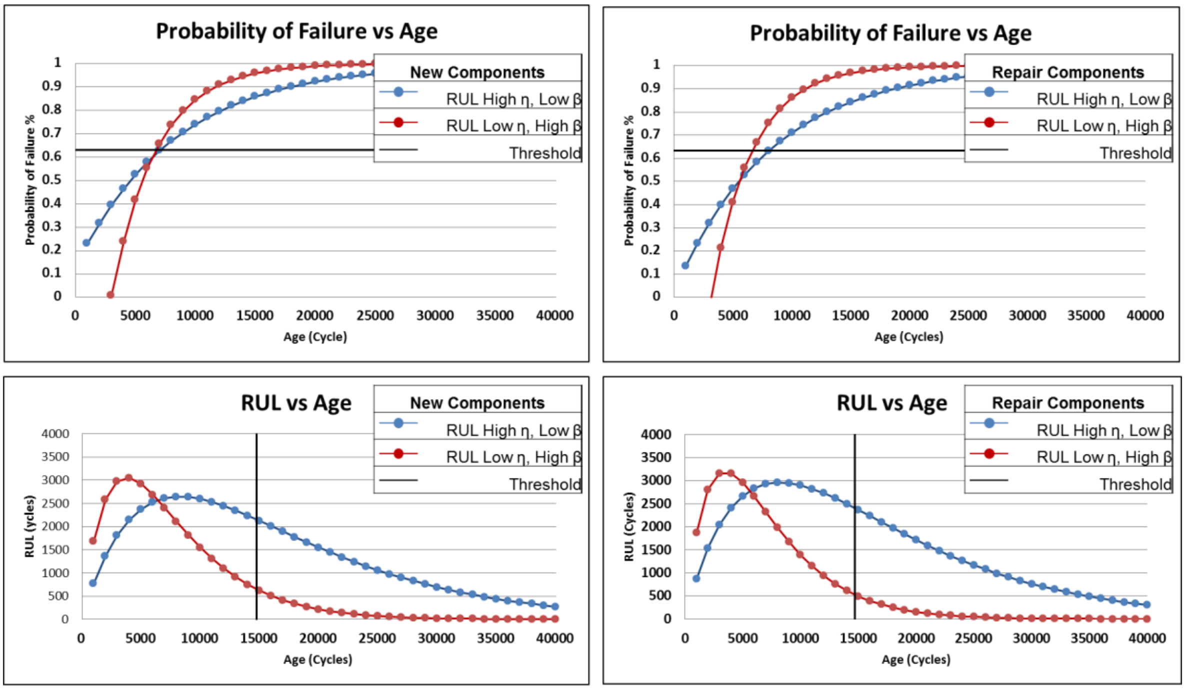


Figure 7-21 Failure rate and RUL for optimised new and repaired η,β

7.3 Scenario three - Multiple of four stage turbines

The developed framework in Figure 6-8 is modified to include multiple stage turbine as indicated in Figure 7-22 and demonstrated with data (see Table 7-10) from a large centrifugal compressors and turbine equipment in a refinery environment. This equipment is a steam turbine engine. Barringer & Kotlyar (1996) produce the Weibull estimated parameters from failure data of multiple stage compressor and turbine of steam engine.

Table 7-10 Estimated parameters (Barringer & Kotlyar 1996)

Parameters	Row 1 Blades	Row 2 Blades	Row 3 Blades	Row 4 Blades
η	205	179	163	159
β	2.7	2.6	2.5	2.4

The failure data (η and β parameters) were based on assumptions according to (Barringer & Kotlyar 1996) and due to the challenges of acquiring real data from industry. Failure data found in literature (Barringer & Kotlyar 1996) are applied to assess through-life performance of components.

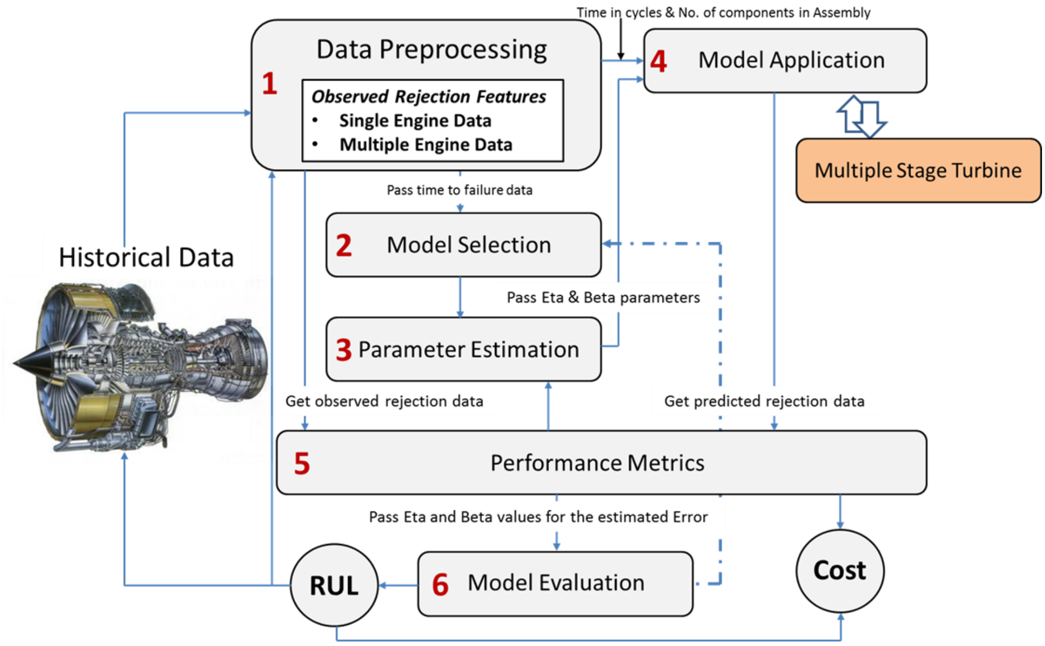


Figure 7-22 Framework for multiple stage turbine

The reliability is the survival rate calculated based on lack of failures. The failure data are a different combination of η and β values, with η values given in months. This third scenario focuses on the multiple stages of a turbine. The turbine is designed for operation ranging from 8,000 to 14,000 rpm with continuing operation of 12,500 and over-speed set of 13,758 rpm. The turbine has four different stages with blades. The mean tip speed of the final stage is 1289 feet per second (fps). The blade roots are dovetailed and the shrouds are riveted.

The through-life performance prediction model is applied to a single stage (Row 1 to 4 Blades) based on individual engine data in Table 7-11 using the η and β parameters from literature illustrated in Table 7-10. The outcome is presented in Table 7-12 showing the number of rejections at each overhaul state for multiple blades using Engine No 10015.

Table 7-11 Data with multiple engines and overhaul state used for the analysis (validation data)

Engine No	Time (hrs)	Time (Months)	Scrapped Quantity
10010	6000	8	2
10010	12000	17	4
10010	18000	25	9
10011	6000	8	2
10011	15000	21	4
10011	19800	28	9
10012	6000	8	2
10012	19200	27	4
10012	36000	50	9
10012	48000	67	11
10012	66000	92	14
10013	12000	17	2
10013	21000	29	4
10013	36000	50	9
10013	60600	84	11
10014	6000	8	2
10014	15000	21	4
10014	36000	50	9
10014	48000	67	11
10015	6000	8	2
10015	15000	21	4
10015	19200	27	9
10015	36000	50	11
10015	48000	67	14
10015	66000	92	20
10016	5880	8	2
10016	13200	18	4
10016	21600	30	9
10016	36000	50	11
10017	5520	8	2
10017	8400	12	4
10017	15000	21	9
10017	33000	46	11
10017	48000	67	14
10019	6000	8	2
10019	12000	17	4
10019	18000	25	9
10019	24000	33	11
10019	30000	42	14

Table 7-12 Failure data with predicted rejection data for the turbine stages

Stage Blades	η	β	OS1	OS2	OS3	OS4	OS5	OS6	Total
Row 1 Blades	205	2.7	0	0	0	1	1	2	4
Row 2 Blades	179	2.6	0	0	0	1	2	3	6
Row 3 Blades	163	2.5	0	0	0	2	2	4	8
Row 4 Blades	159	2.4	0	0	1	1	2	4	8

The failure starts at OS3 of Row 4, while the least failure begins at OS4 of Row 1. All rows of blades are concurrently in operation with an end of life is 200 months. The ageing of the blades is defined by the β factor/parameter between 2.4 and 2.7. The η varies from 159 and 205 months, depending on the stress levels of their very high temperature environment. Table 7-13 illustrates the failure data with zoom-in/optimised values. The optimised values represent the range of η and β values of the failure data.

Table 7-13 Failure data values with optimised values

No	η	β	Zoom-in (optimised)	η	β
Row 1 Blades	205	2.7	High η and Low β	261.3	1.7
			Low η and High β	205	2.195
Row 2 Blades	179	2.6	High η and Low β	224	1.60
			Low η and High β	179	2.16
Row 3 Blades	163	2.5	High η and Low β	198	1.50
			Low η and High β	163	2.00
Row 4 Blades	159	2.4	High η and Low β	194	1.40
			Low η and High β	159	1.94
All Row Blades	45.2	1.7	High η and Low β	70.2	0.775
			Low η and High β	45.2	1.525

These values signify that any η and β parameters within the specified range are realistic, producing a distribution relative to historical failure data as shown in Figure 7-23. The range of error values shows the same number across the colour gradient. The difference in the colour gradient means that the exact values vary based on approximation. The nature of operation between a gas turbine in an aerospace domain and a steam turbine in power generation differs. While the latter is usually running continuous non-stop until schedule maintenance, the former is run based on the start and stop flight cycles. The essence of the framework is to proffer a predictive maintenance strategy in the power generation sector to determine number of components expected fail prior to overhaul, maintenance, repair, logistics and remaining useful life.

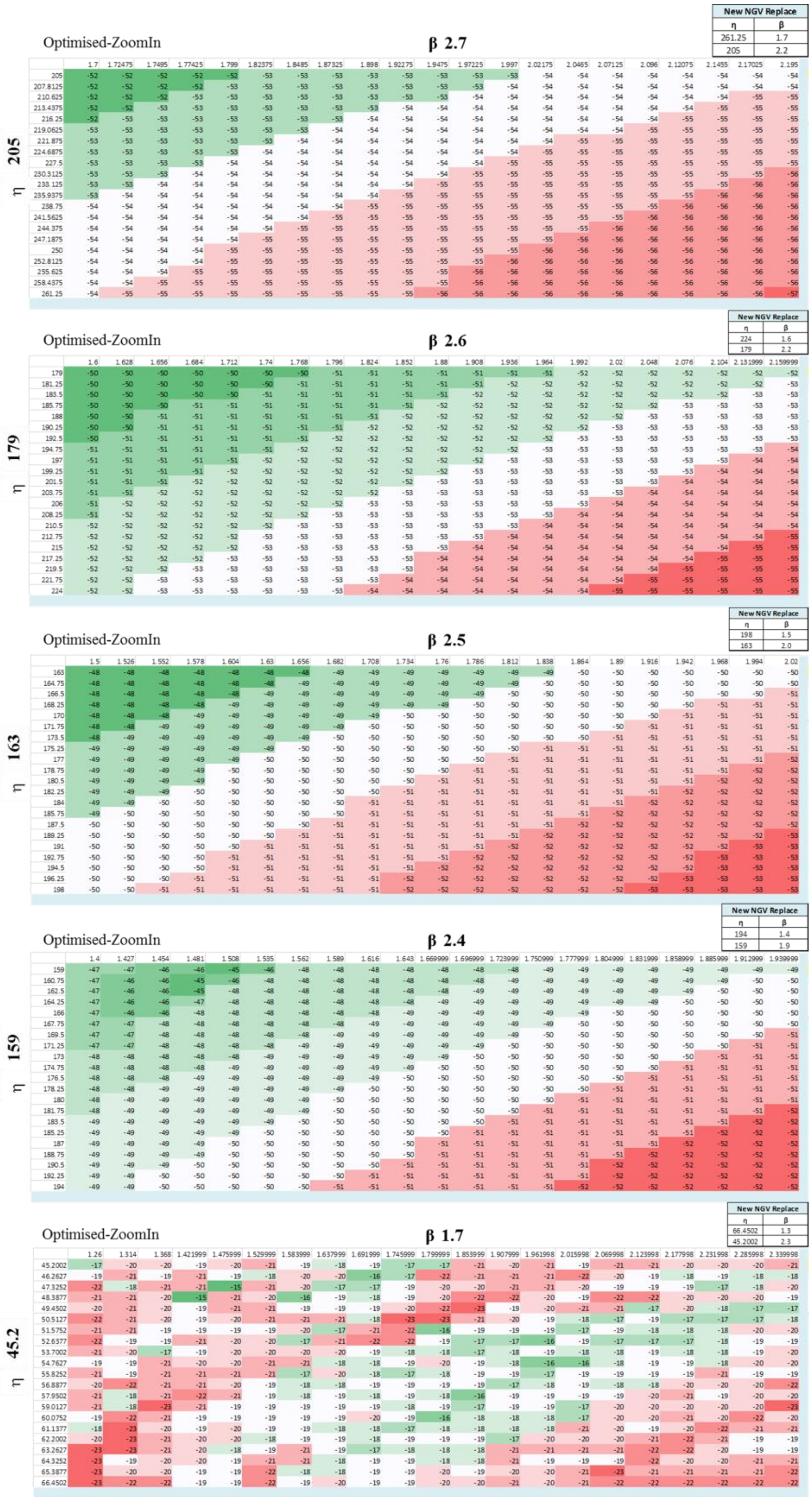


Figure 7-23 Optimised error values, η and β parameters of multiple stage turbine

The distribution is further analysed to calculate probability of survival or fraction of remaining useful life. The fraction of remaining useful life is converted to remaining useful life in months. Overall multiple assemblies with multiple components working concurrently show calculation of number of rejections using estimated parameters (η and β). The remaining useful life of components is predicted using optimised parameters in Table 7-13.

Figure 7-24 illustrates the output for the blades in the four different rows based on Table 7-13. The results show the performance relative to lifecycle costs and maintenance from a reliability estimate stand point. The outcome highlights when components fail in the rows of the turbines. The estimation of parameters determines at what point components should be serviced or replaced in individual rows.

The analysis shows that excessive replacement cost can be curtailed and to improve customer satisfaction. The data quality and resulting distributions can influence cost-saving decisions in the cause of design development and customer use. Furthermore, in relation to environmental applicability and operating mode of an industrial system, the deterioration of the components is gradual, unlike a gas turbine for aircraft operation. With this, remaining useful life is lengthy for land base / prime mover application as shown in Figure 7-24 based on optimised solutions. The results illustrated are relative to overall intricacy of multiple components of multiple stages of a gas turbine.

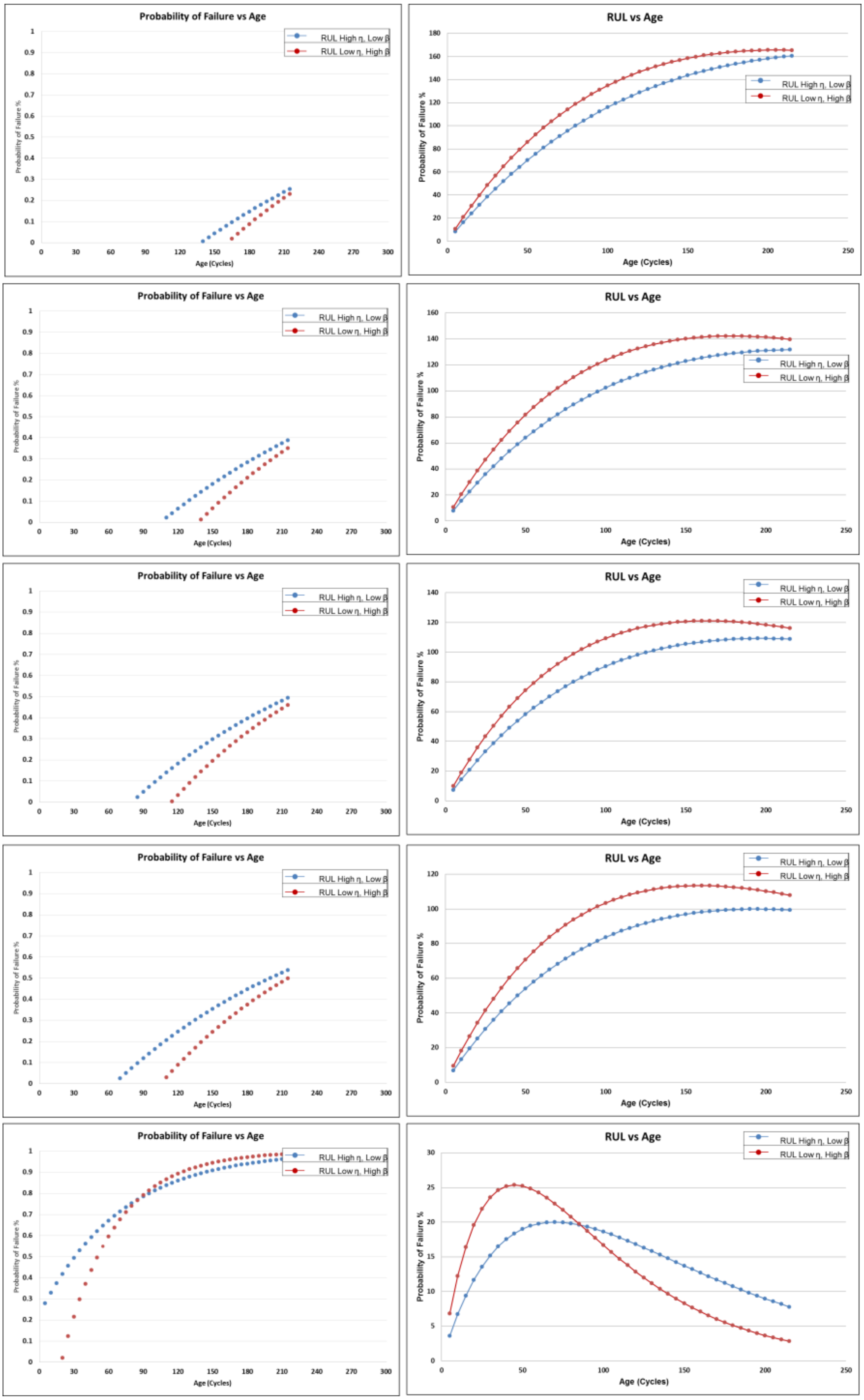


Figure 7-24 Overall results of multiple stage turbine probability of failure and RUL

Application of literature data to case study Scenarios

The acquired data from literature, which are analysed and optimised as shown in Table 7-14 are applicable to different scenarios discussed and results presented in Figure 7-25.

Table 7-14 Failure data from literature with optimised values

No	Turbine	η	β	Zoom-in (optimised)	η	β
A	Single Stage	159	2.4	High η and Low β	3996.50	2.10
				Low η and High β	3659	3.30
B/ C	Repair	4948	1.5	High η and Low β	8218	0.98
				Low η and High β	3468	2.49
D	Row 1 Blades	205	2.7	High η and Low β	5205	1.70
				Low η and High β	4682	2.08
E	Row 2 Blades	179	2.6	High η and Low β	5179	1.60
				Low η and High β	4579	2.20
F	Row 3 Blades	163	2.5	High η and Low β	5163	1.63
				Low η and High β	4513	2.22
G	Row 4 Blades	159	2.4	High η and Low β	5159	1.60
				Low η and High β	4559	2.20
H	All Row Blades	53.2	1.7	High η and Low β	3987.70	2.14
				Low η and High β	3620.20	2.70

The results in Figure 7-25 are generated with the following values in Table 7-14. The result in A of Figure 7-25 indicates RUL for single stage turbine of multiple engines. The solution is close to the outcome produced in section 7.1 relating to a single stage turbine. The outcome is determined by the data. The solutions in B and C of Figure 7-25 represent repaired and new components. The results in D, E, F, G and H are for multiple stage turbines.

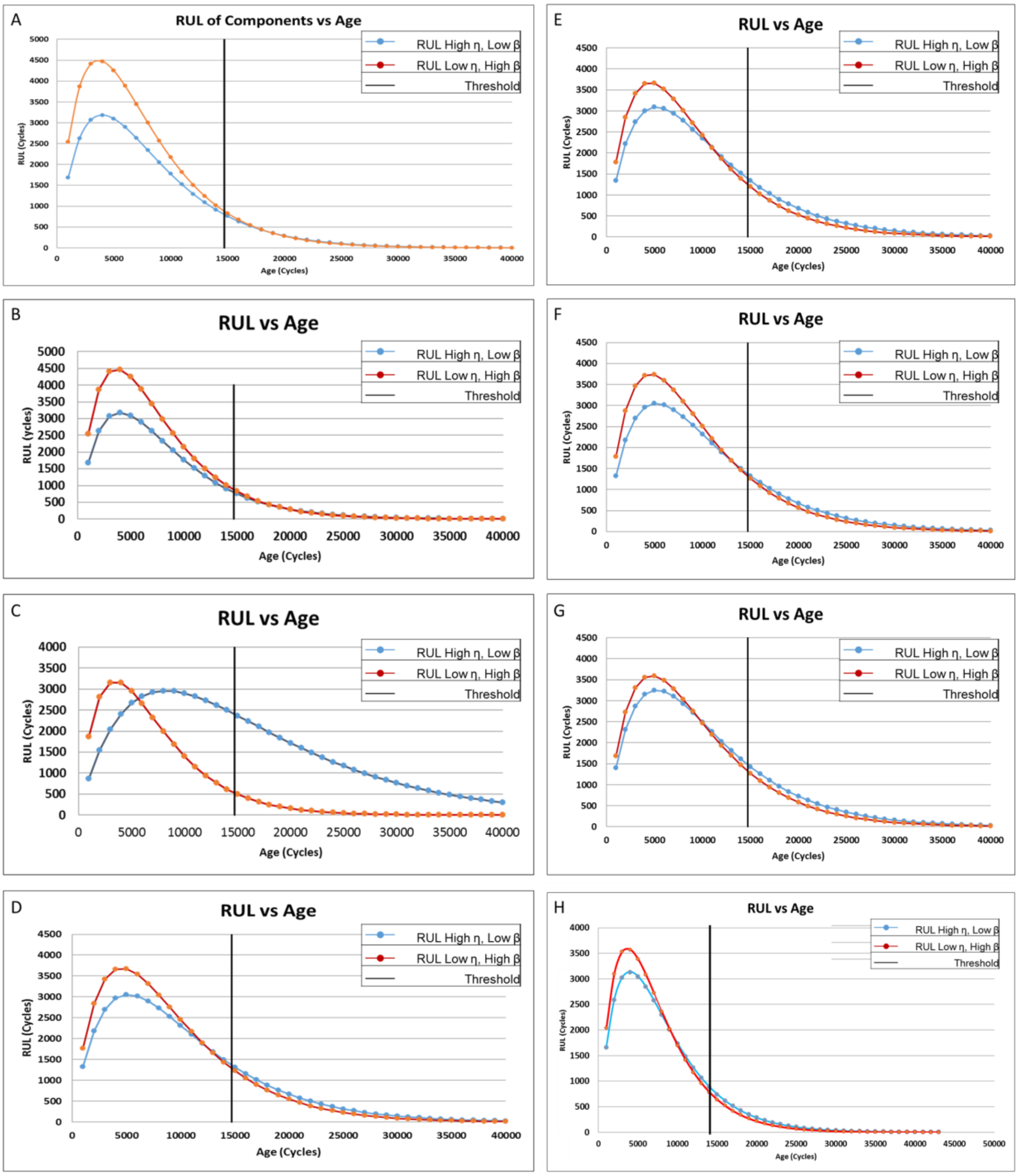


Figure 7-25 Overall RUL results for all three scenarios

The outcomes are dependent of the analysis and any of the two trajectories on each graph to estimate the RUL prediction of the engine components in the assembly of the different scenarios. Figure 7-25 illustrates all distributions depict Weibull analysis relating to individual components RUL prediction. At the mean time of about 15000 cycles on the x-axis, while y-axis contains the outcome (contains the component RUL signifying total components replacement within an assembly) which is a function of x. Graphs C, D, and F have a maximum value of about 3000 cycles on the components RUL due the shape value being between 1 <= 1.70. Graphs A, B, E, G and H are a little more than 3000 and 3500 cycles at maximum components RUL with shape value of between 2 and 2.50. The sharp contrast in C is due to the introduction of repaired components. F shows more skewness to the left because of the optimised low and high β values are 2.14 and 2.70 respectively – more components renewals are expected in the overall multiple stage turbine.

Comparing scenarios and RUL prediction

The scenarios in the case study are applicable to gas turbine engine in the aerospace and power generation. While the single stage turbine is analysed to determine the components RUL prediction in an assembly, the multiple stage turbine is assessed to estimate the component RUL prediction. The former is relative to aerospace and the latter is attributed the land base power generation. Whereas the RUL prediction shows the need for consistent inspection and maintenance of the air based turbine, the RUL prediction in land based turbine reveals longer time interval between maintenance. The outcome is affected due to start and stop flight cycles for aircraft, and longer hours of start and stop for land base turbines. The repair and replace scenario reflects the implementation of measure for constant and accurate deliver of spare parts. The development of the framework has been applied to different scenarios of complex machines showing significant failure distributions. The reliability of the complex equipment is based on the function of the collaboration of the individual independent components failure distribution and RUL prediction. The scenarios and RUL prediction provide an avenue to ensure predictability and reliability, thereby reducing infantile exclusions. The approach does consider for variability of nature factors such as accident braking, fuel types but where catastrophic incident occurs, the approach do not support. The approach can be applied to real application, however, the system should be trained in accordance with the model to achieve the expected outcome. Further numerical analysis of the scenarios are illustrated in appendix L.

7.4 Summary

The parameter estimation methods show differences in β values (failure modes). The framework applies to gas turbine and steam turbine applications. The WTPPM framework can be applied to other fields, whereby components are collectively and concurrently operating in same environment. The framework uses a prognostic data-driven methodology to produce acceptable results. The data used for this analysis showing multiple engines and overhaul states are presented. The results of rejected components from through-life performance model application are illustrated, GET and GOT outcomes with 3D shape visualisation are shown, and remaining useful life trajectory presented. The data from literature are applied to all three scenarios showing various results.

8 VALIDATION AND VERIFICATION

The validation and verification of the WTPPM framework are conducted to ensure the technique, input and output results are validated and verified with respect to accuracy and the process of ensuring procedures provide assurance. Verification and validation are independently conducted with reference to independent procedures used for checking viability that a software meets its requirements and specifications to fulfil its intended purpose (Global Harmonization Task Force, 2004). While validation ensure tool meets end users operational needs, verification provides assurance assessment that the developed tool meets a set of design specifications (ISO/IEC/IEEE 24765:2010(E), 2010).

In validating and verifying the WTPPM framework, data for input are extracted from literature, sample data from documents and data developed with experts. Initial verifications were conducted relating to assessing accuracy of the calculations. For each segment of the case study, input, output and validation outcomes are presented. Participants' initial suggestions and modifications are effected. Validation results from questionnaire administered through semi-structured interviews are evaluated. The questionnaire assesses framework logic, suitability, generality, usability and results. The sample data are applied to the framework for single stage, repair and multiple stages scenarios of the case study.

8.1 Internal verification

Internal verification revolves around the development strategy of the calculations for each segment within the framework, which was applied to ensure assessment accuracy and validity of the calculations. At the different stages of development of the framework, verifications were conducted with the industry sponsor, my supervisors, subject adviser and industry partner. The verification in the first stage lasted for 1 hour 45 minutes and the three other stages for an hour each. The calculations within the WTPPM seemed appropriate with provision of expected outcomes. Suggestions from the meetings include representative results, estimation of the Weibull parameters, providing means to know the total number of engines being analysed, components being scrapped and the data to validate the tool.

During the initial verification in the first stage of development, the outcome of the first overhaul inspection state is assessed. The calculation of number of components expected to fail within the assembly is presented in Table 8-1. The significance of the calculation is assessing the failure rate from a statistical standpoint. The number of components in assembly are fixed depending on the model of the engine. The estimated parameters are derived from averaging the overhaul times. The overhaul times are start and stop times in cycles of flight. The formula is an enhanced Weibull function for determining the rate of failure. The proportion of components degraded is the probability of failure outcome, which is then converted to number of components degraded. Other calculations including summation of the number of components for R-Cube are validated and verified to produce the expected results for each overhaul state versus each population (replacement renewal).

Table 8-1 Calculation of the number of components degraded

Inputs			Process	Output	
Number of components rejected	Estimated parameters	Overhaul time in cycles	Formula: Weibull	Proportion of components degraded	Converted to number of components rejected at each overhaul state

Table 8-2 illustrates the strategy for assessing the error values by comparing the predicted and observed values. The values are the outcomes from the model calculation, while observed values are the real-world outcomes. The MAE is mean absolute error formula, which compares both values to output a single value indicating how close or far the predicted deviates from the observed.

Table 8-2 Technique for conducted error calculation.

	Inputs		Process	Output
Technique for calculating error	Predicted values	Observed values	Formula: MAE	Error value

Table 8-3 shows the assessment of range of high and low η and β parameters with their error values. The η and β parameters are split into a matrix with their representative error values. Change in η and β parameters are defined to enable iteration focus on the matrix. Each representative error value is dependent on the η and β parameters relative to the Weibull function. The application of colour is dependent on the error values, for example, if the error value is high a red colour is assigned and if low, a green colour applies.

Table 8-3 Presentation of a range of η and β parameters

Input			Process		Output
Range of scale and slope factors	change in estimated parameters		Define matrix	Apply colours	Show results

Table 8-4 presents the assessment of probability of failure of the optimised η and β parameters. The optimised η, β and error values are translated to calculate the probability of failure for the components.

Table 8-4 Assessment of probability of failure

Inputs			Process	Output
Probability of failure	optimised parameters	Time in cycles	Formula: Weibull	Probability of failure results

In Table 8-5, the calculation for remaining useful life is conducted by multiplying the time intervals in cycles with the outcome of probability of survival (a nominal value minus the probability of failure).

Table 8-5 Assessment of remaining useful life

Inputs		Process	Output
Remaining useful life	Time in cycles	Formula: Converting probability of failure	Visualise results

Table 8-6 provides calculation for estimating η and β parameters using least squares and maximum likelihood estimation methods. The times in cycles are aggregated to estimate η and β parameters relevant for the model to calculate expected number of degraded components within an assembly through the life of the engine at the various overhaul states.

Table 8-6 Estimation of scale and slope parameters

Inputs		Process	Output
Estimate parameters	Time in cycles	Formula: Weibull/MLE/LSM	Shows results

Table 8-7 illustrates the cost and safety margin calculation to determine when to scrap the entire multi-component and replace with pristine components. A safety margin is pre-determined in line with the number of rejected components and the cost per component.

Table 8-7 Calculation of cost to scrap entire components in an assembly

Inputs				Process	Output
Cost analysis	Safety margin	Cost	Number of rejected components at each overhaul	Formula: scrap	Shows results

8.2 Case study

Gas turbine engine

With reference to chapter 1, scenario one of the case study demonstrates the through-life performance of components in an assembly of a single stage turbine, which includes application of renewals (new components) to show a proportion of degraded components at each overhaul times in cycles. Scenario two illustrates the through-life performance of the components in an assembly with renewals (repaired components) of a single stage turbine. The attention is on an assembly of HP-NGV of a complex engineering system.

Steam turbine engine

The developed framework is then applied to scenario three. Scenario three is an industrial power generator application with multiple stages turbine as described in chapter 7 to examine the behaviours of the four-stage turbine and predict the remaining useful life of the components.

The case study is selected to assess the nature and level of component degradation and its through-life performance at design stage by using the WTPPM framework. The case demonstrates the components deterioration to estimate reject, replace and reuse occurrences. The product of the study will enable domain experts select a realistic characteristic life and the slope to determine the life of an assembly of components for better maintenance decision, thereby predicting remaining useful life of the components. The case is an aspect of a research project which has been split into a number of sub-project concentrating on providing support to in-service characterisation of components relating to maintenance, spare parts, manufacturing and design.

8.3 Qualitative validation

In conducting the validation and verification, the research problem was introduced and the aim of the research stated describing the process of the framework. The questionnaire is then presented for feedback. The feedback is summarised, the analysis of the feedback and suggested changes to the framework are presented. The questionnaire for the validation technique used in this research is produced using Likert scales of four with granularity of 1 to 10. The scale ensures more precise data collection, increases reliability and validity of data from a statistical analysis perspective (Pearse, 2011). The Likert scale of four with granularity of ten is chosen over five because it delivers more value in terms of accuracy, reliability and validity of the responses for analysis (Pearse, 2011). The analysis of the validation is further discussed relating to scenarios of the case study.

In summarising the feedback from the questionnaire, the validation and verification of the framework are conducted in conjunction with experts, who have experience in academia and industry. The comments on the generality, responsibility, benefits, limitations, usability, assessment of the framework and quality of the results are analysed. The experts are statisticians and engineers with academic and industry experience in different fields of endeavours. Only years of experience and letter identifying respondents are disclosed, but names of the respondents are not disclosed for confidentiality as shown in Table 8-8 and the questionnaire validation and verification of the technique for the RUL prediction framework is presented in appendix M. The user manual is available in appendix N.

Table 8-8 Failure data values with optimised values

Respondents	A	B	C	D	E	F	G
Experience (years)	3	7	20	6	40	21	13

Validation results per section with observation

The responses from the respondents are presented in tabular form (see Tables 8-9 – 8-15) describing the results for each section of the questionnaire together with observations. The aim outlines specific individual assessment of the framework to reduce or eliminate bias from the researcher. The respondents are identified by the supervisors, so there was no influence on the hand of the researcher.

Table 8-9 Assessing the prediction modelling logic in the framework

Respondent	Logic
A	The logic and suitability have a score of "8" and "9" respectively, which show an agreement with each section in the framework. The framework can be applied to "industrial component failure".
B	The logic and suitability were given a score of "8" and "9" respectively. The framework can be useful for "other manufactured products with complex composition."
C	The logic and suitability had a score of "7" and "7 respectively, stating that "in general it is logical, to the extent that deterioration can be modelled in the specified probabilistic terms" and "in general yes, to the extent that deterioration can be modelled by the proposed probabilistic framework." The framework can be applied in another scenario "…but with significant customisation."
D	The logic and suitability had a score of "8" and "8" respectively, stating that "prediction modelling could potentially provide a close enough relation establishing an approximation of remaining useful life of the part. And this could safe both inspection downtimes and improve reliability."
E	The logic and suitability have a score of "7" and "7" respectively, showing an agreement with each of the sections in the framework whilst considering the relationship with cost. The framework can be applied to "any complex system of subsystem".
F	The logic and suitability have a score of "8: a logical approach has been adopted. Role uncertainty would be good to consider further" and "7: would be good to clarify input from literature". "The framework looks adaptable."
G	The logic and suitability have a score of "8: A closed loop framework is suggested, which allows the produced model is valid" and "9: More real data are required to valid this application." "The framework itself is general."

Table 8-10 Assessing the generality of the framework

Respondent	Generality
A	The generality of the framework can be applied in a broad variety of components in assemblies based on "Consideration of repair option in addition to new parts".
B	The generality of the framework has a wider "applicability in relation to automotive engine is a possibility."
C	The generality of the framework in the aerospace industry "Significant customization is needed for more generic applicability." The generality of the framework in other industries "The framework is applicable to other industry but the details out of necessity will have to be re-worked and tailored to problems in other sectors."
D	The generality of the framework "This framework in the current state does fit in with the aerospace model dealing with HVM parts. However, the level at which this might be applied to is a discussion that is needed with the end users especially to improve its fidelity."
E	The generality of the framework "highly applicable to many industries and any complex equipment with sufficient historical data."
F	The generality of the framework in aerospace industry "the steps are general and clearly applicable for aerospace." In relation to other industries "would be, but need to clarify the drivers."
G	The generality of the framework "Although the framework is general, the performance of this modelling quite depends on the model selected, which will be different case by case.

Table 8-11 Assessing the responsibility for the use of the framework

Respondent	Responsibility
A	Responsibilities include who should use the tool and take ownership. “The designers, maintenance engineers and maintenance department.”
B	Responsibility includes the “designers, manufacturers, maintainers and results overview should be presented to managers. The design and manufacturing department can take responsibility of the model”
C	Responsibility includes the “All of the above, but the framework should specify its own validity limitations” as stated in the questionnaire. “Would ownership by a single department be consistent with a whole-lifecycle management approach?”
D	Responsibility: “This framework should be handled by designers, manufacturers and maintenance personnel in the first instance as it involves the actual users who are based in the working field. This should further be adapted to the requirements of the job itself.” “A dedicated technology / research team overlooking all processes should own and maintain this framework.”
E	Responsibilities include who should use the tool and take ownership “maintenance and business managers in an availability contract.”
F	Responsibilities include who should use the tool and take ownership. “Designers and service engineers.”

Table 8-12 Assessing the benefits and limitations of the framework

Respondent	Benefits and limitations
A	The benefits to organisation include “lower cost due to the on - time intervention for corrective maintenance”. The limitations are “the historical data needed in a big consistent datasets, new parts in the behaviour that is not predictable and catastrophic failure is impossible to predict.”
B	The benefits to organisation can lead to “full lifecycle assessment of the parts and engine performance.” “The user knowledge of the tool is a limitation and user guidance may be needed.” “Automated input can impact the background of people entering the data and processing should be considered.”
C	The benefits to organisation can lead to “Improve maintenance planning; feedback observations from operations and maintenance to improve design; available to policymakers for strategic choices.”
D	The benefits to organisation can lead to “Immediate benefits would be improved performance, especially in maintenance routines, which could lead to reduction in inspection downtimes, improved parts inventory and overall reduction in maintenance cost.” Limitations: “The tool does not have real-time information and to my understanding the tool currently uses simulated data. It needs real-time data to make sure it is fit for purpose, in other words it needs full validation and needs to use real-time data to check the reliability of the tool. This would only be possible when it gets into an actual working environment. Further, training and tuning of the tool for the specific job needs to be undertaken.” “The major limitation would arise in the actual field where the data handling capacity of the tool is challenged.” “The major concern could be the type of data that is being fed into the tool, where the data and the scenarios might be completely new and the tool fails to provide corrective measures.”
E	The benefits to organisation include “reduction in WLC”. The limitation is “availability of historical data and company willingness to invest in resources, validation process, and needs competent users, not simply number crunchers”
F	The benefits to organisation include “Reliable/robust RUL calculation for multi-component”. The limitations are “risk and uncertainty, how much data are needed, and potential subjective opinions as input.”
G	The benefits to organisation include “RUL prediction using limited number of data.” The limitation is “The number of samples is different.”

Table 8-13 Assessing the usability of the framework

Respondent	Usability
A	Usability considers the "historical data presentation and style as strength, summary of data in one view as weakest feature and possible improvement". The tool offers an adequate guide to a user. The time required to populate the tool for implement is very good. The scale of 1 to 5 (worse, less worse, moderate, good, very good) assesses the facets of the tool, a score of "4" is assigned to the layout, ease of navigation and level of awareness, while a scale of "5" is given to the use of colour. The flexibility of the tool to different levels of information available has a scale of "3".
B	Usability – "better user guidance should be made available to help users to effectively use the tool". "An e-help file should be provided". The facets of the tool in terms of layout, use of colour and ease of navigation had a score of "4". Level of awareness should be improved since it was given a score of "3". The prototype is flexible and needs to be communicated to the users.
C	The benefits to organisation can lead to "Improve maintenance planning; feedback observations from operations and maintenance to improve design; available to policymakers for strategic choices."
D	Usability – "The tool is appropriate as a prototype. It allows fast experimentation showcasing benefits. As a next step, once the prototype is validated, further effort could look into going beyond an excel tool, handling uncertainty in the data and designing a proper data generalisation approach with adequately designed cross validation, to reduce learning data bias, especially in cases of either limited or not sufficiently rich data." "In general the tool is best used after a demo with explanations." "If data entry remains manual it may be slow and prone to errors; however, the time required for a rapid prototyping of a solution is relatively limited, making it appropriate for a research prototype." The facets of the tool contain layout with a score "5" was assigned, use of colour had "4", ease of navigation had a score of "4" and the level of awareness was given a score of "3" which requires improvement. Compare the tool flexibility with different levels of information available "Although have not seen it working with different levels of information, it could in principle be applicable, but with limitation regarding the nature of data (data richness) and uncertainty management."
E	Usability: "Excel based as the strongest feature with unknown weakness"
F	Usability considers the historical data presentation and style as strength; "lack of guidance on how to use the tool." The tool offers an adequate level of information to guide a user. Layout had a scale of "4 – need further guidance on the steps."
G	Usability – assessing feature: "The selection of optimal parameters." The tool offers an adequate level of information to guide to a user. The scale of 1 to 5 (worse, less worse, moderate, good, very good) assesses the facets of the tool, a score of "4" was assigned to layout, ease of navigation, level of awareness, and use of colour. The flexibility of the tool to different levels of information available had a scale of 3.

Table 8-14 Assessment of the framework

Respondent	Assessment of the framework
A	Assessment of the framework in terms of completeness and suitability for input has a score of “7”. The approach used for the parameter estimation has a score of “8”; a score of “9” is given to the modelling and simulation. The comparison of the observed and predicted data has a granularity of “8”. A granularity score of “9” was assigned the optimisation approach to the solution, while the unreliability distribution of the optimised solution gives a score of “8”. The transformation of the unreliability distribution to survival distribution was given a score of “8” and the remaining useful life has a score of “7”. The cost logic to scrap the entire assembly as a granularity of “8”, while the iterative process for multiple stage turbines case study has a score of “7”.
B	Assessment of the framework in terms of completeness and suitability for input has a score of “8”. The approach used for the parameter estimation has a score of “8”; a score of “8” is given to the modelling and simulation. The comparison of the observed and predicted data has a granularity of “8”. A granularity score of “8” is assigned the optimisation approach to the solution, while the unreliability distribution of the optimised solution gives a score of “8”. The transformation of the unreliability distribution to survival distribution is given as a score of 8 and the remaining useful life has a score of “8”. The cost logic to scrap the entire assembly as a granularity of “8”, while the iterative process for multiple stage turbines case study has a score of “8”.
C	Assessment of the framework in terms of completeness and suitability for input has a score of “7: The framework is adequate but strongly depends on data availability”. The approach used for the parameter estimation has a score of “4: deficiency 1: how can it be ensured that data fit a specified probability distribution? Deficiency 2: solving a more difficult problem (that of fitting a probability distribution) compared to make a direct empirical estimation/prediction on the basis of limited data availability could be an issue of concern. Otherwise parameter estimation could be sound and is well understood”; a score of “6: although comprehensible, the concerns of the previous question apply here too” is given to the modelling and simulation. The comparison of the observed and predicted data has a granularity of “8: Easy to understand”. A granularity score of “6: The principle is sound but the underlying assumptions not tested or guaranteed to hold” is assigned the optimisation approach to the solution. The conversion to remaining useful life has a score of “7: comprehensible”. The logic to scrap the entire assembly based on cost has a granularity of “8”, while the iterative process for multiple stage turbines has a score of “9”.
D	Usability – “The tool is appropriate as a prototype. It allows fast experimentation showcasing benefits. As a next step, once the prototype is validated, further effort could look into going beyond an excel tool, handling uncertainty in the data and designing a proper data generalisation approach with adequately designed cross validation, to reduce learning data bias, especially in cases of either limited or not

Respondent	Assessment of the framework
	sufficiently rich data." "In general the tool is best used after a demo with explanations." "If data entry remains manual it may be slow and prone to errors; however, the time required for a rapid prototyping of a solution is relatively limited, making it appropriate for a research prototype." The facets of the tool contain layout with a score "5" was assigned, use of colour had "4", ease of navigation had a score of "4" and the level of awareness was given a score of "3" which requires improvement. Compare the tool flexibility with different levels of information available "Although have not seen it working with different levels of information, it could in principle be applicable, but with limitation regarding the nature of data (data richness) and uncertainty management."
E	Assessment of the framework in terms of completeness and suitability for input has a score of "7". The approach used for the parameter estimation has a score of "6"; a score of "6" is given to the modelling and simulation. The comparison of the observed and predicted data has a granularity of "7". A granularity score of "6" is assigned the optimisation approach to the solution, while the unreliability distribution of the optimised solution gives a score of "5". The transformation of the unreliability distribution to survival distribution is given as a score of 6 and the remaining useful life has a score of "6". The cost logic to scrap the entire assembly as a granularity of "6", while the iterative process for multiple stage turbines case study has a score of "7".
F	Assessment of the framework in terms of completeness and suitability for input has a score of "8". The approach used for the parameter estimation has a score of "8 – need more openness about the calculation and avoid black box"; a score of "9" is given to the modelling and simulation. The comparison of the observed and predicted data has a granularity of "8". A granularity score of "8" was assigned the optimisation approach to the solution, while the unreliability distribution of the optimised solution gives a score of 8. The conversion to remaining useful life has a score of "9". The cost logic to scrap the entire assembly as a granularity of "9", while the iterative process for multiple stage turbines case study has a score of "9".
G	Assessment of the framework in terms of completeness and suitability for input had a score of "5 – the data are not sufficient for me". The approach used for the parameter estimation had a score of "6 – some optimisation methods can be used". A score of "7" is given to the modelling and simulation. The comparison of the observed and predicted data had a granularity of "8". A granularity score of "6" was assigned the optimisation approach to the solution, while the unreliability distribution of the optimised solution had a score of "6". The transformation of the unreliability distribution to survival distribution was given a score of "6" and the remaining useful life had a score of 6. The cost logic to scrap the entire assembly as a granularity of "6", while the iterative process for multiple stage turbines case study had a score of "6".

Table 8-15 Assessing the quality of the results of the framework

Respondent	Quality of the results
A	Results quality with realistic outcome has a score granularity of “9”. The significance of the result compares to the understandings of similar components is “8”. The visual representation of the output of the tool is clear. Suggested improvements of the overall framework are inclusive of “repair parts and design of a lean GUI for tool usability”
B	Results quality with realistic outcome has a score granularity of “8”. The significance of the result compares to the understandings of similar components is “8”. The visual representation of the output of the tool is clear and user guide required. Suggestions included “improvements of the overall framework diagram are inclusive of repair parts and design of a lean GUI for tool usability.”
C	Results quality with realistic outcome has a score granularity of “6 results are realistic to the extent that data are too and also to the extent that probabilistic assumptions hold.” The significance of the result compares to the understandings of similar components is 8. The visual representation of the output of the tool is clear. Suggestions “1. Include cross validation / generalisation options for learning approach, 2. Include uncertainty handling mechanisms, 3. Include software - enable data management (reduce manual data management), and 4. Once validated, consider moving beyond an excel prototype to full software development”.
D	Results quality with realistic outcome has a score granularity of “5”. The significance of the result compares to the understandings of similar components is “5”.
E	No comment
F	Results quality with realistic outcome has a score granularity of “9”. The significance of the result compares to the understandings of similar components is “9”. The visual representation of the output of the tool is clear.
G	Results quality with realistic outcome has a score granularity of “6 – the observed data are not sufficient. It is not clear for me”. The significance of the result compares to the understandings of similar components is 8. The visual representation of the output of the tool is clear “the resolution can be improved”.

Suggested observations

The suggested observations provided improvements of the overall framework;

i. The repaired component inclusion and design of a lean GUI for tool usability
ii. The comparison of parameter estimation outcome with existing software. The handling of data is relative to processing historical data in-line with the format presented to reduce noise and ensure accuracy. The data are not manually entered; however, the pre-processed data are transferred from one application to another or copy and paste the data into the specified format. The Excel working prototype is converted to a software showing only the required features.
iii. The outcome of the distribution is challenged; however, the distribution depicts the model selected and is appropriate when compared with other responses from respondents. The RUL distribution outcome resulted from renewals of multiple components
iv. The RUL describes relationship with cost and risk, whereby a comparative analysis of how RUL influences cost on subsystem and a whole system lifecycle.
v. Inclusion of model selection. Why and how is minimum and maximum value of shape and scale? The minimum and maximum values are determined to get a variation of inputs and outputs in the matrix to aid visual view of the error values and selection of the optimised parameters. The RUL representation solution holds true because it follows the Weibull distribution resulting from the multiple replacement renewals through the lifecycle. The range of η and β are calculated by dividing the η and β using a matrix value of 20.
vi. The approach for conducting the scenario three of the case study was validated for input, output and framework verification through a comparison of the results obtained from literature and domain expert knowledge. The model developed captures the through-life performance objectives of the research.

Results from the questionnaire

In the validation and verification of the framework, the results presented show Respondents A, B, D, F, and G have common response, while Respondents C and E differ in opinion, however, the respondents gave a high score for the framework logic and suitability.

All Respondents agree that the framework is generic with a wide applicability to many industries. Respondent A mentioned the inclusion of repair, while Respondent C argue that re-worked details for specific problem are needed. Respondent C note that performance of the modelling depends on the chosen model.

Respondents A, B, E and F agree that designers, maintenance engineers and department should take ownership of the framework, while Respondents C and D differ.

All Respondents agree with different responses to the benefits of the framework to an organisation, which include reduction in cost and on-time maintenance, supports full lifecycle assessment of the engine, improvement of maintenance and spare parts management, enhanced performance and robust RUL calculation for multi-component. The limitations highlighted by Respondents include number of samples and real-time data being fed into the framework.

Respondents agree that e-help should be included with the user manual provided. All Respondents assigned scores for colour, ease of use and level of awareness indicating framework performs well regarding usability.

In assessing the framework, Respondents A gives an average score of 8, Respondent B with a mean score of 8, Respondent C with a mean score of 7, Respondent D assigns an average of 4 because the section is not completed, Respondent E with a mean score of 6, Respondent F with a mean score of 8 and Respondent G gave an average score of 6.

In assessing the results quality, Respondents A, B, F gave similar high score, Respondents C and G gave same score for the quality and realistic outcomes and Respondent D assigns marginal resulting from the notion of the knowledge and understanding of the subject area in this context.

Based on the validation and verification of the framework, there are insignificant changes to the framework modelling. The change reflected in the RUL distribution where the dots of the probability of failure and remaining useful life are connected with lines signifying a cumulative strategy. The outcomes leverage the Weibull distribution to provide insights and further explore root causes from the data. The reason for a proportion of component to have same RUL at different interval of life shows that multiple engines with same overhauls (shop visits), but this rarely occurs. Whereas there are multiple engines data with similar overhauls, a match of same RUL at different interval can be unrealistic and not feasible, which might be due to the nature of the data.

However, in relation to the first scenario of the case study validation, the idea of applying repaired components is to observe the complexity of the framework. The algorithm solves the through-life performance of the degradation data for a single stage engine with replacing new components. The algorithm produces reasonable results with accuracy. In the replacement of the repaired component population, the algorithm produced accurate results. In the repetition of the process, the algorithm behaves in a consistent manner with the results obtained from validating the through-life performance model. The expected visualisation of the results is accurate and depict the new and repaired components. The results show repaired components will have slightly early failure and new components having slightly late failure and survive longer. These results prove true because the life of the new part is assumed to have a nominal life, while the repaired component is expected to have a less than nominal life. The outcome of the visualisation provides maintenance engineer with a strong tool for decision making when combining new and repaired components of an industrial product-services system. The decision to use a mixture of the components can lead to variations in the operation of an engine, which calls for close monitoring and assessment of components, and engines on-wing with consistent maintenance activities.

The results of the approach in the third scenario of the case study follow the validation of the first scenario. The algorithm calculates the through-life performance of the components in a multiple stage turbine with multi-component. The results are indicative of the types of gas turbine. The results are compared with literature and validated by domain experts. The visualisation of the results proves that the algorithm accurately predicts the probability of failure at each stage of the multiple stages turbine. The visualisation indicates the accuracy of the results and the consistency of the algorithm to generate the probability of failure and the remaining useful life of the proportion of the population.

The approach for developing the framework and the predicted results were validated using domain expert knowledge. The framework is designed to capture crucial historical data required for input to assess through-life performance of the components in an assembly. The accuracy of the model is determined to validate the results from the through-life performance algorithms. An assessment is conducted to determine the accuracy of the different aspects of the through-life performance approach that make up the framework. The objectives of the research are compared with the models and evaluated by subject matter experts with many years of experience.

The validation assesses the integrity check on the historical data for input to ensure no tampering with the data and no changes to the important input data. For example, overhaul times, quantity rejected, the η and β parameters are the same for the framework. The data should be strongly typed with the correct syntax, within specified boundaries and contains only permitted numbers. The validated data should follow the specified business rules. For example, failure rates can be decreasing, increasing and remain constant. The use of the correct terms in research as business rules can ensure financial gain and stability to an organisation.

The visualisation of the results in the modelling section show the algorithm calculates the number of components expected to fail and the distribution of the rejection rates and RUL prediction. The algorithm accepts the input data and accurately calculates the results. The algorithm performs accordingly as expected in a prognostics modelling of a reliability problem. The visualisation of the results in the performance metric section show the algorithm is able to auto-calculate the predicted values and compare with the observed values to produce a single residual value. The single residual extends to a range of residuals with respect to variations of η and β parameters with accuracy. The optimised results provide accurate outcomes after re-calculation. The results illustrate the algorithm is able to produce a good estimate for the degradation problem with getting the representative values. The visualisation of the results in the model evaluation section show the equations are rightly applied and algorithms correctly estimates the outcomes. The graph is properly and clearly presented to depict the proportion of components expected to fail as well as their remaining useful life. These outcomes relate to (i) the single engine data and (ii) multiple engines data for this case study. These outcomes also confirm the algorithm performed well for degradation and reliability problems.

In the course of the study, implementation challenges are noted during tool verification. In addition, few changes are initiated on the linking of the sheets rather than processing its sheet-by-sheet to ease translation of input and output data. The user manual with references is presented electronically to make the tool more user friendly and interactive. The input to the tool was verified to ensure the data were processed as expected. The estimated parameters presented to the tool calculates the number of components degraded/rejected. A couple of the respondents argued that the RUL output representation should be a “straight line” rather than “curvy line – Weibull representation”. The tool verification and validation were demonstrated using observed data presented by the sponsor via WebEx to show the relevance of the tool. In conducting the validation, the observed data were converted to “failure rate” and positioned in the probability of failure distribution.

8.4 Quantitative validation

The quantitative validation evaluates the framework to assess the usefulness, applicability, reliability and verification of the equations. The validation of the equations is a statistical assessment conducted by an expert in the field of statistics/engineering with many years of experience. The objectives of the research were clearly outlined in a walk-through format for easy follow-up of the equations and the rationale. The equations for each section of the framework were introduced and the formulae were clearly stated in chapter 6. Some of the questions relate to the appropriate application of the equations in each phase of the framework development.

The datasets analysed were overhaul inspection states. The overhaul inspection state is when an engine "starts and stops". The overhaul inspection states are considered failure times and the unit is in cycles. The failure times are used in the parameter estimation section to estimate the required values for input to the Weibull model. These values are the η and the β of the Weibull cumulative distribution function. An analysis of the failure data was conducted to get a statistical correlation of the regression data which indicated that p-value is less than 0.05 with a statistical significance in the data.

The research relates to the presence of assembly level failure data, with no trace of component level records. Designers assume life at design stage and need realistic basis of their assumptions. The scope is to optimise a predictive strategy for component degradation and remaining useful life of components within an assembly of the gas turbine engine. The tool aims to provide a predictive modelling of component degradation and remaining useful life prediction of components of a single stage turbine. The objective of the tool is to estimate the failure rate at component level, given only the failure data at the assembly level.

The process of this section of the research has five phases: -

Phase 1 – to statistically analyse the failure time data in cycles. The analysis is conducted using mean, standard deviation and confidence interval.

i. Phase 2 – to conduct a parameter estimation on the failure time data in phase 1 using least square method and maximum likelihood estimation method. The estimated parameters are η and β for the Weibull cumulative distribution function
ii. Phase 3 – to model the number of components expected to fail at any overhaul inspection state over nth overhaul states. The input data used include estimated η and β parameters, failure times over nth overhauls and the total number of components starting before the first overhaul state
iii. Phase 4 – to perform prediction performance metric to assess the close fitness of the observed and estimated rejection rates of the data
iv. Phase 5 – to evaluate the model using optimised parameters in phase 4 to estimate probability of failure and remaining useful life

The validation of the statistics in the Thesis clearly follows the process outline above. The statistics adheres to the data-driven approach developed for the research. The step by step calculations from the data gathering through the parameter estimation process, then the model application with renewal theory application followed by the performance metric and finally the remaining useful life prediction are explicitly represented in the equations in chapter 6. The input data through the processing presented the expected results in chapter 7 in terms of the Weibull distribution in the aspect of maintenance and reliability.

Changes to the framework resulting from the final validation

After the final validation, the effected changes comprise, modification to the framework design to show model selection section in the process information flow. Included electronic user manual about the tool usability. Each section of the software is linked to ensure a smooth transition and communication.

8.5 Summary

The validation and verification were conducted at the initial and final stages of the framework development. The framework validation and verification chapter focuses on internal verification with various stakeholders, a case study with different scenarios relating to gas turbine engines for the aerospace sector and the power sector respectively. A quantitative assessment and validation of the equations were conducted to ensure the suitability of the research and applied correctly in developing the framework.

9 DISCUSSION, CONCLUSIONS AND FUTURE WORK

9.1 Discussion of the research findings

9.1.1 Literature review

The purpose of this research assesses components degradation within a multi-component assembly for predicting the remaining useful life of components. The analysis of the research relates to a reliability problem of complex engineering system and conducted through investigating the following fields “Through-life Engineering Services” considering the Industrial Product-Service Systems (complex engineering systems), “Maintenance Strategies” concerning “Condition-based (Predictive)” and “Prognostics and Health Management” involving “Remaining Useful Life”.

This research in TES centre focuses on predictive maintenance strategy with the application of prognostic tool-set to estimate time to overhaul based on the calculated rejections, thereby predicting the remaining useful life of components with assembly level data. In the through-life engineering services domain, the themes relate to the following scope: critical-enabling maintenance, repair and overhaul functions to align with the operational strategy of an organisation. The efficient application of service knowledge in the TES and advances in technology can lead to the estimation of accurate and precise remaining useful life prediction to enhance decision making. The simulation tools, adaptability procedures, modular maintenance systems, and informed disposal decision can facilitate the prediction of reliable life expectation.

However, information technology for distribution and collaboration; condition monitoring, and prognostics can lessen interruptions and provide availability of assets. The issue of degradation management is a key aspect in TES as well as maintenance of autonomous systems for developing capabilities in a collaborative environment can enhance the life-span of components. The concept of cost engineering provides performance-based service approach and a whole-life cost model, which is applicable to the whole system maintenance and service delivery systems in order to deliver effective business solutions. The modelling and simulation techniques for technological and business uncertainties are capabilities to improve component/product designs.

The aforementioned toolsets and methodologies can support obsolescence management in relation to service network for capability assessment and cost estimation to improve the design. These can deliver significant improvement in quality, reliability, availability and safety whilst yielding feedback to designers and manufacturers.

The research focuses on the Through-life Engineering Services theme of the advanced information technology called diagnostics and prognostics. The diagnostics and prognostics are applicable to predictive maintenance. The predictive maintenance is a classification in the maintenance strategies discussed in chapter 2. The remaining useful life prediction approaches are data-driven models, physical-model, knowledge-based models and hybrid models. In literature, there is an established international standard organisation definition for remaining useful life. A standard classification of the maintenance strategies was used in this Thesis. The researcher identified a pattern in literature for the categorisation of maintenance strategy and remaining useful life. The analysis shows the remaining useful life prediction research is predominantly conducted in the engineering and computer science domains. Components / subsystems / systems for remaining useful life prediction are identified during the literature review. The systematic literature review aided in identifying the trend in the research area and the industry to ascertain the research gap. The modelling of multi-component degradation in an assembly and predicting the remaining useful life using a predictive maintenance strategy is yet to be explored. However, in future, chronological analysis can be considered whilst conducting literature reviews relating to finding root causes and research gaps.

9.1.2 Research methodology

In chapter 3, the research methodology adopted include both quantitative and qualitative research techniques. The qualitative research is usually prone to bias from the participants and the researcher. But bias in qualitative research is a liability that can affect the validity of the research findings. With the introduction of a mitigation concept known as triangulation, the minimisation of the bias guaranteed reasonable outcomes. Semi-structured questionnaires were used at different stages of the interviews to collect data. In the course of this research, triangulation was applied to produce validated and verified results from the data collection by cross-checking the information against literature.

In other words, a methodological triangulation is used in this research to gather information from the responders, interviews with stakeholders, questionnaires to validate and verify the data applied in the framework and the expected outcomes. Internal documents and literature reviews validate the methods and techniques relating to the research to eliminate bias. While systematic bias can occur in a research data collection, it is interesting to know that this bias can happen in validation when an outcome is chosen over another, that is, design, procedural, interviewer and response bias can impact on a research. A weakness of the selection bias is the selection of the data provided by the sponsor for validation because only the sponsor has foreknowledge of the nature of the data.

The research is an industry collaboration to gain contextual and sufficient understanding of the most appropriate methods to engage when collecting data. The researcher engaged more than one method to ensure the weakness of a singular method did not impair the research outcomes. As described in chapter 3, the methods engaged in collecting data from disparate sources for this research include face-to-face interviews, telephone conferences, WebEx meetings, reports and documents from industry provided by the sponsor, workshop/brainstorming, and case study scenarios. The methods agreed with the qualitative information gathering from domain experts. The regular collaboration with industry partners was very effective in the development of the framework as a research product.

In this research, the use of case study enabled the researcher gain an all-inclusive view of the area of interest to identify gaps within industry practice and literature. The case study research technique gave more insights into the understanding of this complex field of interest. The case study created a platform for developing state-of-the-art solutions which would be a contribution to the industry and the academic body of knowledge. In a broad-spectrum, the inability to manage large data may stray this research's aim and justification of the assumptions using quantitative data – large datasets should be prepared systematically for use in a research.

9.1.3 Current practice in industry

In chapter 4, the AS-IS industry practice was discussed. The researcher upon conducting face-to-face interviews relating to the case study captured the current practice. The current practice of component degradation analysis from a maintenance or through-life engineering services perspective. The component degradation analysis revealed the level and nature of the degradation mechanisms found in assets, and how the analysed textual data were captured by domain experts. The domain experts are responsible for recording the events that occurred during maintenance, repair and overhauls. This recording includes the collection of historical data sets for further studies to assess and gain understanding of the behaviour of the system.

The investigation is based on an aerospace gas turbine asset with a focus on the component assembly of the single stage turbine in the hot section, which is usually affected by corrosion and fatigue. The analysis shows the link between product, system, commodity, features and damage mechanism. The data analysis requires the extraction of the terms found in a database. The terms identified and extracted are categorised into product, system, commodity, features and damage mechanism. A terminology recognition tool was used to identify and extract the relevant terms from the report with the aid of both the taxonomy and the ontology. The domain experts' tasks attributed to a conventional maintenance strategy is time consuming, expensive with long hours of manpower and cost. With this conventional strategy, a more rigorous approach is required to accurately estimate components rejections and predict remaining useful life of components in an assembly. Through-life performance prediction provides schedule maintenance support and spare parts management. The analysis supports service delivery improvement for spare parts inventory management, shortens longer hours of spreadsheet data analysis, reduces interruption time, minimises lifecycle costs, but the predictive strategy can be expensive to implement.

9.1.4 Analysis of through-life maintenance cycles

In chapter 5, the analysis is conducted to identify gaps and industry needs relating to multiple overhauls and maintenance cycles, timeline visualisation for prompt access to relevant maintenance information. The relevant maintenance information is the history of events throughout the life of the engine from conception, in service and to disposal. There is a need to visualise the information on a timeline in the aerospace sector from a Through-life engineering service perspective. While literatures show cases of timeline visualisation in the medical field, none is attributed to a maintenance domain. The analysis focuses on through-life maintenance cycles by grouping various events, represented in different colour schemes then display on a timeline. The timeline represents a 2D display method graphing engine identification as rows (multiple engines) and years as columns. The points on the graph are the relevant maintenance information showing different colours depicting various events. The different maintenance events are high level events (taxonomy) required for the visualisation of various maintenance cycles. The 2D display is a single page visualisation serving as a summarisation view of complex information on a concise single screen. It will be beneficial for the large and complex data visualisation. The understanding of the analysis of the events timeline visualisation at system level and investigation at component level have further been developed to calculate for R-Cube, thereby predicting the remaining useful life of the component within an assembly.

9.1.5 A framework of Through-life Performance Prediction Model

In chapter 6, the researcher presented a comprehensive description of the WTPPM as a generic framework. The developed framework resulting from the initial findings in chapters 4 and 5 is then applied to different scenarios of a case study in chapter 7. The framework can be applied to multi-component system (the same component designed and manufactured to operate in the same condition). This framework facilitates extraction of degradation data which helps to estimate the specific number of components expected to be rejected at any inspection time. The WTPPM calculates the rejection at next inspection/overhaul for predictive maintenance. It informs the domain expert of the time when a system should expect maintenance treatment, so that, the spare parts needed are transported just-in-time to reduce downtime. When the outcome in the WTPPM becomes zero, this means the system does not require any form of overhaul maintenance.

The renewal theory is a technique for replacing a population in the prognostics model application. The analysed information is converted and represented in the through-life performance predictive model. The through-life performance predictive model demonstrates the prediction of the number of failed components at each inspection time space thereby predicting the RUL. The WTPPM can be used to predict the expected failure in the next inspection, which can help ascertain when the system needs to undergo detailed maintenance, repair and overhaul. The number of fitted components based on reuse, reject and replace must equal the number of components at the start for validation purpose. The data pre-processing results show the time-to-failure and run-to-failure data are used to determine the accuracy of the data and the model validated by the domain expert. Data mining of the historical data was conducted to capture the specific input data required for the model.

On the maintenance shop floor, the actual number of rejected components is a whole number and not a fraction. The model outcome should show what the users understand is scientifically and mathematically proven. The maintainer is expected to view and use whole numbers and not fractions for better decision making. The prognostics modelling in through-life performance prediction model can serve as a predictive maintenance decision making tool for policy makers to decide whether there should be the continuous replacement of rejected components, and to determine when to stop in order to minimise cost and for safety purposes. The research provides a model for statistical analysis of component degradation of a batch of component to predict the remaining useful life of a component in the assembly. A decision to stop replacement of the components can result from overall cost.

The distribution describes each overhaul inspection time, observed and predicted failure rate. The outcome of the TPM compares the behaviour of the performance based on the observed and predicted failure rates. The GET produces error values relative to the range of η and β parameters. The GET is a back-fitting approach that shows the solved error values for the η and β parameters. The combination of the high η and low β parameters, and low η and high β parameters give different shades of red and green. The region where $\beta<1$ and $\beta>1$ with low η give large error values in red and components in these regions are unfit for use. The GOT is further introduced to optimise the error values with η and β parameters respectively by recalculating selected regions to achieve the realistic parameters.

The optimised η and β parameters generate a closely matched distribution that shows the failure rate. The optimised low η is close to the initially estimated η, while the low β closely follows the initially estimated β. The distributions show the combination of the parameters gives confidence that the optimised η and β parameters are close to the initially estimated η and β parameters indicating the components being investigated are from the same batch. The GOT approach might not select the most low and minimal values for the optimised parameters. The approach selects two numbers from the matrix and returns four parameters, which can be attributed to selection bias for the output. Numerical data of independent variables have been collected and applied in the framework. The numeric data should be presented in the format described in chapter 6 for better accessibility and performance. Introducing text or ordinal data of categorical variable might become an implementation challenge. Uncleaned data can pose quality issues relating to the results and distortion in the framework.

While studies in literature mentioned remaining useful life methods highlighted in chapter 2, the remaining useful life reflects the Weibull principles applied in this framework to deal with reliability issues. The shape shows that the higher the operational use of the components, the less the life remaining and vice versa. The distribution clearly depicts the Weibull distribution because the β parameters affects and drives shape of the graph. The β parameter shows the components are designed and manufactured to the specification and experience failure modes such as low cycle fatigue and corrosion.

The modelling of component degradation and replacement present probability prediction of nth components failing at the next service. The results show the performance of the failure data in the Weibull model and demonstrate the effect of the β parameter. The effect signifies the components had undergone low cycle fatigue, corrosion and erosion; an early lifetime is probable at the beginning to ageing effect on the components with less overhaul, production and misassembly problems are suspected. The β parameter indicates that there is the absence of foreign object damage, human errors in maintenance of the components in the assembly.

A through-life performance prediction model has been developed to assess component reliability. The recursive and iterative process has been applied at the state transition to assess the component failure rate, rejected components, replacement of the failed components and reuse of the remaining components. The through-life performance prediction model would allow optimisation for RUL prediction and minimising of the replacement costs. The input and output parameters were used to demonstrate the prognostics modelling of a through-life performance behaviour of an engine's mechanical component assembly. The research can be used to gain a deeper understanding of how an assembly of a complex system will operate in the real-world through the life cycle.

The through-life model with six overhaul states was increase from an initial four due to the nature of data available. If the available data contain seventh overhaul state, then the model would require an adjustment, however, the model is designed to handle data below six overhaul states. Only the 2-Parameter Weibull function is used due to the reliability problem and no utilisation of a mixture of numeric and text data. The model does not support categorical variable in the statistical predictions. The outputs are numerical data of dependent variables. The overhaul states assess the through-life performance of the component assembly. The spreadsheet model visually illustrates the view of the exact parameters and values for the input and output. The cost analysis conducted determines when to scrap the entire component in an assembly and replace with new parts. In relation to cost and benefit to organisation shows that at 63.2% (probability of failure) is the threshold at which the entire replacement is expected to happen. The outcome shows that it is economically viable to replace all components with new components to ensure reliability, reduce downtime and whole lifecycle cost. However, result of repair analysis show increase in whole lifecycle cost, expensive to maintain and high maintenance schedule with respect to reduced component cost.

In assessing the performance and complexity of the algorithm for the framework, the “Big O notation” was considered. The outcome shows that the speed of processing is less than 30 seconds to return the results in each scenario. The outcome is consistent if the process is repeated with the same data. The outcome is inconsistent if the process is repeated with same data and inclusion of Monte Carlo method. The Monte Carlo method can be applied to assess the sensitivity to simulate the effect of the failure rate.

9.1.6 Case study scenarios

In chapter 7, the results of the initial data for developing the framework and three scenarios of the case study were presented. Run-to-failure and time-to-failure data were used in developing the framework. The first scenario relates to gas turbine NGVs assembly. The results from the framework were compared based on the outcome from the LSM and the MLE statistical techniques. The MLE gave a low β parameter; LSM produced a high β parameter. Where the failure rate equals 1, this leads to a random failure from a maintenance perspective. The Weibull β parameter, which is an indicator of the distribution in the data – the larger the β parameter, the smaller the number of degraded components. The outcomes from the prognostics modelling application show the LSM had a high number of rejections compare to MLE as a result of the β parameter. In literature, the method for estimating parameters in line with best practice has been LSM. The procedures have been presented, researchers and experts alike can apply various data depending on their expected outcomes.

The second scenario of the case study incorporates repaired components into the through-life performance model. This analysis follows the renewal theory from the probabilistic point of view, the renewals are considered component rejections and replacement. The remaining useful life becomes the function of the proportion of the probability of survival and the time. The introduction of repair NGVs in the Weibull through-life performance prediction model supports performance assessment of the population. The performance of the repaired population is examined in order to predict the remaining useful life as a contribution in this research. The comparison of the new and repaired replacement shows a difference in the sixth overhaul state with higher quantity of rejections (see Section 7.2). The high number of rejections resulted from the introduction of the repaired components.

The third scenario of the case study uses failure data collected from a steam turbine which system operating condition is affected by very high temperature. The data are η and β parameters, which is the shape factor and characteristic life of a four-stage turbine (see Section 7.3). The observed rejection data were similar to those used in the first scenario of the case study (see chapter 7) due to the format and pattern. However, the data were further translated to months from hours. The framework was adopted for the steam turbine application after the data conversion (see Section 7.3). There were no data quality issues during the introduction of the data to the model. The study illustrates the developed framework delivers accurate and robust results when applied to various similar applications. Furthermore, time and access to data have had influence on this research.

9.1.7 Verification and Validation

In chapter 8, the WTPPM was applied to the three scenarios. The validation was conducted to determine the statistical model responded as expected regarding the number of component rejections, probability of failure and remaining useful life. The research proves the framework works across the three scenarios and produces realistic RUL results as an approximation for the individual component of an assembly. The verification signifies that the WTPPM performed appropriately as expected by subject matter experts. The questionnaire required domain experts and academics as well as research fellows to compare the behaviour of the WTPPM according to their experiences and rank their responses on a scale of (1: illogical; 2-5: major deficiencies; 6-9: minor deficiencies; 10: logical) and (1: very incomprehensible; 2-5: major deficiencies; 6-9: minor deficiencies; 10: very comprehensible). The validation in chapter 8 examines the usability, logic, quality and overall the consistency of the WTPPM in the application in chapter 7.

The validity of the through-life performance approach for the second and third scenarios shows reasonable consistency as indicated in chapter 7, Sections 7.2 and 7.3. The WTPPM shows some confidence when optimising for realistic solutions because the same results are achieved when rerun with the same data. The validation of the results was performed in relation with the visualisation of the proportion of the probability of failure and remaining useful life of the components in an assembly. A visual comparison of the results show the approach applied conforms to renewal of pristine and repaired components operating in the same environmental conditions. The approach would require constant visual inspection and maintenance. The results achieved from the algorithm provided an acceptable prediction. The application of the algorithms on the through-life performance and reliability problems validate the competence of dealing with the replacement of repaired components of single stage turbine. The assessors certified that the WTPPM is consistent with the through-life process domain. The proposed WTPPM is an approach to remaining useful life prediction of multi-component assembly based on only assembly level data. The outcomes from the validation and verification indicate that the framework is generic and has a wide applicability for only multi-component system.

9.1.8 Implementation issues

Putting the software tool derived from the developed framework to use analyses component degradation and remaining useful life prediction. The implementation of the application should be installed in a computer system with the following configuration:

i. Microsoft Windows operating system – Windows 7 Professional and Windows 10.
ii. Microsoft Office 2010 and higher (Excel)
iii. Hard disk size 120GB
iv. Memory 4GB

The installed application on the computer system is a combination of input, processing and output to perform specific tasks. The input section is an interface where extracted and clean datasets are introduced following specific format. The format accepts only continuous and independent variables data. The data set is a combination of multiple engines, multiple overhauls states and number of observed components, which have degraded at each overhaul states. The output section presents components degradation, probability of failure and remaining useful life prediction. While the component degradation outputs number of components expected to degrade at a point in time, the probability of failure shows the failure rate of the multiple components in the assembly relating to their remaining useful life in the framework. The study conducted supports experts in delivering state-of-the-art approach for statistical analysis of large data sets for decision making to feedback to designers and manufacturers on the status of the components. The findings support investigative and forensic analysis to unveil the root cause of the expected component degradation. The outcome of the findings can be applied to improve future new product development. The new product development, therefore, are tested to further investigate and identify issues which may likely arise when the components are put in service. Based on the analysis, the components should be able to withstand long hours of operation.

The results of this research can provide feedback to designers and manufacturers by identifying the expected component degraded for further root cause analysis, determining the region in the distribution where the performance loss of the components is at 63.2%, the appearance of the observed components on the distribution and the Weibull distribution, which shows the remaining useful life of the proportion of the components through the different renewals. The research provides some benefits already highlighted, but, there are implementation issues that should be considered. These implementation issues include culture change, management and technical. These issues are probably likely to impact the successful implementation of the developed framework.

In the implementation, significant training resource would be required to use the tool. It would be useful to engage end users as stakeholders in the development stage to establish acceptance from onset. It is important to ensure user requirements and interface issues are captured, agreed and reflected in the model design strategy. The development, implementation, data gathering and training overhead costs should be considered. Change culture should be emphasised during validation and testing, so that, end users can react in a positive manner whilst using the tool.

9.2 Research contributions and limitations

9.2.1 Research contributions

This research provides an understanding of modelling through-life performance assessment, thereby estimating the rejections of component in an assembly using a framework. The research has produced a component assembly prediction system which could facilitate proactive maintenance decision making and insights creation for gaining understanding that would inform domain experts. The research provides experts with forensic capability and serves as an enabler to similar future areas of focus.

The contributions are as follows: -

i. Identification of the specific types of data required for the remaining useful life prediction of a component within an assembly
ii. Development of a timeline visualisation approach to analyse multiple maintenance cycles thereby summarising the various events and displaying multiple events on a stack representation for relevant information. The timeline visualisation approach contains an embedded conceptual-logic relating to database design with association ensuring data normalisation
iii. Applied a renewal theory knowledge to the Weibull cumulative distribution function for estimating the failure rate for R-Cube assessment of through-life performance of components. It enhances prediction accuracy and robustness
iv. Developed a framework for through-life performance assessment of components by applying a data-driven prognostic approach in predictive maintenance for predicting the remaining useful life
v. Applied the framework for through-life performance prediction in predictive maintenance to assess the through-life performance of components in Through-life Engineering Services, where failure data at the assembly level are available, but unavailable at the individual component level

9.2.2 Research limitations

The research limitations presented relates to the methodology adopted and the findings. The applied qualitative research, case study and interviews relate to the research limitations of the methodology. The limitations regarding the findings are described based on the research context.

i. The application of qualitative technique can affect reproducibility of results.

ii. The findings in the study from the industry practice cannot be shared with a wider community unlike quantitative analysis.

iii. The Weibull method used as the underlying distribution of the analysis is unsuitable where failure data are unavailable – Weibull is selected due to its popularity in addressing mechanical component failure analysis.

iv. Where there are unknown cycles for components, the Weibull method become inappropriate

v. The framework, the Weibull reliability function and categorical variable data have impact on the results of the analysis

vi. The framework does not accept datasets with more than six overhauls states. The number of time the zoom-in is rendered to optimise for the best Weibull parameters is applied could further be extended if the matrix enumeration occupied a wider area.

vii. The framework would not support data format other than the specified format in the input section

viii. The framework is unsuitable for calculating component degradation and remaining useful life of one individual item.

Furthermore, the framework developed for the aerospace sector (aero engine assemblies) can apply to non-aerospace domain. The Engineering systems identified during the validation stage can utilise the framework, however, certain changes to the parameters are eminent and must relate to degradation and reliability. The named domain use of duration or time are used instead of flight cycles.

9.3 Fulfilling research aim and objectives

In general, this research has satisfied the aim and objectives outlined in chapter 1.

i. The first objective focuses on performing critical analysis and review of literature in relation to prediction methodology. The analysis of historical data and current health degradation information are classified into the predominant failure mechanism. The critical review performed identified the research gaps, classifying existing methods, techniques, methodologies and selecting the data-driven approach for this research.

ii. The second objective relates to the investigation of the current (AS-IS) practice to understand the level and nature of degradation available on the aero component. This objective identified the specific format for presenting the data for input and numerical data of independent and dependent variables for continuous data.

iii. The third objective gives insight into the design of the model for through-life performance of component degradation based on the analysis of maintenance cycles of historical events on multiple engines and multiple overhaul states. This objective was achieved by designing a novel framework for the entire research showing how collected data from multiple sources are applied and analysed for degradation analysis. The analysis also considers multiple engines and overhauls using timeline visualisation and conceptual database design approaches. The outcomes met the expected requirements.

iv. The fourth objective aims to develop a framework to assess through-life performance assumptions taken at the design stage, thereby predicting the remaining useful life of the mechanical components in an assembly. The process involves using a data-driven approach in estimating parameters of the historical datasets, prognostics modelling application of through-life performance prediction, performance metric to calculate the error values to back-fit the initial estimated parameters. The Weibull distribution is used to determine the probability of failure of a component and further predicts the remaining useful life of a component in an assembly. This objective was achieved by assessing through-life performance, where at the design stage, the data introduced to the framework is used to determine the behaviour of the component performance to evaluate the nature and strength of the component under stated conditions. The developed framework provides significance outcome from modelling of multi-component.

v. The fifth objective is validating the developed framework using expert judgement and industry case study scenarios. The results of the framework were analysed from the perspective of the observed data and identifying the types of data required. The outcomes from the parameter estimation methods were presented in chapter 6 for the single, repair application and multiple stages scenarios. The validation and verification as well as the case study results shows consistent value and the distribution depicts several renewals as confirmed by experts during the validation stage.

9.4 Recommendations for future research

The WTPPM predictive modelling approach is designed for predictive maintenance strategy to address conventional maintenance issues. The predictive maintenance strategy uses a data-driven prognostic approach. The predictive modelling approach incorporates the statistical technique and the reliability Weibull method for further analysis and decision making. The WTPPM consists of six overhaul states to demonstrate through-life performance procedures. The overhaul states can be increased depending on the available historical data of the engine overhauls (initially the state were four, then five and increased to six). The WTPPM focuses on a single stage component assembly. The process of renewal is continuous until a policymaker decides to end the process based on cost. The logic in stopping the renewal process relates to the engine health maintenance and cost of replacing the components and threshold based on 63.2% of the average design life of the assembly.

This research is a useful calibration for future research focusing on: -

i. Incorporating multiple repaired components in the assembly and extending the through-life performance prediction model to accommodate more overhaul states

ii. Applying and comparing other relevant statistical models in assessing through-life performance considering the input data format
iii. Data indicating a variety of life of the gas turbine components should be considered to examine the behaviour of the engine using the developed model
iv. The developed model can serve as a trigger for further investigation into a trade-off between maintenance and availability of asset management
v. The advent of Internet of Things (IoT), massive data would be available and the data could be analysed using advanced technologies. These technologies can interact with sensors, online and databases of structured and unstructured data from disparate sources for meaningful insights. The flow of data can allow manufacturers to identify problems as fast as they happen with the availability of streamed sensor data from equipment at a low cost. The results from the analysed data can help to proffer repair of equipment proactively with guided maintenance.

This data-driven predictive strategy can keep equipment running with less risk of incidents and reduces maintenance costs.

9.5 Conclusions

In this Thesis, the aim and objectives outlined in chapter 3 have been achieved. The through-life performance prediction framework for the assessment of component degradation in an assembly and calculating R-Cube, scrapping of component in an assembly based on a cost estimate of the components and predict remaining useful life has been developed. The research focuses on a single stage component assembly in a three shaft spool gas turbine, adding repaired components population to the model and assessment of a four-stage steam turbine engine.

This Thesis presented a review of the prognostics methodologies, techniques and methods applicable to predictive maintenance strategy. The strategy supports reliability, availability, maintainability and safety of Industrial Product-Service System relating to TES. The research gaps were identified during the current industry practice assessment and literature review, which led to the study of this research. The analysis in the current practice shows that the start and stop (time to failure) times were not applicable to the generation of the master index representation. The run-to-failure data were considered and are represented in the component degradation representation. In the through-life performance prediction model, the time-to-failure and run-to-failure data are crucial for the framework development.

In designing the framework, data quality relating to data management strategy is considered to handle data and to ensure the data is assessed, noise-free and cleansed. Data management strategy leverages and manages the data for strategic advantage for data quality to enhance reproducibility of the results and repeatability of the analysis of a research. It improves maintainability of the data to avoid inconsistency such as noise and to ensure better performance of results. The improvement on the data can enhance prediction results. Results from different assemblies can be combined and compared to ascertain the performance of the components and engines with regards to the operating environment and for further investigative purposes.

Within the framework, the procedures showed connected associations of relevant input to the processing and resulting output. The approach described each segment of the framework following the standard norm “input-process-output”. A data-driven approach uses LSM and MLE statistical techniques to estimate the two parameters of the Weibull distribution from the historical data. The renewal theory relates to the replacement for the rejections and the components to be reused. The process is iterative and recursive because of the re-application of the same equation at each population section for every overhaul state. The comparison of the predicted values and the observed values are calculated using mean absolute error equation. The scrapping of the components within an assembly is calculated if the cost of components at any one overhaul state is higher than the average cost of replacing the entire component assembly. The Weibull function is applied to produce probability of failure distribution. The probability of failure is converted to remaining useful life prediction. The representation of the remaining useful life as a Weibull distribution is based on components renewals.

The results from the WTTPM showed different rejections at each overhaul based on the MLE and LSM estimation techniques with same historical data. The overall total numbers of rejections on all six overhaul states were different. The η and β parameters played a significant role in the outcome of the predictive model. The predictive model can be used to forecast the R-Cube and determine the next planned visit of a system to an MRO shop floor.

In industry, the entire NGV components in the assembly of a single stage turbine can be scrapped and replaced with either new or repaired components. The predictive model shows a typical operation of the engine for predictive maintenance from an industry perspective. However, in academia, there is a need to observe or monitor the behaviour of a mixture of both repaired and new components. It is obvious from the results that this complexity in the system can lead to a less efficient system operation when compared with only new replacement. The replacement intervals can increase, increase in system maintenance and increase in whole lifecycle costs. An assumption stipulates that the components renewals with new components follows the TPM phase in the WTPPM. The renewal of components in the assembly with repaired components follows the same pattern but the outcome varies.

The through-life predictive model describes the number of components expected to degrade at each inspection time and the cumulative failure distribution. The through-life predictive model compares the behaviour of the through-life performance of components in the assembly. The through-life performance approach can help researchers and practitioners make informed choices of when to replace the entire components in the assembly instead of continually replacing components expected to fail at each overhaul inspection state. The framework applies to different applications such as railway, oil and gas, industrial machinery and marine because they contain concurrently working components. The modelling application depicts the way a real-world system could operate in its life cycle. The human operating factor in terms of the technique used and the maintenance strategy might impact on the machine. The framework uses a discrete model application technique to help understand how a component in an assembly degrades over time. This research in its own right has a scope of remaining useful life of multi-component of an assembly by using only assembly level data, which describes the reason for scrap at each overhaul state.

REFERENCES

Abernethy, R. (2006) *The new Weibull handbook: Reliability and statistical analysis for predicting life, safety, supportability, risk, cost and warranty claims*. 4th edn, *Barringer & Associates*. 4th edn. North Palm Beach, FL.

Addepalli, S. and Tinsley, L. (2015) 'Active Thermography in Through-Life Engineering', in *Through-life Engineering Services*. Springer, pp. 117–127.

Ahmadzadeh, F. and Lundberg, J. (2014) 'Remaining useful life estimation: Review', *International Journal of System Assurance Engineering and Management, 5(4), pp.461-474.* doi: 10.1007/s13198-013-0195-0.

Allen, R. (1995) 'Interactive Timelines as Information System Interfaces.', in *In Symposium on Digital Libraries*. Tsukuba, Japan, pp. 175–180. Available at: http://boballen.info/RBA/PAPERS/TL/isdl.pdf.

Alonso, D.L., Rose, A., Plaisant, C. and Norman, K.L., (1998) 'Viewing personal history records: A comparison of tabular format and graphical presentation using LifeLines', *Behaviour & Information Technology*. Taylor & Francis, 17(5), pp. 249–262.

Ameen, H. A., Hassan, K. S. and Mubarak, E. M. M. (2011) 'Effect of loads, sliding speeds and times on the wear rate for different materials', *American journal of scientific and industrial research*, 2, pp. 99–106.

An, D., Choi, J.-H. and Kim, N. H. (2013) 'Prognostics 101: A tutorial for particle filter-based prognostics algorithm using Matlab', *Reliability Engineering & System Safety*, 115(0), pp. 161–169.

Avison, D. and Fitzgerald, G. (2006) *Information systems development: methodologies, techniques and tools*. 4th edn. McGraw Hill.

Bagnall, S. M., Shaw, D. L. and Mason-Flucke, J. C. (2000) 'Implications of Power by the Hour on Turbine Blade Lifing', in *Design for Low Cost Operation and Support.* Ottawa, Canada: Rolls-Royce Ltd Bristol (United Kingdom).

Bagul, Y. G., Zeid, I. and Kamarthi, S. V (2008) ‘Overview of Remaining Useful Life Methodologies’, in *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. New York, USA: ASME, pp. 1391–1400. doi: 10.1115/DETC2008-49938.

Baines, T., Lightfoot, H., Peppard, J., Johnson, M., Tiwari, A., Shehab, E. and Swink, M., (2009) ‘Towards an operations strategy for product-centric servitization’, *International Journal of Operations and Production Management*, 29(5), pp. 494–519. Available at: http://publications.aston.ac.uk/16074/.

Balaban, E., Saxena, A., Narasimhan, S., Roychoudhury, I., Koopmans, M., Ott, C. and Goebel, K., (2015) ‘Prognostic health-management system development for electromechanical actuators’, *Journal of Aerospace Information Systems*, 12(3), pp. 329–344. doi: 10.2514/1.I010171.

Barringer, H. P. and Kotlyar, M. (1996) ‘Reliability of critical turbo/compressor equipment’, in *Fifth International Conference on Process Plant Reliability.* Marriot Houston Westside, Houston, Texas.

Barringer & Associates (2010) *Can You Use Weibull Analysis On Repairable Items?* Available at: http://www.barringer1.com/jan10prb_files/jan10prb.pdf [Accessed: 27 January 2018]

Bechhoefer, E., Bernhard, A. and He, D. (2008) ‘Use of Paris Law for Prediction of Component Remaining Life’, in *Aerospace Conference, 2008 IEEE*, pp. 1–9. Big Sky, MT, USA

Bechhoefer, E., Schlanbusch, R. and Waag, T. I. (2015) ‘Estimating Remaining Useful Life Using Actuarial Methods’, in *Annual Conference of the Prognostics and Health Management Society*, p. 8.

Bernard, H. R. and Bernard, H. R. (2012) *Social research methods: Qualitative and quantitative approaches*. Sage.

Biagetti, T. and Sciubba, E. (2004) ‘Automatic diagnostics and prognostics of energy conversion processes via knowledge-based systems’, in *Energy*, pp. 2553–2572. doi: 10.1016/j.energy.2004.03.031.

Bian, L. and Gebraeel, N. (2014) ‘Stochastic modeling and real-time prognostics for multi-component systems with degradation rate interactions’, *IIE Transactions*. Taylor & Francis, 46(5), pp. 470–482.

Biederman, I., Glass, A. L. and Stacy, E. W. (1973) ‘Searching for objects in real-world scenes.’, *Journal of Experimental Psychology*. American Psychological Association, 97(1), p. 22.

Bolander, N.E.E.H.N., Qiu, H., Eklund, N., Hindle, E. and Rosenfeld, T., 2009, September. Physics-based remaining useful life prediction for aircraft engine bearing prognosis. In Annual conference of the prognostics and health management society.

Borges, V. (2015) *Opportunistic Maintenance*. Available at: http://blogs.dnvgl.com/software/2015/08/opportunistic-maintenance/. [Accessed: 03 February, 2016]

Boritz, J. E. (2005) ‘IS practitioners’ views on core concepts of information integrity’, *International Journal of Accounting Information Systems*, 6(4), pp. 260–279. doi: http://dx.doi.org/10.1016/j.accinf.2005.07.001.

Boyce, M. P. (2006) *Gas Turbine Engineering Handbook*, *Gas Turbine Engineering Handbook*. doi: 10.1016/B978-075067846-9/50008-0.

Boyd-Lee, A. D., Harrison, G. F. and Henderson, M. B. (2001) ‘Evaluation of standard life assessment procedures and life extension methodologies for fracture-critical components’, *International Journal of Fatigue*, 23, pp. 11–19.

Breitman, K. and Leite, J. (2002) ‘Managing user stories’, in *International Workshop on Time-Constrained Requirements Engineering*, p. 168.

Brock, A., Brulé, E., Oriola, B., Truillet, P., Gentes, A. and Jouffrais, C., (2016) ‘A Method Story about Brainstorming with Visually Impaired People for Designing an Accessible Route Calculation System’, in *ACM CHI 2016-chi4good*.

Brotherton, T., Jahns, G., Jacobs, J. and Wroblewski, D., 2000. Prognosis of faults in gas turbine engines. In Aerospace Conference Proceedings, 2000 IEEE (Vol. 6, pp. 163-171). doi: 10.1109/AERO.2000.877892.

Brown, P. and Sondalini, M. (2016) *The Evolution of Maintenance Practices*, Lifetime Reliability Solutions. Available at: http://www.lifetime-reliability.com/free-articles/maintenance-management/Evolution_of_Maintenance_Practices.pdf. (Accessed: 27 January, 2018)

Bryman, A. (2016) *Social research methods*. Oxford university press. United Kingdom. 5th Edition. ISBN: 978-0-19-968945-3

Camci, F. and Chinnam, R. B. (2010) 'Health-state estimation and prognostics in machining processes', *Automation Science and Engineering, IEEE Transactions on*. IEEE, 7(3), pp. 581–597.

Chen, C., Vachtsevanos, G. and Orchard, M. E. (2012) 'Machine remaining useful life prediction: An integrated adaptive neuro-fuzzy and high-order particle filtering approach', *Mechanical Systems and Signal Processing*, 28(0), pp. 597–607.

Cheng, S. and Pecht, M. (2007) 'Multivariate state estimation technique for remaining useful life prediction of electronic products', in *AAAI Fall Symposium Artificial Intelligence. Prognostics, Arlington, VA.*, pp. 26–32.

Cheng, Y. and Johansen, J. (2016) 'The servitisation of manufacturing function: empirical case studies', *International Journal of Manufacturing Technology and Management*. Inderscience Publishers (IEL), 30(6), pp. 369–391. doi: https://doi.org/10.1504/IJMTM.2016.081587.

Chiachío, J., Chiachío, M., Sankararaman, S., Saxena, A. and Goebel, K., (2015) 'Condition-based prediction of time-dependent reliability in composites', *Reliability Engineering and System Safety*, 142, pp. 134–147. doi: 10.1016/j.ress.2015.04.018.

Chinnam, R. B. and Baruah, P. (2003) 'Autonomous diagnostics and prognostics through competitive learning driven HMM-based clustering', in *Proceedings of the International Joint Conference on Neural Networks, 2003.* doi: 10.1109/IJCNN.2003.1223951.

Chopra, A., Sachdeva, A. and Bhardwaj, A. (2016) 'Productivity enhancement using reliability centred maintenance in process industry', *International Journal of Industrial and Systems Engineering*. Inderscience Publishers, 23(2), pp.155–165.

Clough, P. and Nutbrown, C. (2012) *A student's guide to methodology*. Sage.

Cohn, M. (2004) *User stories applied: For agile software development*. Addison-Wesley Professional. Pearson Education. ISBN: 0-321-20568-5

Connolly, T. M. and Begg, C. E. (2005) *Database systems: a practical approach to design, implementation, and management*. Pearson Education.

Coppe, A., Pais, M.J., Haftka, R.T. and Kim, N.H., (2012) 'Using a Simple Crack Growth Model in Predicting Remaining Useful Life', *Journal of Aircraft*, 49(6), pp. 1965–1973.

Cox, D. R. (1962) *Renewal theory*. Methuen London.

Crespi, V., Galstyan, A. and Lerman, K. (2008) 'Top-down vs bottom-up methodologies in multi-agent system design', *Autonomous Robots*, 24(3), pp. 303–313. doi: 10.1007/s10514-007-9080-5.

Dadzie, A.S., Bhagdev, R., Chakravarthy, A., Chapman, S., Iria, J., Lanfranchi, V., Magalhães, J., Petrelli, D. and Ciravegna, F., (2009) 'Applying semantic web technologies to knowledge sharing in aerospace engineering', *Journal of Intelligent Manufacturing*, 20(5), pp. 611–623. doi: 10.1007/s10845-008-0141-1.

Daigle, M. and Goebel, K. (2010) 'Improving computational efficiency of prediction in model-based prognostics using the unscented transform', *Annual Conference of the Prognostics and Health Management Society*. Portland, Oregon

Van Damme, Jacky; Stolk-Oele, M. (2015) *Jet Engine Maintenance: This Is How We Do It.*, *KLM*. Available at: https://blog.klm.com/jet-engine-maintenance-this-is-how-we-do-it/ (Accessed: 25 August 2017).

Dong, M. and Yang, Z. (2008) 'Dynamic Bayesian network based prognosis in machining processes', *Journal of Shanghai Jiaotong University (Science)*. Shanghai Jiaotong University Press, 13(3), pp. 318–322. doi: 10.1007/s12204-008-0318-y.

Doob, J. L. (1948) 'Renewal theory from the point of view of the theory of probability', *Transactions of the American mathematical society*, 3(63), p. 422–438.

Dunglinson, C. and Lambert, H. (1983) 'Interval reliability for initiating and enabling events', *IEEE Transactions on Reliability*. IEEE, 32(2), pp. 150–163.

Eker, O.F., Camci, F., Guclu, A., Yilboga, H., Sevkli, M. and Baskan, S., (2011) 'A simple state-based prognostic model for railway turnout systems', *Industrial Electronics, IEEE Transactions on*. IEEE, 58(5), pp. 1718–1726.

Engel, S.J., Gilmartin, B.J., Bongort, K. and Hess, A., (2000) 'Prognostics, the real issues involved with predicting life remaining', *Proceedings* of *IEEE Aerospace Conference.*. doi: 10.1109/AERO.2000.877920.

Fan, J. B., Yung, K.-C. and Pecht, M., (2014) 'Predicting long-term lumen maintenance life of LED light sources using a particle filter-based prognostic approach', *Expert Systems with Applications*, 42(5), pp. 2411–2420. doi: 10.1016/j.eswa.2014.10.021.

Farnsworth, M., Bell, C., Khan, S. and Tomiyama, T., (2015) 'Autonomous Maintenance for Through-Life Engineering', in *Through-life Engineering Services*. Springer, pp. 395–419.

Fernandes, P., Roy, R., Mehnen, J. and Harrison, A., (2011) 'An Overview on Degradation Modelling for Service Cost Estimation. in Hesselbach J, Herrmann C, (Eds.) Functional Thinking for Value Creation', in *Proceedings of 3rd CIRP International Conference on Industrial Product Service Systems*, pp. 309–314.

Ferreiro, S., Arnaiz, A., Sierra, B. and Irigoien, I., (2012) 'Application of Bayesian networks in prognostics for a new Integrated Vehicle Health Management concept', *Expert Systems with Applications*, 39(7), pp. 6402–6418.

Field, A. (2009) *Discovering statistics using SPSS*. Sage publications. 3rd Edition. ISBN: 978-1-84787-906-6

Gasperin, M., Juricic, D. and Boskoski, P. (2012) ‘Prediction of the remaining useful life: An integrated framework for model estimation and failure prognostics’, in *Prognostics and Health Management (PHM), 2012 IEEE Conference on*, pp. 1–8.

Gåsvik, K.J., Robbersmyr, K.G., Vadseth, T. and Karimi, H.R., (2014) ‘Deformation measurement of circular steel plates using projected fringes’, *The International Journal of Advanced Manufacturing Technology*, 70(1), pp. 321–326.

Gerson, K. and Horowitz, R. (2002) ‘Observation and interviewing: Options and choices in qualitative research’, *Qualitative research in action*, pp. 199–224.

Ghodrati, B., Ahmadzadeh, F. and Kumar, U. (2012) ‘Mean Residual Life Estimation Considering Operating Environment’, in *International Conference on Quality, Reliability, Infocom Technology and Industrial Technology Management ICQRITTM, 26-28 Nov 2012, Newdelhi, India*.

Giourntas, L.G., Brownlie, F., Karafyllias, G., Hodgkiess, T. and Galloway, A., (2016) ‘Effect of corrosion on abrasive wear in a range of materials’, in *23rd International Conference on Fluid Sealing 2016*, pp. 171–182.

Global Harmonization Task Force (2004) *Quality Management Systems - Process Validation Guidance*, *GHTF/SG3/N99-10*.

Gobbato, M., Conte, J.P., Kosmatka, J.B. and Farrar, C.R., (2012) ‘A reliability-based framework for fatigue damage prognosis of composite aircraft structures’, *Probabilistic Engineering Mechanics*, 29(0), pp. 176–188.

Goode, K. B., Moore, J. and Roylance, B. J. (2000) ‘Plant Machinery Working Life Prediction Method Utilizing Reliability and Condition-monitoring Data’.

Gorjian, N., Ma, L., Mittinty, M., Yarlagadda, P. and Sun, Y., (2009) ‘A review on degradation models in reliability analysis’, in *Proceedings of the 4th World Congress on Engineering Asset Management*.

Gruber, T. R. and Gruber, T. R. (1993) ‘A translation approach to portable ontology specifications’, *Knowledge Acquisition*, 5(2), pp. 199–220. doi: 10.1.1.101.7493.

Gummesson, E. (2000) *Qualitative methods in management research*. Sage.

Hafsa, W., Chebel-Morello, B., Varnier, C., Medjaher, K. and Zerhouni, N., (2015) ‘Prognostics of health status of multi-component systems with degradation interactions’, in *Industrial Engineering and Systems Management (IESM), 2015 International Conference on*, pp. 870–875.

Harrison, A. (2002) ‘Case study research’, *Essential skills for management research*. Sage London, pp. 158–180.

Hart, C. (2001) *Doing a literature search: a comprehensive guide for the social sciences*. Sage.

Hoddenbach, J. (2014) *Aircraft Engine Overhaul*, *Disciples Flight*. Available at: https://disciplesofflight.com/aircraft-engine-overhaul/ (Accessed: 25 August 2017).

Hong, S. and Zhou, Z. (2012) ‘Remaining useful life prognosis of bearing based on Gauss process regression’, in *Biomedical Engineering and Informatics (BMEI), 2012 5th International Conference on*, pp. 1575–1579.

Imran, M., Mativenga, P.T., Gholinia, A. and Withers, P.J., (2014) ‘Comparison of tool wear mechanisms and surface integrity for dry and wet micro-drilling of nickel-base superalloys’, *International Journal of Machine Tools and Manufacture*. Elsevier, 76, pp. 49–60.

International Standard Organisation (2015) *Condition monitoring and diagnostics of machines — Prognostics — Part 1: General guidelines*, *International Standard Organisation ISO 13381-1:2015(en)*. Available at: https://www.iso.org/obp/ui/#iso:std:iso:13381:-1:ed-2:v1:en (Accessed: 25 January 2018).

International Standard Organisation ISO/IEC/IEEE 24765:2010(E) (2010) *Systems and software engineering - Vocabulary*. Available at: https://www.iso.org/obp/ui/#iso:std:iso-iec-ieee:24765:ed-1:v1:en. (Accessed: 27 January, 2018)

Jardine, A. K. S., Lin, D. and Banjevic, D. (2006) ‘A review on machinery diagnostics and prognostics implementing condition-based maintenance’, *Mechanical Systems and Signal Processing*, pp. 1483–1510. doi: 10.1016/j.ymssp.2005.09.012.

Javed, K., Gouriveau, R., Zerhouni, N. and Hissel, D., (2015) ‘Improving accuracy of long-term prognostics of PEMFC stack to estimate remaining useful life’, in *Proceedings of the IEEE International Conference on Industrial Technology*, pp. 1047–1052. doi: 10.1109/ICIT.2015.7125235.

Johnson, G. R. and Cook, W. H. (1985) ‘Fracture characteristics of three metals subjected to various strains, strain rates, temperatures and pressures’, *Engineering Fracture Mechanics*, 21(1), pp. 31–48.

Karam, G. M. (1994) ‘Visualization using timelines’, in *Proceedings of the 1994 ACM SIGSOFT international symposium on Software testing and analysis*, pp. 125–137.

Keller, A. Z., Kamath, A. R. R. and Perera, U. D. (1982) ‘Reliability analysis of CNC machine tools’, *Reliability Engineering*, 3(6), pp. 449–473. doi: http://dx.doi.org/10.1016/0143-8174(82)90036-1.

Kim, H.E., Tan, A.C., Mathew, J. and Choi, B.K., (2012) ‘Bearing fault prognosis based on health state probability estimation’, *Expert Systems with Applications*. Elsevier, 39(5), pp. 5200–5213.

King, C. J. (1981) ‘Sequence of Events Recording Systems’, *IEEE Transactions on Power Apparatus and Systems*. IEEE, (9), pp. 4250–4254.

Kirk, J. and Miller, M. L. (1986) *Reliability and validity in qualitative research*. Sage.

Kirschen, D. G. and Laby, D. M. (2006) *Sports Vision Testing: An Innovative Approach To Increase Revenues*, *Optometric Management*. Available at: https://www.optometricmanagement.com/issues/2006/may-2006/sports-vision-testing-an-innovative-approach-to-i, (Accessed: 28 January, 2018)

Kiser, B., (2016) 'CIRCULAR ECONOMY Getting the circulation going', *Nature*. Macmillan Publishers Ltd., London, England, 531(7595), pp. 443–444.

Kocherlakota, S. M. and Healey, C. G. (2005) *Summarization Techniques for Visualization of Large, Multidimensional Datasets*.

Kulkarni, C.S., Gorospe, G., Daigle, M.J. and Goebel, K., (2015) 'A testbed for implementing prognostic methodologies on cryogenic propellant loading systems', *IEEE Instrumentation and Measurement Magazine*, 18(4), pp. 5–15. doi: 10.1109/MIM.2015.7155766.

Kumar, S. and Mahto, D. (2013) 'Recent Trends In Industrial And Other Engineering Applications Of Non Destructive Testing: A Review', *International Journal of Scientific & Engineering Research*, 40(4), pp. 265–275. doi: 10.1016/S1365-1609(03)00027-3.

Kumar, V., Furuta, R. and Allen, R. B. (1998) 'Metadata visualization for digital libraries: interactive timeline editing and review', in *Proceedings of the third ACM conference on Digital libraries*, pp. 126–133.

Lapan, S. D., Quartaroli, M. T. and Riemer, F. J. (2011) *Qualitative research: An introduction to methods and designs*. John Wiley & Sons.

Lee, D. and Pan, R. (2017) 'Predictive maintenance of complex system with multi-level reliability structure', *International Journal of Production Research*. Taylor & Francis, 55(16), pp. 4785–4801.

Lesieutre, G. A., Fang, L. and Lee, U. (1997) 'Hierarchical Failure Simulation for Machinery Prognostics', in *Biennial conference; 12th, Reliability, stress analysis and failure prevention: A critical link; 1997; Virginia Beach; VA*.

Li, C. J. and Lee, H. (2005) ‘Gear fatigue crack prognosis using embedded model, gear dynamic model and fracture mechanics’, *Mechanical Systems and Signal Processing*, 19(4), pp. 836–846. doi: 10.1016/j.ymssp.2004.06.007.

Liao, L. and Kottig, F. (2014) ‘Review of Hybrid Prognostics Approaches for Remaining Useful Life Prediction of Engineered Systems, and an Application to Battery Life Prediction’, *Reliability, IEEE Transactions on*, 63(1), pp. 191–207.

Liao, W., Wang, Y. and Pan, E. (2012) ‘Single-machine-based predictive maintenance model considering intelligent machinery prognostics’, *The International Journal of Advanced Manufacturing Technology*. Springer, 63(1–4), pp. 51–63.

Liu, J., Djurdjanovic, D., Ni, J., Casoetto, N. and Lee, J., (2007) ‘Similarity based method for manufacturing process performance prediction and diagnosis’, *Computers in Industry*, 58(6), pp. 558–566.

Liu, J., Wang, W., Ma, F., Yang, Y.B. and Yang, C.S., (2012) ‘A data-model-fusion prognostic framework for dynamic system state forecasting’, *Engineering Applications of Artificial Intelligence*, 25(4), pp. 814–823.

Louen, C., Ding, S. X. and Kandler, C. (2013) ‘A new framework for remaining useful life estimation using Support Vector Machine classifier’, in *Control and Fault-Tolerant Systems (SysTol), 2013 Conference on*, pp. 228–233. doi: 10.1109/SysTol.2013.6693833.

Majidian, A. and Saidi, M. H. (2007) ‘Comparison of Fuzzy logic and Neural Network in life prediction of boiler tubes’, *International Journal of Fatigue*, 29(3), pp. 489–498. doi: 10.1016/j.ijfatigue.2006.05.001.

Makkonen, M. (2009) ‘Predicting the total fatigue life in metals’, *International Journal of Fatigue*, 31(7), pp. 1163–1175.

Malinowski, S., Chebel-Morello, B. and Zerhouni, N. (2015) ‘Remaining useful life estimation based on discriminating shapelet extraction’, *Reliability Engineering and System Safety*, 142, pp. 279–288. doi: 10.1016/j.ress.2015.05.012.

Marasco, A. (2008) ‘Third-party logistics: A literature review’, *International Journal of production economics*. Elsevier, 113(1), pp. 127–147.

Maria, A., 1997, December. Introduction to modeling and simulation. In Proceedings of the 29th conference on Winter simulation (pp. 7-13). IEEE Computer Society.

Marshall, C. and Rossman, G. B. (2016) *Designing qualitative research*. Sage publications. 6th Edition. ISBN: 9781452271002

Mazhar, M. I., Kara, S. and Kaebernick, H. (2007) ‘Remaining life estimation of used components in consumer products: Life cycle data analysis by Weibull and artificial neural networks’, *Journal of Operations Management*, 25(6), pp. 1184–1193. doi: 10.1016/j.jom.2007.01.021.

Medjaher, K., Tobon-Mejia, D. A. and Zerhouni, N. (2012) ‘Remaining Useful Life Estimation of Critical Components With Application to Bearings’, *Reliability, IEEE Transactions on*, 61(2), pp. 292–302.

Metropolis, N. and Ulam, S. (1949) ‘The monte carlo method’, *Journal of the American statistical association*. Taylor & Francis Group, 44(247), pp. 335–341.

Microsoft (2008) *RND Function*, *Microsoft*. Available at: https://msdn.microsoft.com/en-us/vba/language-reference-vba/articles/rnd-function, (Accessed: 27 January, 2018)

Morant, A., Gustafson, A. and Söderholm, P. (2016) ‘Safety and availability evaluation of railway signalling systems’, in *Current Trends in Reliability, Availability, Maintainability and Safety*. Springer, pp. 303–316.

NDT Resource Center (2014) *Visual Acuity of the Human Eye*. Available at: https://www.nde-ed.org/EducationResources/CommunityCollege/PenetrantTest/Introduction/visualacuity.htm, (Accessed: 27 January, 2018)

Nguyen, K.-A., Do, P. and Grall, A. (2015) ‘Multi-level predictive maintenance for multi-component systems’, *Reliability Engineering & System Safety*. Elsevier, 144, pp. 83–94.

Norman, E. D. (2013) *Mechanical Behavior of Materials*. 4th Edition. England: Pearson.

Okoh, C., Roy, R., Mehnen, J., Redding, L.E. and Harrison, A., (2014) 'Development of an Ontology for Aerospace Engine Components Degradation in Service', in *6th IC3K Conference on Knowledge Engineering and Ontology Development*. pp. 108-119. Rome, Italy. doi: 10.5220/0005090201080119

Okoh, C., Roy, R., Mehnen, J. and Redding, L., (2014) 'Overview of Remaining Useful Life prediction techniques in Through-life Engineering Services', in *Procedia CIRP*, pp. 158–163. doi: 10.1016/j.procir.2014.02.006.

Oppenheimer, C. H. and Loparo, K. A. (2002) 'Physically based diagnosis and prognosis of cracked rotor shafts', *Proc. SPIE*, pp. 122–132. doi: 10.1117/12.475502.

Pearse, N. (2011) 'Deciding on the scale granularity of response categories of Likert type scales: The case of a 21-point scale', *The Electronic Journal of Business Research Methods*, 9(2), pp. 159–171.

Pecht, M. and Jaai, R. (2010) 'A prognostics and health management roadmap for information and electronics-rich systems', *Microelectronics Reliability*, 50(3), pp. 317–323. doi: 10.1016/j.microrel.2010.01.006.

Peng, T., Liu, Y., Saxena, A. and Goebel, K., (2015) 'In-situ fatigue life prognosis for composite laminates based on stiffness degradation', *Composite Structures*, 132, pp. 155–165. doi: 10.1016/j.compstruct.2015.05.006.

Peng, Y., Dong, M. and Zuo, M. J. (2010) 'Current status of machine prognostics in condition-based maintenance: A review', *International Journal of Advanced Manufacturing Technology*, 50(1–4), pp. 297–313. doi: 10.1007/s00170-009-2482-0.

Pham, H.T., Yang, B.S. and Nguyen, T.T., (2012) 'Machine performance degradation assessment and remaining useful life prediction using proportional hazard model and support vector machine', *Mechanical Systems and Signal Processing*, 32, pp. 320–330.

Pintelon, L. M. and Gelders, L. F. (1992) 'Maintenance management decision making', *European journal of operational research*. Elsevier, 58(3), pp. 301–317.

Plaisant, C., Milash, B., Rose, A., Widoff, S. and Shneiderman, B., (1996) 'LifeLines: visualizing personal histories', in *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 221–227.

Probst, L., Frideres, L., Cambier, B., Ankeraa, J. and Lidé, S., (2016) *Servitization Service and predictive maintenance contracts*, *Business Innovation Observatory*. doi: Contract No 190/PP/ENT/CIP/12/C/N03C01.

Prozhega, M.V., Tatus, N.A., Samsonov, S.V., Kolyuzhni, O.Y. and Smirnov, N.N., (2014) 'Experimental study of erosion-corrosion wear of materials: A review', *Journal of Friction and Wear*. Springer, 35(2), pp. 155–160.

Przytula, K. W. and Choi, A. (2007) 'Reasoning framework for diagnosis and prognosis', in *IEEE Aerospace Conference Proceedings*. doi: 10.1109/AERO.2007.352872.

Rahman, Hafeezur; Sugat, P. Santosh; Ganesan, S. (2015) 'Evolution of an Overhaul Methodology for a High Speed Combat Aircraft Gearbox', *Journal of Mechanical and Civil Engineering*, 12(2), pp. 18–27.

Rausand, M. and Høyland, A. (2004) *System reliability theory: models, statistical methods, and applications*. John Wiley & Sons.

Redding, L., Shaw, A., Roy, R. and Bardo, B., (2015) 'Future Challenges and Opportunities in Through-Life Engineering Services and Concluding Remarks', in *Through-life Engineering Services*. Springer, pp. 439–452.

Ren, G. and Gregory, M. (2007) 'Servitization in manufacturing companies', in *16th Frontiers in Service Conference*. San Francisco, California.

Robson, C. (2002) 'Real world research. 2nd', *Edition. Blackwell Publishing. Malden*.

Rodrigues, L. (2017) 'Remaining Useful Life Prediction for Multiple-Component Systems Based on a System-Level Performance Indicator', *IEEE/ASME Transactions on Mechatronics*. IEEE.

Rolls Royce (2005) *The Jet Engine*. John Wiley & Sons.

Rolls Royce (2016) *TotalCare*, Available at: http://www.rolls-royce.com/products-and-services/civil-aerospace/services/services-catalogue/totalcare.aspx. (Accessed: 29 August 2017).

Rolls Royce (2017) *Repair and Overhaul*, *Rolls Royce*. Available at: https://www.rolls-royce.com/products-and-services/defence-aerospace/services/repair-and-overhaul.aspx (Accessed: 29 August 2017).

Rosemann, M. and vom Brocke, J. (2015) 'The six core elements of business process management', in *Handbook on business process management 1*. Springer, pp. 105–122.

Roy, R., Shaw, A., Erkoyuncu, J.A. and Redding, L., (2013) 'Through-Life Engineering Services', *Journal of Measurement and Control*, 46(6), pp. 172–175.

Rumsey, D. J. (2016) *Checking Out Statistical Confidence Interval Critical Values - For Dummies*. 2nd Edition. ISBN: 978-1-119-29352-1

Sachdeva, J. K. (2009) *Business research methodology*. Himalaya Publishing House.

Saxena, A. *et al.* (2008) 'Metrics for evaluating performance of prognostic techniques', in *2008 International Conference on Prognostics and Health Management, PHM 2008*. doi: 10.1109/PHM.2008.4711436.

Schmenner, R. W. (2009) 'Manufacturing, service, and their integration: Some history and theory', *International Journal of Operations and Production Management*, 29(5), pp. 431–443.

Shao, Y. and Nezu, K. (2000) 'Prognosis of remaining bearing life using neural networks', *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 214(3), pp. 217–230.

Shokri, A., Bradley, G. and Nabhani, F. (2016) 'Reducing the scrap rate in an electronic manufacturing SME through Lean Six Sigma methodology'.

Si, X.S., Wang, W., Hu, C.H. and Zhou, D.H., (2011) 'Remaining useful life estimation – A review on the statistical data driven approaches', *European Journal of Operational Research*, 213(1), pp. 1–14. doi: http://dx.doi.org/10.1016/j.ejor.2010.11.018.

Si, X.S., Wang, W., Chen, M.Y., Hu, C.H. and Zhou, D.H., (2013) 'A degradation path-dependent approach for remaining useful life estimation with an exact and closed-form solution', *European Journal of Operational Research*, 226(1), pp. 53–66. doi: http://dx.doi.org/10.1016/j.ejor.2012.10.030.

Siegel, D., Ly, C. and Lee, J. (2012) 'Methodology and Framework for Predicting Helicopter Rolling Element Bearing Failure', *Reliability, IEEE Transactions on*, 61(4), pp. 846–857.

Sikorska, J. Z., Hodkiewicz, M. and Ma, L. (2011) 'Prognostic modelling options for remaining useful life estimation by industry', *Mechanical Systems and Signal Processing*, 25(5), pp. 1803–1836. doi: 10.1016/j.ymssp.2010.11.018.

Soleymani, H. R. and Ismail, M. E. (2004) 'Comparing corrosion measurement methods to assess the corrosion activity of laboratory OPC and HPC concrete specimens', *Cement and Concrete Research*, 34(11), pp. 2037–2044.

Spring, M. and Araujo, L. (2017) 'Product biographies in servitization and the circular economy', *Industrial Marketing Management*. Elsevier, 60, pp. 126–137. doi: 10.1016/J.INDMARMAN.2016.07.001.

Sulzer (2016) *Gas Turbine Component Refurbishment*. Available at: https://www.sulzer.com/en/shared/services/2017/03/31/13/48/component-repair, (Accessed: 27 January, 2018)

Symon, G. and Cassell, C. (2012) *Qualitative organizational research: core methods and current challenges*. Sage. ISBN: 9780857024114

Tang, T. (2012) *Failure Finding Interval Optimization for Periodically Inspected Repairable Systems*. PhD Thesis. University of Toronto.

TES Centre (2013) *TES Centre Capability*, *Through-life Engineering Services Centre*. Available at: https://www.through-life-engineering-services.org/index.php/about/tes-centre-capability (Accessed: 29 August 2017).

Thomas, J. (2002) *Set Theory: Third Millennium Edition*, *Springer Monographs in Mathematics*. Page 642

Tobon-Mejia, D.A., Medjaher, K., Zerhouni, N. and Tripot, G., (2011) 'Estimation of the remaining useful life by using wavelet packet decomposition and HMMs', in *Aerospace Conference, 2011 IEEE*. IEEE, pp. 1–10.

Tory, M. and Moller, T. (2004) 'Rethinking Visualization: A High-Level Taxonomy', in *Information Visualization, 2004. INFOVIS 2004. IEEE Symposium on*, pp. 151–158.

Tufte, E. R. and Graves-Morris, P. R. (1983) *The visual display of quantitative information*. Graphics press Cheshire, CT.

Uhlmann, E., Stark, R., Rethmeier, M., Baumgarten, J., Bilz, M., Geisert, C., Graf, B., Gumenyuk, A., Grosser, H., Heitmüller, F. and Manthei, M., (2015) 'Maintenance, repair and overhaul in through-life engineering services', in *Through-life Engineering Services*. Springer, pp. 129–156.

Vachtsevanos, G.J., Lewis, F., Hess, A. and Wu, B., (2006) 'Fault Prognosis', in *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*. John Wiley & Sons, Inc., pp. 284–354. doi: 10.1002/9780470117842.ch6.

Van Dongen, L. A. M. (2015) 'Through-life engineering services: the NedTrain case', in *Through-life Engineering Services*. Springer, pp. 29–51.

Viswanathan, R. (1989) *Damage mechanisms and life assessment of high temperature components*. ASM international.

Wang, T. *et al.* (2008) 'A similarity-based prognostics approach for Remaining Useful Life estimation of engineered systems', in *Prognostics and Health Management, 2008. PHM 2008. International Conference on*, pp. 1–6.

Wang, T. (2010) *Trajectory Similarity Based Prediction for Remaining Useful Life Estimation*. PhD Thesis, University of Cincinnati.

Wang, W. (2002) ‘A model to predict the residual life of rolling element bearings given monitored condition information to date’, *IMA Journal Management Mathematics*, 13(1), pp. 3–16. doi: 10.1093/imaman/13.1.3.

Watson, M., Byington, C., Edwards, D. and Amin, S., (2005) ‘Dynamic modeling and wear-based remaining useful life prediction of high power clutch systems’, *Tribology Transactions*. Park Ridge, IL: The Society, 1988-, 48(2), pp. 208–217.

Welch, C. and Rogers, B. (2010) ‘Estimating the remaining useful life of residential appliances’, in *ACEEE Summer Study on Energy Efficiency in Buildings*, pp. 316–327.

White, J.S., 1964. Weibull renewal analysis (No. 640624). SAE Technical Paper.

Johnstone, S., Dainty, A. and Wilkinson, A., (2009) ‘Integrating products and services through life: an aerospace experience’, *International Journal of Operations & Production Management*. Emerald Group Publishing Limited, 29(5), pp. 520–538.

Willmott, C. J. and Matsuura, K. (2005) ‘Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance’, *Climate research*, 30(1), pp. 79–82.

Wisker, G. (2007) *The postgraduate research handbook: Succeed with your MA, MPhil, EdD and PhD*. Palgrave Macmillan.

Xiongzi, C., Jinsong, Y., Diyin, T. and Yingxun, W., (2011) ‘Remaining useful life prognostic estimation for aircraft subsystems or components: A review’, in *Electronic Measurement & Instruments (ICEMI), 2011 10th International Conference on*. IEEE, pp. 94–98.

Yang, S., Liu, C., Zhou, X., Liang, W. and Miao, Q., (2012) ‘Investigation on data-driven life prediction methods’, in *International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering (ICQR2MSE),*. IEEE, pp. 674–680.

Yin, R. K. (2013) *Case study research: Design and methods*. Sage publications. 5th Edition. ISBN: 9781452242569

You, M.Y., Li, L., Meng, G. and Ni, J., (2010) 'Two-zone proportional hazard model for equipment remaining useful life prediction', *Journal of manufacturing science and engineering*, 132(4).

Zaidan, M. A., Mills, A. R. and Harrison, R. F. (2013) 'Bayesian framework for aerospace gas turbine engine prognostics', in *Aerospace Conference, 2013 IEEE*, pp. 1–8.

Zhang, J., Cheng, X. and Li, Z. (2010) 'Total fatigue life prediction for Ti-alloys airframe structure based on durability and damage-tolerant design concept', *Materials & Design*, 31(9), pp. 4329–4335.

Zhang, Y. and Pham, H. (2016) 'Reliability and Maintenance of the Surveillance Systems Considering Two Dependent Processes', in *Quality and Reliability Management and Its Applications*. Springer, pp. 277–306.

Zhao, F., Tian, Z. and Zeng, Y. (2013) 'Uncertainty Quantification in Gear Remaining Useful Life Prediction Through an Integrated Prognostics Method', *Reliability, IEEE Transactions on*, 62(1), pp. 146–159.

Zhu, D., Zhang, X. and Ding, H. (2013) 'Tool wear characteristics in machining of nickel-based superalloys', *International Journal of Machine Tools and Manufacture*. Elsevier, 64, pp. 60–77.

Zikmund, W., Babin, B., Carr, J. and Griffin, M., (2012) *Business research methods*. Cengage Learning. 9th Edition. ISBN 9781111826925.

Appendix A **Permission to use image**

This appendix presents the permission for image use to describe fracture in chapter 2.

unify

Reply Reply All Forward

Kamal MEDJAHER <kamal.medjaher@ens2m.fr> | Okoh, Caxton

Re: Request for Permission to use Image

You replied to this message on 20/11/2014 08:18.

Good day Caxton,

You can use the figure. Please, just cite our paper.

Regards,

Kamal

Le 19/11/2014 21:09, Okoh, Caxton a écrit :

Good day Kamal,

Thanks for the permission to use one of your images in the last conference paper.

I am currently writing a Journal paper and would like to ask for permission to use the same I found in your paper.

Paper Title. "Remaining Useful Life Estimation of Critical Components With Application to Bearings".

Names of Author(s): Kamal Medjaher, Diego Alejandro Tobon-Mejia, and Noureddine Zerhouni

It is for a Journal publication (International Journal of Production Research – CRITICAL ANALYSIS OF REMAINING USEFUL LIFE PREDICTION TECHNIQUES FOR GAS TURBINE COMPONENTS

Please, I would like permission to use Fig 8 to show Fracture.

Regards

Caxton

From: Kamal MEDJAHER [mailto:kamal.medjaher@ens2m.fr]
Sent: 11 January 2014 08:45
To: Okoh, Caxton
Cc: pubs-permissions@ieee.org; noureddine.zerhouni@ens2m.fr
Subject: Re: Request for Permission

Dear Caxton,

Yes, you can use the figure at a condition that you cite our paper in the figure's caption and in the text of your publication. Here is a suggestion of citing our paper:

- In the text of your publication: "...as shown in figure ?? [reference of our paper]..."
- In the caption of the figure: "Caption [reference of our paper]"

Hope that this helps you and your paper will be accepted!

Regards,

K. Medjaher

Le 11/01/2014 05:47, Okoh, Caxton a écrit :

Good day,

Appendix B **RUL techniques from Literature Review**

This appendix present the techniques for remaining useful life prediction extracted from reviewing literature. Samples of the analysis is described in this appendix.

Machine remaining useful life prediction: An integrated adaptive neuro-fuzzy and high-order particle filtering approach - (Chen, Vachtsevanos and Orchard, 2012).

Input	**Techniques**	**Output**
Time in seconds, prediction step, number of previous time steps, one-step-ahead prediction, Threshold value. Nonlinear function is ANFIS predictor Number of variable Multiple samples used.	**Combined techniques:** Bayesian, estimate, high order hidden Markov model, posterior pdf, ANFIS predictor (recursive method, least square method, gradient descent method, Fuzzy Sugeno model) with process noise as fault growth model and High-order particle filtering **Comparative study:** **Pre-analysis techniques**: Bayesian, estimate, high order hidden Markov model, posterior pdf, **Final prediction techniques:** ANFIS integration with High-order particle filtering	RUL of a gear plate

Total fatigue life prediction for Ti-alloys airframe structure based on durability and damage-tolerant design concept - (Zhang, Cheng and Li, 2010).

Input	**Techniques**	**Output**
Effective mass intensity factor, Number of cycles, Stress ratio. Long crack growth in mm, short crack growth, and crack initiation in mm. material constant Actual Cyclic number , constant amplitude cyclic number, k total number of discrete amplitude number	S-N curve method Damage tolerance Miner's rule predicts crack initiation life Plasticity induced crack closure model is used to predict short crack growth **Combined techniques**: long crack growth is presented first and **Comparative study:** crack initiation life, short crack growth and long crack growth based on constant and variable amplitude loading **Pre-analysis techniques:** **Final prediction techniques:**	RUL of Titanium alloy airframe Unit in Cycles

Remaining Useful Life Prognosis of Bearing based on Gauss Process Regression - (Hong and Zhou, 2012).

Input	Techniques	Output
Temp. Vibration Signal in kHz Sound Emission Signal Days (Time) Load in pound Rotation speed in RPM Inputs generated from degradation bearing data in run-to-failure 4 hours of data 1 data point = 20 m Vibration data collected every 20 Mins Data length 20,480 points	**Combined techniques**: Bayesian Machine Learning method is a Gaussian Process Regression for bearing Features tracking **Functions**: Covariance functions for bearing feature tracking are Squared Exponential, Matern covariance when trend of data is smooth and monotonic. Neural Network (NN) has good performance when data changes dramatically Kurtosis and RMS – Root Mean Square used to detect fault **Comparative study:** **Pre-analysis techniques:** **Final prediction techniques:** Kurtosis and RMS	RUL of Bearing Measurement point in Mins Kurtosis RMS

Methodology and Framework for Predicting Helicopter Rolling Element Bearing Failure - (Siegel, Ly and Lee, 2012)

Input	Techniques	Output
Vibration, load in pound, acoustic emission signal, number of samples in Hz, weight, residual value, number of instance, Time in minutes Kurtosis and RMS Functions	**Combined techniques**: Bayesian filtering techniques, usage based methods, times series prediction methods, Paris Law **Signal Processing technique:** Wavelet decomposition, Spectral Kurtosis, RMS, Time Synchronize Average **Feature selection method:** Expert selection, filter methods, Wrapper methods **Health Assessment Method:** Weighted sum of features, Distance from normal, Regression, Neural Network. **Anomaly Detection Method:** Health Based threshold, One-class classifiers, Bayesian Filtering Approach **Comparative study:** **Pre-analysis techniques:** **Final prediction techniques:** Regression-based methods, Similarity-based Prediction, Bayesian Filtering Approach	RUL of Oil Cooler Bearings Can also be used for Shafts and gears RMS in g, Sample in Hz Load in lb, Envelope in g RUL in Minutes and Time in Minutes

Predicting the total fatigue life in metals -(Makkonen, 2009).

Input	**Techniques**	**Output**
Sample size, length depth, surface area, diameter, Lowest stress range in MPa, endurance limit in mm, stress amplitude in MPa, shape parameter, scale parameter, Sample test 50 100 crack per mm^2 Real data type	Paris's law, SN Curve The distribution of maximum and minimum in a sample – nth order The generalised extreme value distribution - GEV Linear elastic fracture mechanics Crack initiation and stable crack growth **Combined techniques:** The distribution of maximum and minimum in a sample – nth order (cumulative distribution function for maximum value and probability density function for minimum value) Paris's law and Crack initiation and stable crack growth **Comparative study:** The distribution of maximum and minimum in a sample – nth order The generalised extreme value distribution - GEV **Pre-analysis techniques:** **Final prediction techniques:** Paris's law and stable crack growth	RUL of a steel (metal) Probability Initiate Life Stress Cycle in MPa Fatigue crack initiation N Initial Life, Probability

Implication of Power "Power by the Hour" on Turbine Blade Lifing - (Bagnall, Shaw and Mason-Flucke, 2000).

Input	**Techniques**	**Output**
Damage incurred Temperature, stress material Creep damage: Low Cycles fatigue: Oxidation:	Turbine Blade Lifing Methodology Database Lifing algorithm Weibull Statistical Estimate 2D and 3D model Robinson rule to sum individual rating times Miner's rule for total life at each point **Combined techniques**: **Comparative study:** **Pre-analysis techniques:** **Final prediction techniques**	RUL of a specimen and blades

Prognosis of Remaining Bearing Life using Neural Networks -(Shao and Nezu, 2000).

Input	**Techniques**	**Output**
Sampling period, bearing condition set, warning limit Temperature, stress, stiffness. Measured vibration amplitude, frequency, the bearing load Kgf, unknown function, weights, rotating speed r/min Number of Output neurons Training samples 25 – 80 patterns	Neural network computation Progression based prediction model Statistical regression model - Linear, polynomial, exponential and compound models Moving-window method for building the prediction model Auto-Regression integrated moving average models are a method for time series approach to forecasting. **Combined techniques**: linear model, polynomial model, exponential model and compound model. Multi-layer network, back propagation and forward propagation **Comparative study:** Auto-Regression model and compound model of neural networks. Compound model of Neural network and root mean square condition variables to forecast. **Pre-analysis techniques:** reoccurrence trace method used to remove disturbance and to improve the prediction accuracy **Final prediction techniques:** 3 layer network – back propagation (input lay, hidden layer and output layer	Remaining Life of bearing Time in hours

Use of Paris Law for Prediction of Component Remaining Life - (Bechhoefer, Bernhard and He, 2008)

Input	Techniques	Output
Range of strain Material, Constant, Rate of change of the half crack length, Gross strain, geometric correction factor, exponent of crack growth equation, number of cycles. Vibration in inches per second Vector of CI, covariance critical value. Real data type	**Combined techniques**: Paris Law, range of Strain, Kalman Filter-Kinetic model which a filter gain is set based on measurement and system variance. Nakagami probability distribution – multi dimensional hypothesis testing State Propagation, Predicted Covariance, Kalman gain, State Covariance, State Update and Jacobian equation **Comparative study:** **Pre-analysis techniques:** Nakagami probability distribution, Range of Strain, Kalman Filter-Kinetic **Final prediction techniques:** Paris Law	RUL of Rotor Aircraft Bearing, shaft Flight hours Flight hour Remaining Health Index, half crack length in mm, cycles N in Millions, Cycles Remaining, Estimated D

Estimation of the Remaining Useful Life by using Wavelet Packet Decomposition and HMMs - (Tobon-Mejia *et al.*, 2011)

Input	**Techniques**	**Output**
Number of states of model, number of distinct observations in each state, The state transition probability distribution The observation probability distribution, The initial state distribution Mean, standard deviation, mixture coefficient, mixture matrix, observation matrix, mixture in the state, log concave, mixture component in state, mean vector, time in hours, mins, and frequency in kHz observation vector. Data type: real, double	**Combined techniques**: Wavelet Packet Decomposition, MoG-HMM. **Comparative study:** Wavelet Packet Decomposition and MoG-HMM **Pre-analysis techniques:** Wavelet Packet Decomposition extracts features of processed raw data MoG-HMM provide a flexible way of time frequency representation and filtering of a signal by allowing variable sized windows and different detail levels Parameters for each MoG-HMM are learned by using Baum-Welch Algorithm Viterbi algorithm is used to learn temporal parameters and for decoding final state **Final prediction techniques:** Wavelet Packet Decomposition and MoG-HMM	RUL of Bearings Time in minute, Error in % Failure in minutes

Appendix C **Methods grouped based on types of data**

This appendix presents the methods for remaining useful life prediction

Types of data include;

i. Numerical data are quantitative – **Discrete:** can be counted fixed and finite or **Continuous:** measurement cannot be counted are described using interval and on the real numbers
ii. Categorical data – qualitative yes/no, true or false
iii. Ordinal data – mixture of categorical and numerical data. For example: "Is the noise in the system poor, reasonable, good, or excellent?" responses may be represented as 1st, 2nd, 3rd, and 4th.

Methods	**Numerical Data**		**Categorical Data**	**Ordinal Data**
	Discrete	Continuous		
Paris Law with Weibull distribution	●	●	●	
Adaptive Neuro-Fuzzy Inference System ANFIS	●	●	●	●
Neural Network	●	●		
Auto Regressive Moving Average (ARMA)	●	●		
Miner's Linear Accumulative Damage model	●			
Linear Elastic Fracture Mechanics	●			
Plasticity-Induced crack-closure model	●			
Bayesian – Gaussian Process Regression	●	●		
Regression based model	●	●		
Similarity-based prediction	●	●		
Bayesian Filtering Approach	●	●		
Wavelet Packet Decomposition	●	●		
Mixture of Gaussian Hidden Markov Model	●	●		
Paris Law	●			
Kalman Filter	●			
RVM Regression model	●			
Monte Carlo	●			
Inverse FORM	●			

Appendix D Grouped approaches, techniques and methods for input data

This appendix presents approaches, techniques and methods for input data

Model-based: Basic science, physics and equation already established, and experiments

Hybrid-based: A combination of different methods.

Knowledge-based: Collection of information from subject matter experts and existing databases. Examples include expert systems, Fuzzy and experience.

Data-Driven-based: Understanding the system based on data available to apply techniques such as neural network and regression

Approach	Small Data Input	Large Data Input
Data-driven based	Paris Law with Weibull distribution Auto Regressive Moving Average (ARMA) Dynamic Bayesian Network Inverse FORM (First Order Reliability Method) Bayesian Filtering Approach Bayesian – Gaussian Process Regression	Adaptive Neuro-Fuzzy Inference System ANFIS Neural network Paris Law Regression based model Similarity-based prediction Wavelet Packet Decomposition Mixture of Gaussian Hidden Markov Model Particle filter approach with Bayesian updating RVM Regression model
Model based	Miner's Linear Accumulative Damage model Linear Elastic Fracture Mechanics Plasticity-Induced crack-closure model Kalman Filter-Kinetic Model	Paris Law Multi component equilibrium algorithm High-Schmidt number Brownian diffusion The distribution of maximum and minimum in a sample
Knowledge based		Adaptive Neuro-Fuzzy Inference System ANFIS
Hybrid based	A combination of the model+data-driven; knowledge+data-drive; model+knowledge; mode+knowledge+data-driven methodology	

Appendix E **Current Practice Historical Data**

This appendix describes the data analysed in the current practice for identification and retrieval of keywords for taxonomy in ontology.

Current state of the deterioration process dataset “AS-IS”

Deterioration Process											
appearance	**blockage**	**contamination**	**corrosion**	**cyclic movement**	**electrical deterioration**	**misposition**	**non specific mechanism**	**property change**	**mechanical deterioration**	**relative movement**	**thermal deterioration**
burnish	block	Contaminate	blister	oscillate	short circuit	misalign	broken	embrittle	break	clash	blueing
discolour	clog	deposit	galvanic corrosion	resonate	Leak	misassemble	damage	harden	deform	close	burn
glaze	coke		oxidise	vibrate	air leak	misclock	irritate	soften	**bulk deformation**	contact	coke
mark	ingest	**surface deformation**	pit		fuel leak	mismatch	lose		bend	debond	creep
polish	ingress	burr	rust		major leak	non-fitment	material loss		bulge	loosen	
roughen		chip	sulphidate		minor leak		weaken		collapse	ratchet	melt
scuff		dent			oil leak		wreck		compress	release	
shingle		depress							elongate	seize	scorch
stain		dimple			**wear**		**fracture**		extrude	separate	thermal erosion
streak		hit			abrade		burst		flatten		
tarnish		lap			brinell		crack		puncture		
		scallop			cavitate		cut		shrink		
		score			chafe		perforate		twist		
		disintegrate			erode		rupture				
		fatigue			scrape		snap				
		high cyclic fatigue			fray		tear				
		low cyclic fatigue			fret		impact damage				
		strain			gall		bruise				
		stress			rub		foreign object damage				
		vibrate									

Updated state of the deterioration process datasets “AS-IS”

Deterioration Process											
appearance	**blockage**	**contamination**	**corrosion**	**cyclic movement**	**electrical deterioration**	**misposition**	**non specific mechanism**	**property change**	**mechanical deterioration**	**relative movement**	**thermal deterioration**
burnish	block	Contaminate	blister	oscillate	short circuit	misalign	broken	embrittle	break	clash	blueing
discolour	clog	deposit	galvanic corrosion	resonate	Leak	misassemble	damage	harden	deform	close	burn
glaze mark	coke ingest	**surface deformation**	oxidise pit	vibrate	air leak fuel leak	misclock mismatch	irritate lose	soften	**bulk deformation** bend	contact debond	coke creep
polish	ingress	burr	rust		major leak	non-fitment	material loss		bulge	loosen	frozen
roughen		chip	sulphidate		minor leak		weaken		collapse	ratchet	melt
scuff		dent			oil leak		wreck		compress	release	overheat
shingle stain		depress dimple			Oil wet Fuel wet				elongate extrude	seize separate	scorch thermal erosion
streak		hit			wetted				flatten		
tarnish		lap							puncture		
degradation		scallop score			**wear** brinell		**fracture** crack		shrink twist		
		disintegrate			erode		rupture		stretch		
		fatigue			scrape		snap				
		high cyclic fatigue low cyclic fatigue			fray fret		tear impact damage				
		strain			gall		bruise				
		stress			rub		foreign object damage				
		vibrate			abrade cavitate		burst cut				
					chafe		perforate				

Future State of the deterioration process datasets “TO-BE”

	Deterioration Process		deterioration	degradation				
chemical deterioration	**mechanical deterioration**							
corrosion	**deformation**	**fracture**	**wear**	**cosmetic deterioration**	**deterioration cause**	**location**	**containment**	**material property change**
!!anti-corrosion	deformed	burst	Worn	blueing	friction	fouls	leak	brittled
burnt	bent	cracked	Abraded	polished	fatigue	de-bond	drip	embrittled
Galvanic corrosion	builtup	cut	Brinelled	tarnished	oscillated	clashed	weep	hardened
Oxidised	deposited	perforated	Cavitated	bruised	resonated	contacted	lost	softened
Pitted - corrosion	bulged	disintegrated	Chaffed	burnished	hit	debonded	misfilled	coked
Stress corrosion	collapsed	ruptured	Eroded	stained	bumped	ratcheted	breakout	glazed
Rusted	shingled	snapped	Scrape	streaked	banged	released	spill	dealloyed
Sulphidated	compressed	divided	Frayed	discoloured	wiggled	separated		melted
Microbial Corrosion	elongated	split	Fretted	discolored	vibrated	delaminate		laquered
scorched	extruded	Flaked	Lumped		strained	slipped	**transmission**	weakened
thermal erosion	distorted	punctured	Galled		stressed	displaced	blocked	thermal deterioration
	flattened	Spalled	Picked up		Overheat	pooled	clogged	creeped
	shrunk	Blistered	Roughened		Ingested	hide	starvation	frozen
	twisted	peeled	Plucked		!!fire detector	dislocated	short circuit	
	stretched	wrecked	scalloped		!!injestion	misaligned	jammed	
	Burred	Sheared	material transfer		ingress	misassembled	seized	
	Battered	lifted	Plowed		damaged	misclocked		
	Dented	Broken	Exfoliation		overloaded	mismatched		
	Depressed	Fragmented	Scuffed		overspeed	misfitted		
	Dimpled	chipped	Rubbed		overpressure			
	lapped	Creviced			overfill			
	indented	torn			Contaminated			
	nicked				iced			
	grooved				Fire			
	gouged				bruise			
	scratched				Corrosion fatigue			
	scored				unbalanced			
	Skewed				foreign object damage			

Appendix F **Degradation mechanism taxonomy**

This appendix presents predominant degradation mechanisms and their classification as captured during current practice investigation

Degradation Mechanism

- **Deformation**
  - Deformed
  - bent
  - bowed
  - buckled
  - curled
  - kinked
  - bulged
  - collapsed
  - compressed
  - elongated
  - extruded
  - flattened
  - punctured
  - shrunk
  - twisted
  - burred
  - chipped
  - dented
  - depressed
  - dimpled
  - Nicked
  - Gouged
  - Scratched
- **Wear**
  - Worn
  - abraded
  - Brinelled
  - Chafed
  - Eroded
  - Frayed
  - Fretted
  - Galled
  - Rubbed
  - Burnished
  - Lapped
  - Pick up
  - Pitted
  - Scuffed
  - Seized
  - Plucked
  - Spalled
  - Peeled
  - Flakes
  - Lumps
  - Chip like particle
  - Fine particles
  - Heavy tearing
  - Scratches
  - Plow
  - Cut
  - Fragment
- **Fracture**
  - Cracked
  - Ruptured
  - Cut
  - Disintegrated
  - Broken
  - Dislocated
  - Split
- **Corrosion**
  - blistered
  - galvanic corrosion
  - oxidised
  - pitted - corrosion
  - stress corrosion
  - rusted
  - sulphidated
  - Flaked
  - Uniform - corrosion
  - Fraying
  - Crevice
  - Filiform
  - Intergranular
  - Exfoliation
  - Corrosion fatigue
  - Fretting corrosion
  - Erosion
  - Dealloy
  - Hydrogen
  - Concrete corrosion
  - Microbial Corrosion
  - Pitting-concentration cell

Causes of the predominant deterioration – failure modes taxonomy

Deterioration Causes

Deformation
Creep
Stretching
Debris
Foreign Object damage
Hit
Dead load
Thin Cross section
Stretching

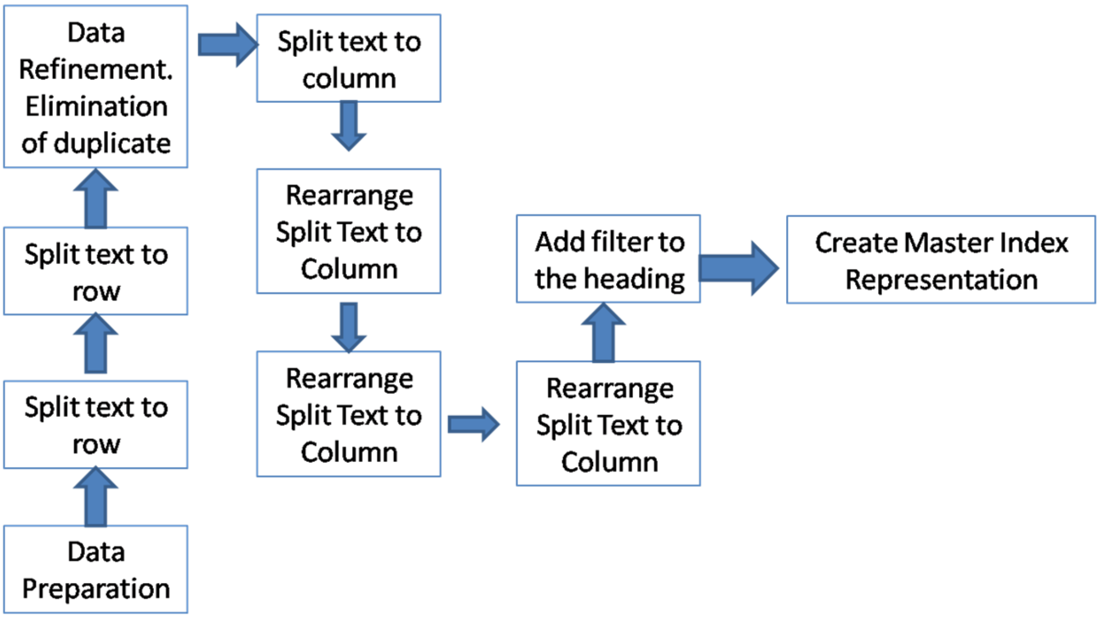
Wear
Dust
Dirt
Lubricant
High friction
Vibration
Misalignment
Interference fit
Direct contact
Plastic deformation
Material transfer
Surface roughness
Cyclic Loading
Particle impact

Fracture
Overload
Excessive manoeuvres
Over speed
Fatigue
Over pressure
Cyclic load
Stretching
Creep

Corrosion
Salt water or air
Surface roughness
Contaminants
Fluid
Fire
Humidity
Diffusion
Moisture leakage
Over heat
Temperature
Welding
Adhesion
Deposit of dirt
Stationary fluid
Quick motion
Fast fluid flow
Overpressure
Gas bubbles
Lubricant

Appendix G **Master Index Representation**

This appendix presents the framework for analysing the textual data during the current practice to develop master index representation



The relationship of components, features and deterioration mechanisms

	Commodity	Feature	Mechanism	Reference
2	blade&&blades&&blade	3d	Deformation	refQ747
3	SEAL&&Spacer&&spacer&&spacer&&ring&&spacer	Adjusting	Damage	refQ1211
4	SEAL&&Spacer&&spacer&&spacer&&ring&&spacer	Adjusting	NICK	refQ1211
5	SUPPORT&&supply&&ignition&&aircraft	aerofoil	contamination	refQ570
6	leading&&blade&&blade&&lead	aerofoil	corrosion	refQ1744
7	segment&&vane	aerofoil	crack	refQ1044
8	VANES&&segment&&segments	aerofoil	Cracking	refQ1077
9	vanes	Aerofoil	Cracking	refQ363
10	segment&&vane	aerofoil	cracking	refQ1044
11	rotor blade&&rotor blades	Aerofoil	cracking	refQ1420
12	leading&&vane	aerofoil	cracking	refQ1438
13	leading	aerofoil	cracking	refQ358
14	BLADES, Rotor&&rotor&&blade&&blades	aerofoil	Cracking	refQ720
15	blades&&Blade&&blade&&leading	aerofoil	cracking	refQ1116
16	rotor blade&&blade	aerofoil	Cracks	refQ1377
17	leading	aerofoil	cracks	refQ912
18	lead&&vane&&segment	aerofoil	cracks	refQ1246
19	leading&&blade&&blade&&lead	aerofoil	creep	refQ1744
20	rotor blade	Aerofoil	damage	refQ1363
21	BLADES, Rotor&&rotor&&blade&&blades	aerofoil	damage	refQ720
22	blades&&Blade&&blade&&leading	aerofoil	damage	refQ1116
23	SUPPORT&&supply&&ignition&&aircraft	aerofoil	degrading	refQ570
24	Vane&&vanes	aerofoil	deteriorate	refQ1630
25	rotor blade	Aerofoil	FOD	refQ1363
26	Blade	Aerofoil	FOD	refQ1223
27	vanes	Aerofoil	Oxidation	refQ363
28	leading	aerofoil	oxidation	refQ358
29	leading&&blade&&blade&&lead	aerofoil	release	refQ1744
30	BLADES, Rotor&&rotor&&blade&&blades	aerofoil	release	refQ720
31	blade&&leading	aerofoil	release	refQ1815
32	Blade&&Blade&&leading	Aerofoil	Release	refQ1636
33	Blade	Aerofoil	release	refQ1631
34	Blade&&Blade&&leading	Aerofoil	released	refQ1636
35	Blade	Aerofoil	released	refQ1631

Reference (All)

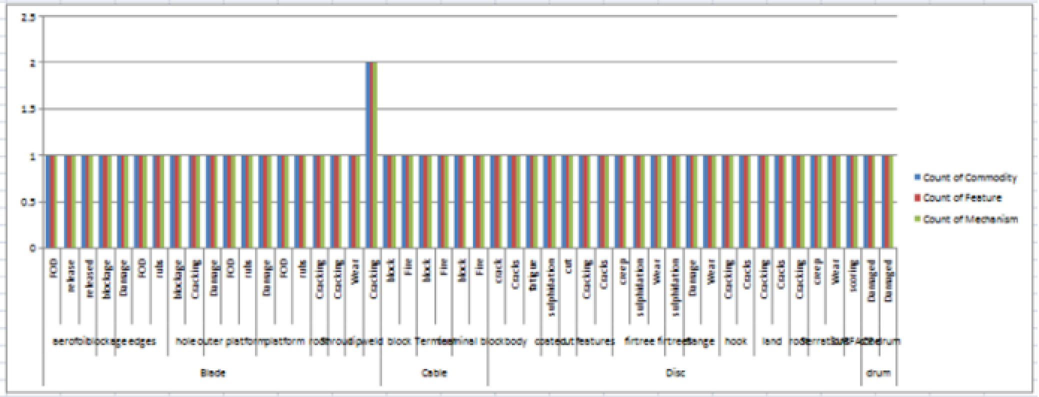
Row Labels	Count of Commodity	Count of Feature	Count of Mechanism
ACTUATION&&VALVE&&manifold&&lead	**2**	**2**	**2**
Coupling	**1**	**1**	**1**
leak	1	1	1
path	**1**	**1**	**1**
leak	1	1	1
Blade	**20**	**20**	**20**
aerofoil	**3**	**3**	**3**
FOD	1	1	1
release	1	1	1
released	1	1	1
blockage	**1**	**1**	**1**
blockage	1	1	1
edges	**3**	**3**	**3**
Damage	1	1	1
FOD	1	1	1
rubs	1	1	1
hole	**2**	**2**	**2**
blockage	1	1	1
Cracking	1	1	1
outer platform	**3**	**3**	**3**
Damage	1	1	1
FOD	1	1	1
rubs	1	1	1
platform	**3**	**3**	**3**
Damage	1	1	1
FOD	1	1	1
rubs	1	1	1
root	**1**	**1**	**1**
Cracking	1	1	1
Shroud	**1**	**1**	**1**
Cracking	1	1	1

CommodityFeatMechRefAddFilter | CommodityFeatMechRefCreatePivot | Sheet3

Ready

Pareto of the relationship of components, features and deterioration mechanisms

	D	E	F	G	H	I
1	Refer ce		Reference	(All)		
2	refQ747					
3	refQ1211			Values		
4	refQ1211		Row Labels	Count of Commodity	Count of Feature	Count of Mechanism
5	refQ570		**Blade**	20	20	20
6	refQ1744		**aerofoil**	3	3	3
7	refQ1044		FOD	1	1	1
8	refQ1077		release	1	1	1
9	refQ363		released	1	1	1
10	refQ1044		**blockage**	1	1	1
11	refQ1420		blockage	1	1	1
12	refQ1438		**edges**	3	3	3
13	refQ358		Damage	1	1	1
14	refQ720		FOD	1	1	1
15	refQ1116		rubs	1	1	1
16	refQ1377		**hole**	2	2	2
17	refQ912		blockage	1	1	1
18	refQ1246		Cracking	1	1	1
19	refQ1744		**outer platform**	3	3	3
20	refQ1363		Damage	1	1	1
21	refQ720		FOD	1	1	1
22	refQ1116		rubs	1	1	1
23	refQ570		**platform**	3	3	3
24	refQ1630		Damage	1	1	1
25	refQ1363		FOD	1	1	1
26	refQ1223		rubs	1	1	1
27	refQ363		**root**	1	1	1
28	refQ358		Cracking	1	1	1
29	refQ1744		**Shroud**	1	1	1
30	refQ720		Cracking	1	1	1
31	refQ1815		**tip**	1	1	1
32	refQ1636		Wear	1	1	1
33	refQ1631		**weld**	2	2	2
34	refQ1636		Cracking	2	2	2
35	refQ1631		**Cable**	6	6	6
36	refQ1493		**block**	2	2	2
37	refQ1493		block	1	1	1
38	refQ158		Fire	1	1	1
39	refQ211		**Terminal**	2	2	2
40	refQ197		block	1	1	1



CommodityFeatMechRefAddFilter | CommodityFeatMechRefCreatePivot | Sheet3

Ready

Appendix H **Brainstorming Questionnaire**

This appendix presents the questionnaire for conducting the workshop to gather relevant requirements. Sample questionnaires with responses from participants are presented.

Participant:

Job Role:

Experience:

Please write out the event(s) for each category of levels in the table below.

Level	Description	Different events
1	Events that determine the availability of the product for customer service	E.g. Service Disruption, delivery, engine overhaul
2	Non-standard or infrequent events with the potential to modify the products availability or functionality	E.g. Borescope, inspection, oil change,
3	Standard daily or weekly activities that maintain health status	E.g. Engine health monitoring data

Brainstorming Session with selected Rolls Royce teams

Task: To present a helicopter view of various events that can happen in and to an engine in a timeline navigator.

any intervention on engine or data analysis on an a[illegible]

The product of this task will be used by domain experts (service engineers).

An engine experiences various events in a specific context. How can these events be grouped and classified into level 1, level 2 and level 3?

Please write out the event(s) for each category of levels in the table below.

Level	Description	Different events
1	Events that determine the availability of the product for customer service	E.g. Service Disruption, delivery, engine overhaul Any major event registered so by OSD Any event that result in a disruption index (e.g. in project zero parto)
2	Non-standard or infrequent events with the potential to modify the products availability or functionality	E.g. Boroscope, inspection, oil change, Any troubleshooting performed on engine Any engine overhaul with detail or type of overhaul (level 2, 3 or 4) and what module of the engine have been swapped
3	Standard daily or weekly activities that maintain health status	Engine health monitoring data Any CDS advisory on data Oil top up Any core wash on engine

Brainstorming Session with selected Rolls Royce teams

Task: To present a helicopter view of various events that can happen in and to an engine in a timeline navigator.

The product of this task will be used by domain experts (service engineers).

An engine experiences various events in a specific context. How can these events be grouped and classified into level 1, level 2 and level 3?

Please write out the event(s) for each category of levels in the table below.

Level	Description	Different events
1	Events that determine the availability of the product for customer service	E.g. Service Disruption, delivery, engine overhaul Fire, Shaft failure, Blade off Crack in the disc.
2	Non-standard or infrequent events with the potential to modify the products availability or functionality	E.g. Boroscope, inspection, oil change, Rejection
3	Standard daily or weekly activities that maintain health status	Engine health monitoring data Oil consumption. TCaF / TCaR Thermal Couple front / Rear temperature.

Brainstorming Session with selected Rolls Royce teams

Task: To present a helicopter view of various events that can happen in and to an engine in a timeline navigator.

The product of this task will be used by domain experts (service engineers).

An engine experiences various events in a specific context. How can these events be grouped and classified into level 1, level 2 and level 3?

Please write out the event(s) for each category of levels in the table below.

Level	Description	Different events
1	Events that determine the availability of the product for customer service	E.g. Service Disruption, delivery, engine overhaul Engine installation Engine removal Aircraft down time Unplanned engine removals. Inflight shut down cancellations. Aborted take-offs delays. diversions
2	Non-standard or infrequent events with the potential to modify the products availability or functionality	E.g. Boroscope, inspection, oil change, - Service bulletins - On-wing repair - Non mod service bulletin. - Air craft deicing. - Controlled service Introduction (controlled introduction of for mod trial). - Bulk data download. - Maintenance message responses - Technical Variance - LRU replacement - Immediate Operational Request. - Diagnostic Magnetic Chip Detection use.
3	Standard daily or weekly activities that maintain health status	Engine health monitoring data - Core washing. - Oil level check (starter + tank). - Walk round checks (pre-flight). - Scheduled borescopes. - LLP remaining life records. - Flight profile monitoring. - Maintenance Planning Document tasks.

- Fan blade maintenance

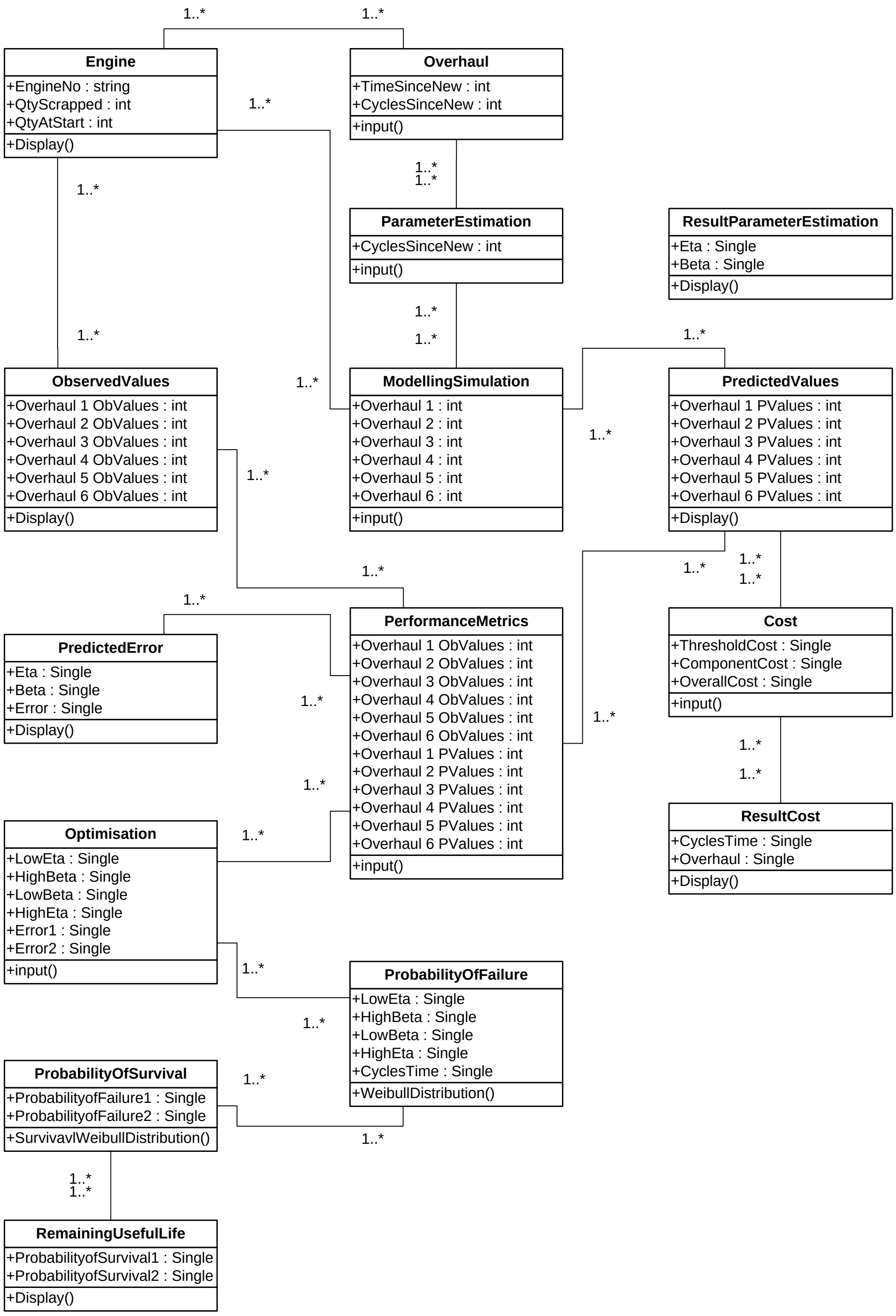
Appendix I **Data dictionary**

This appendix presented the data dictionary for the timeline visualisation of the engine events.

Engine					
P/F	**Field Name**	**Caption**	**Data type**	**Field Size**	**Notes**
P	EngineNo	Engine Number	Varchar	10	
	Model	Model	Varchar	20	
	Name	Name of Engine	Text	20	
Activity					
P	ActivityID		Autonumber		
	StartDate	Start Date	Datetime	20	
	EndDate	End Date	Datetime	20	
F	EngineNo	Engine Number	Varchar	20	
F	EventType	Type of Event	Text	30	
	City	City	Text	30	
	Country	Country	Text	30	
	Comment	Comment	Text	30	
Events					
P	EventType	Type of Events	Text	30	
	Description	Event Description	Text	30	
F	LevelID	Level ID	Integer	2	

Appendix J **Model Class Diagram**

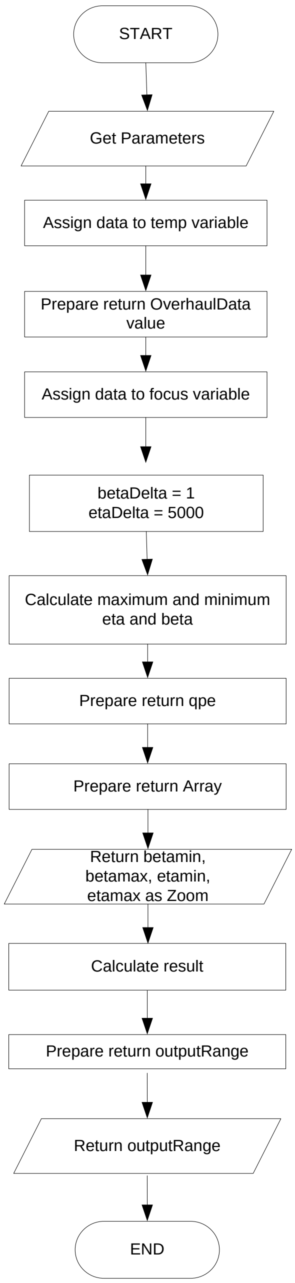
This appendix presents the class diagram for the through-life performance prediction model



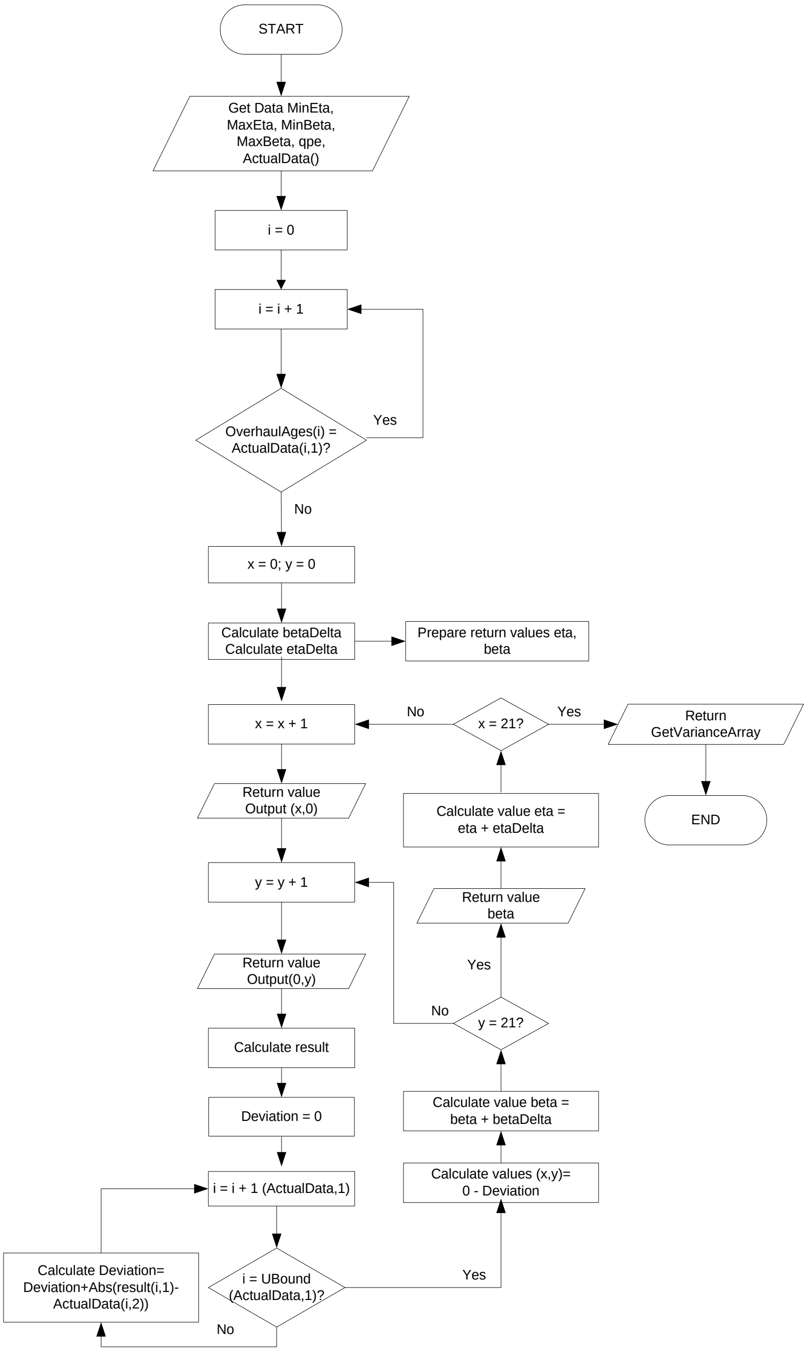
Appendix K **Flowchart for the Through-life model**

This appendix presents the flowchart for developing the through-life performance predictive model.

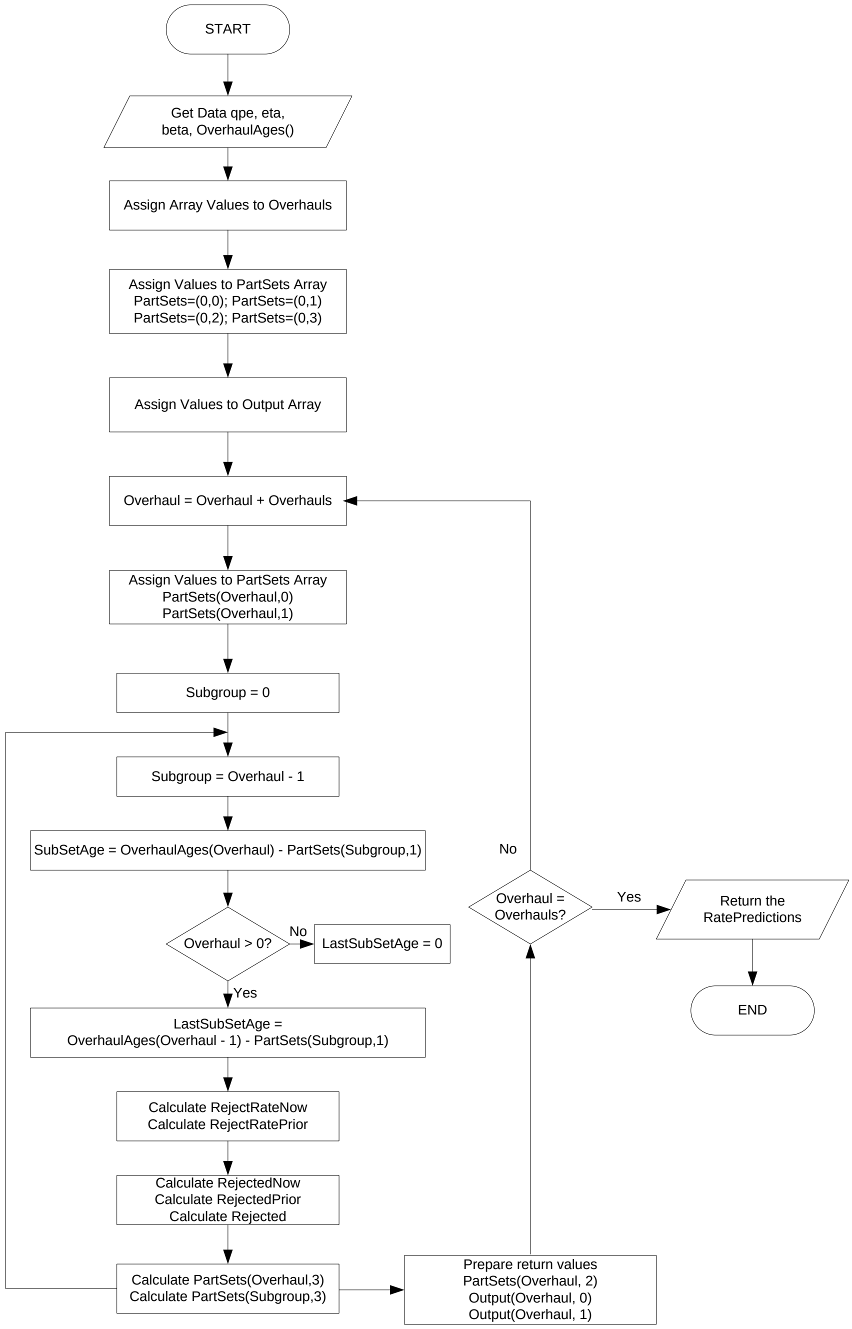
Flowchart of modellingSimulation() Subroutine



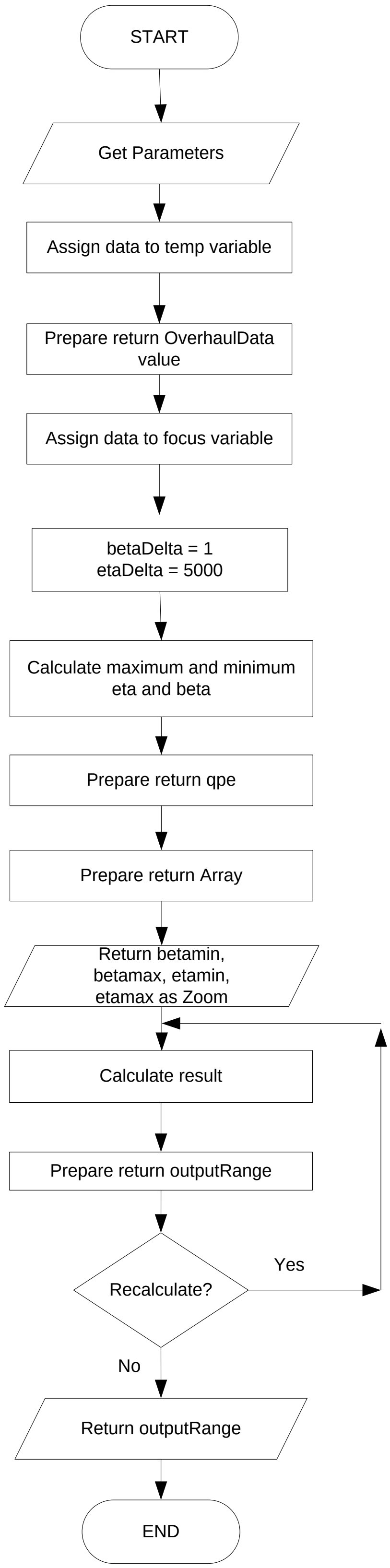
Flowchart of GetVarianceArray() Function



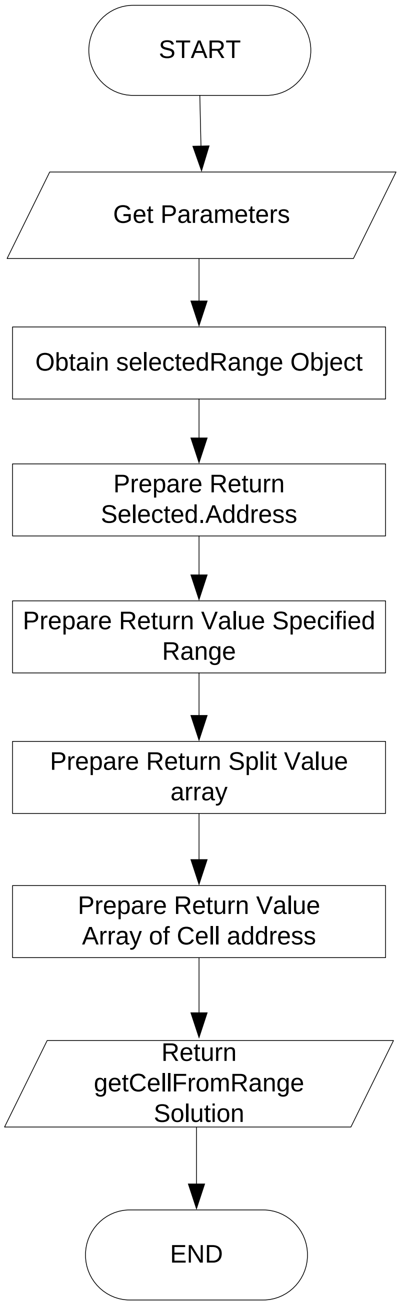
Flowchart of RatePrediction() Function



Flowchart of getSelectedZoomInError() Function



Flowchart of getCellFromRange() Function



Appendix L **Case Study Scenarios Results**

This appendix presents the results from the framework. The outcome presented illustrates the validation of the model when the minimisation of the error between the predicted and observed values equals zero.

Eta	Beta	Engine	Overhaul
4353.8	1.6	10015	Shop Visit (SV)

Predict Beta and Eta Parameters

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	1000	2500	3200	6000	8000	11000
Population 0	Number Off	36	33	24	20	7	3	0
	Overhaul Age		1000	2500	3200	6000	8000	11000
	% Failed		9%	34%	46%	81%	93%	99%
	Number of Failed parts (cum)		3	12	16	29	33	36
	Number of Failed parts (this)		3	9	4	13	4	3
Population 1	Number Off		3	3	2	1	0	0
	Overhaul Age			1500	2200	5000	7000	10000
	% Failed			17%	29%	71%	88%	98%
	Number of Failed parts (cum)			0	1	2	3	3
	Number of Failed parts (this)			0	1	1	1	0
Population 2	Number Off			9	9	4	2	0
	Overhaul Age				700	3500	5500	8500
	% Failed				5%	51%	77%	95%
	Number of Failed parts (cum)				0	5	7	9
	Number of Failed parts (this)				0	5	2	2
Population 3	Number Off				5	3	2	0
	Overhaul Age					2800	4800	7800
	% Failed					39%	69%	92%
	Number of Failed parts (cum)					2	3	5
	Number of Failed parts (this)					2	1	2
Population 4	Number Off					21	16	6
	Overhaul Age						2000	5000
	% Failed						25%	71%
	Number of Failed parts (cum)						5	15
	Number of Failed parts (this)						5	10
Population 5	Number Off						13	7
	Overhaul Age							3000
	% Failed							42%
	Number of Failed parts (cum)							6
	Number of Failed parts (this)							6
	Number Off							23
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		3	9	5	21	13	23
	Scrap Rate		8%	25%	14%	58%	36%	64%

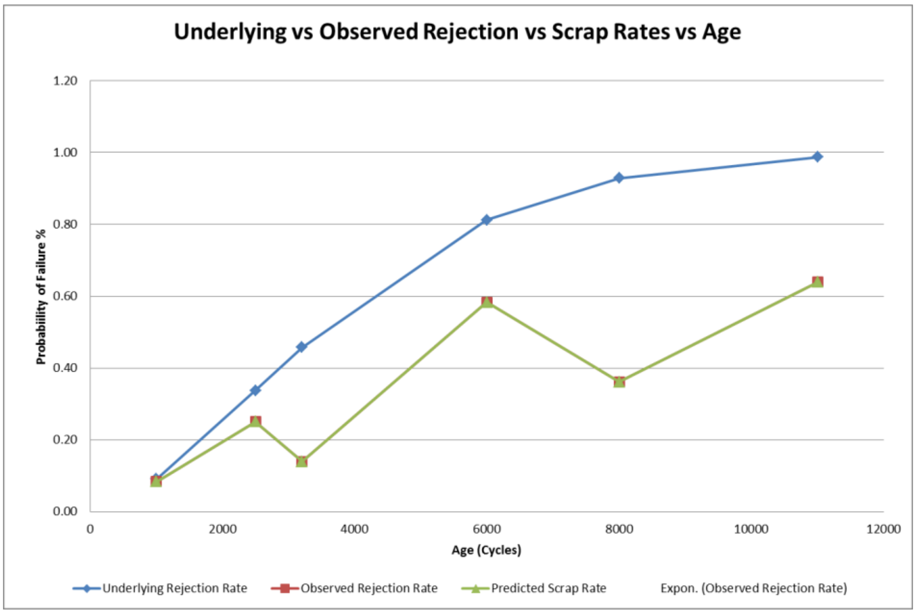
The Underlying Scrap Data Available

Underlying scrap rate		9%	34%	46%	81%	93%	99%

The Observed Scrap Data Available

Observed scrap number		3	9	5	21	13	23
Observed scrap rate		8%	25%	14%	58%	36%	64%
Engine age at Overhaul		1000	2500	3200	6000	8000	11000

LSM single system: β = 1.6 with the same predicted and observed values

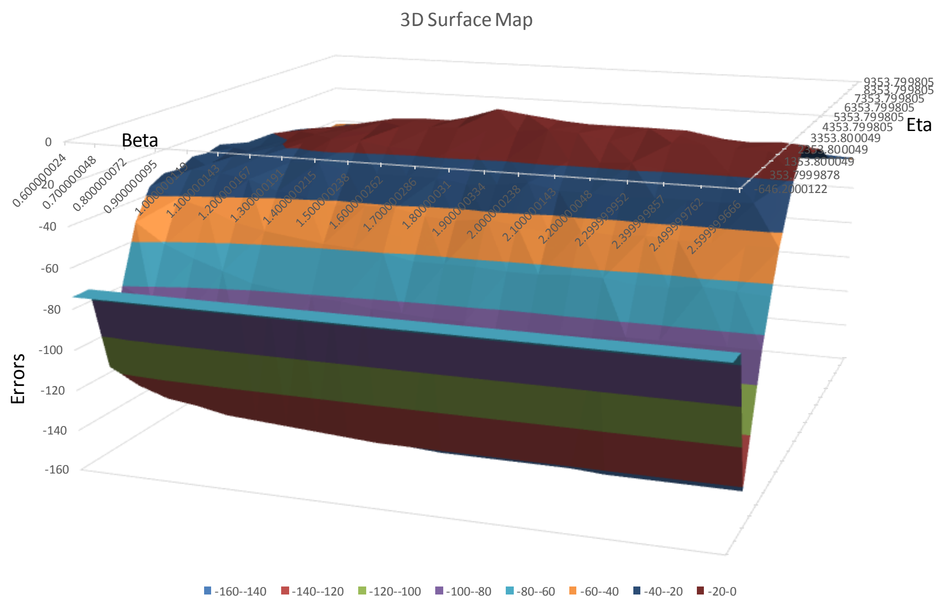


LSM single system: β = 1.6 with probability of Failure model

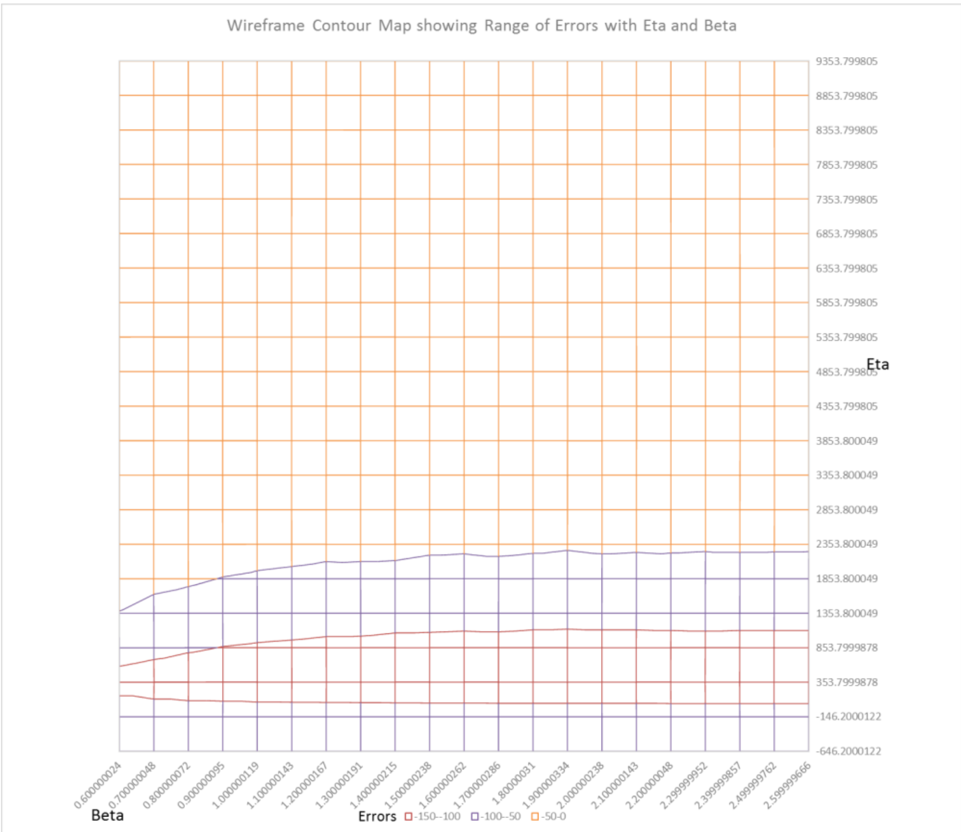
β

η	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6
-646.2	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74
-146.2	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74	-74
353.8	-117	-125	-130	-132	-135	-136	-137	-138	-139	-140	-140	-141	-141	-141	-141	-141	-142	-142	-142	-142	-142
853.8	-80	-87	-95	-101	-104	-106	-109	-109	-112	-112	-113	-112	-113	-114	-114	-114	-114	-113	-114	-114	-114
1353.8	-51	-61	-67	-72	-77	-79	-81	-82	-84	-85	-86	-86	-88	-88	-87	-87	-86	-86	-86	-86	-86
1853.8	-36	-41	-45	-51	-54	-56	-58	-59	-60	-63	-63	-63	-64	-64	-63	-63	-65	-65	-63	-64	-65
2353.8	-32	-29	-30	-32	-37	-39	-42	-41	-41	-44	-45	-43	-45	-47	-45	-46	-45	-46	-46	-46	-46
2853.8	-33	-30	-24	-23	-25	-24	-28	-28	-28	-28	-30	-29	-27	-30	-30	-31	-30	-30	-30	-29	-32
3353.8	-29	-29	-24	-21	-18	-15	-15	-17	-18	-17	-18	-19	-18	-18	-18	-17	-19	-19	-19	-19	-18
3853.8	-30	-26	-24	-20	-16	-14	-13	-9	-9	-8	-8	-8	-6	-7	-10	-11	-9	-9	-10	-10	-10
4353.8	-28	-27	-20	-18	-17	-14	-10	-9	-9	-5	0	-2	-5	-5	-5	-5	-8	-9	-10	-9	-9
4853.8	-32	-28	-23	-19	-17	-14	-11	-10	-10	-8	-10	-14	-7	-8	-8	-8	-8	-12	-12	-11	-16
5353.8	-35	-27	-23	-21	-20	-18	-17	-15	-13	-14	-15	-13	-15	-14	-14	-13	-13	-14	-15	-15	-16
5853.8	-34	-28	-27	-25	-23	-22	-21	-19	-17	-19	-19	-19	-20	-19	-21	-19	-20	-19	-20	-20	-20
6353.8	-34	-32	-30	-26	-25	-24	-25	-22	-21	-23	-23	-24	-23	-24	-25	-26	-24	-24	-25	-25	-26
6853.8	-37	-33	-31	-29	-28	-27	-26	-27	-27	-27	-26	-27	-27	-28	-29	-28	-28	-30	-30	-30	-29
7353.8	-37	-34	-34	-34	-31	-31	-29	-30	-29	-29	-30	-30	-31	-30	-32	-32	-32	-33	-33	-32	-32
7853.8	-38	-36	-34	-32	-32	-33	-32	-33	-32	-32	-32	-33	-35	-34	-35	-35	-35	-36	-36	-36	-35
8353.8	-40	-38	-38	-36	-35	-34	-34	-36	-35	-34	-35	-36	-37	-38	-37	-37	-38	-38	-37	-38	-38
8853.8	-43	-39	-39	-37	-35	-35	-36	-38	-37	-38	-39	-38	-38	-39	-40	-40	-40	-40	-40	-39	-40
9353.8	-42	-41	-40	-39	-37	-36	-39	-39	-40	-40	-40	-40	-41	-41	-42	-42	-43	-42	-42	-43	-44

LSM single system: β = 1.6 with error minimisation



LSM single system: β = 1.6 on 3D surface map



LSM single system: β = 1.6 on Wireframe contour map

Eta	Beta	Engine	Overhaul
4353.8	1.6	10015	Shop Visit (SV)

Predict Beta and Eta Parameters

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	1000	2500	3200	6000	8000	11000
Population 0	Number Off	36	33	24	20	7	3	0
	Overhaul Age		1000	2500	3200	6000	8000	11000
	% Failed		9%	34%	46%	81%	93%	99%
	Number of Failed parts (cum)		3	12	16	29	33	36
	Number of Failed parts (this)		3	9	4	13	4	3
Population 1	Number Off		3	3	2	1	0	0
	Overhaul Age			1500	2200	5000	7000	10000
	% Failed			17%	29%	71%	88%	98%
	Number of Failed parts (cum)			0	1	2	3	3
	Number of Failed parts (this)			0	1	1	1	0
Population 2	Number Off			9	9	4	2	0
	Overhaul Age				700	3500	5500	8500
	% Failed				5%	51%	77%	95%
	Number of Failed parts (cum)				0	5	7	9
	Number of Failed parts (this)				0	5	2	2
Population 3	Number Off				5	3	2	0
	Overhaul Age					2800	4800	7800
	% Failed					39%	69%	92%
	Number of Failed parts (cum)					2	3	5
	Number of Failed parts (this)					2	1	2
Population 4	Number Off					21	16	6
	Overhaul Age						2000	5000
	% Failed						25%	71%
	Number of Failed parts (cum)						5	15
	Number of Failed parts (this)						5	10
Population 5	Number Off						13	7
	Overhaul Age							3000
	% Failed							42%
	Number of Failed parts (cum)							6
	Number of Failed parts (this)							6
	Number Off							23
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		3	9	5	21	13	23
	Scrap Rate		8%	25%	14%	58%	36%	64%

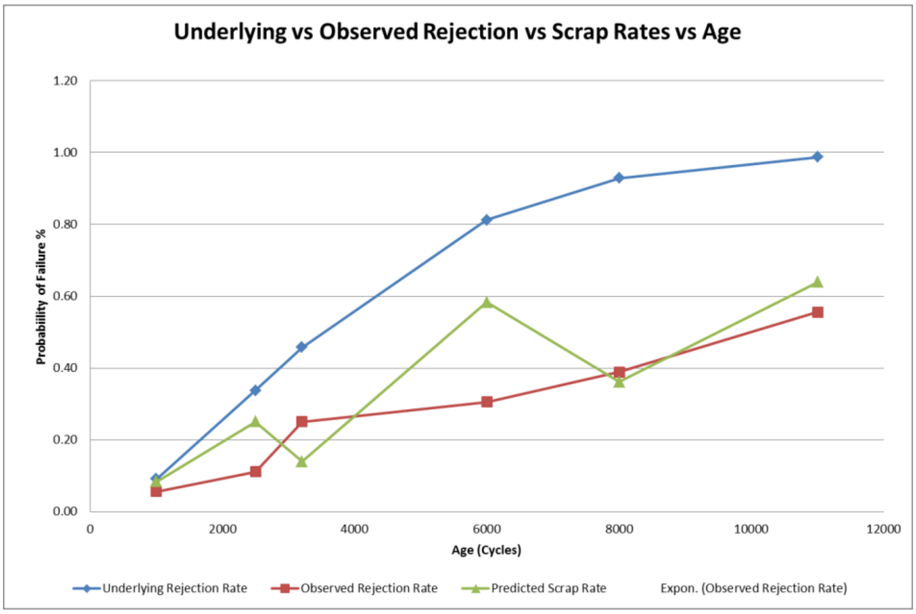
The Underlying Scrap Data Available

Underlying scrap rate		9%	34%	46%	81%	93%	99%

The Observed Scrap Data Available

Observed scrap number		2	4	9	11	14	20
Observed scrap rate		6%	11%	25%	31%	39%	56%
Engine age at Overhaul		1000	2500	3200	6000	8000	11000

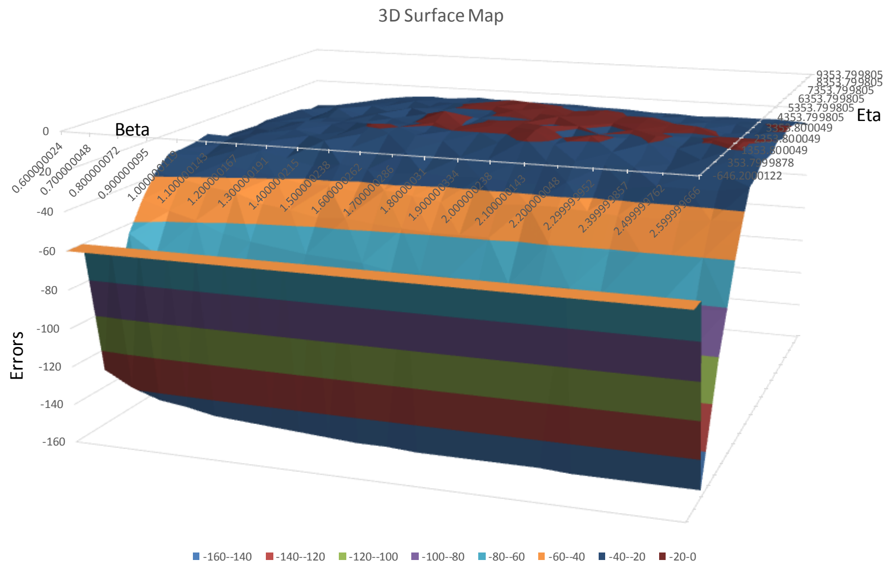
LSM single system: β = 1.6 with similar predicted and observed values



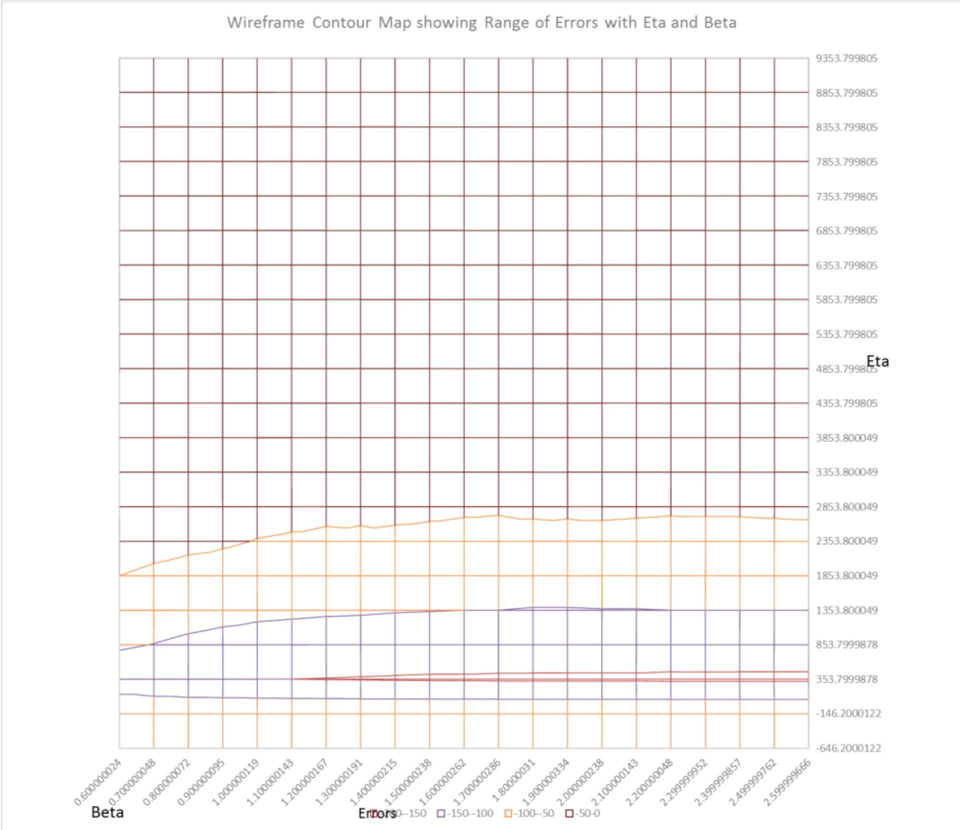
LSM single system: β = 1.6 with similar predicted and observed values failure model

η \ β	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6
-646.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
-146.2	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
353.8	-131	-139	-144	-146	-149	-150	-151	-152	-153	-154	-154	-155	-155	-155	-155	-155	-156	-156	-156	-156	-156
853.8	-94	-101	-109	-115	-118	-120	-123	-123	-126	-126	-127	-126	-127	-128	-128	-128	-128	-127	-128	-128	-128
1353.8	-65	-75	-81	-86	-91	-93	-95	-96	-98	-99	-100	-100	-102	-102	-101	-101	-100	-100	-100	-100	-100
1853.8	-50	-55	-59	-65	-68	-70	-72	-73	-74	-77	-77	-77	-78	-78	-77	-77	-79	-79	-79	-82	-81
2353.8	-38	-41	-44	-46	-51	-53	-56	-55	-57	-58	-59	-59	-59	-61	-59	-60	-61	-60	-60	-60	-60
2853.8	-31	-34	-34	-37	-39	-42	-42	-44	-42	-44	-46	-47	-45	-44	-44	-45	-46	-46	-46	-45	-44
3353.8	-31	-33	-30	-29	-32	-35	-33	-35	-36	-35	-36	-35	-36	-36	-34	-37	-35	-33	-33	-33	-30
3853.8	-30	-30	-26	-26	-28	-24	-27	-29	-27	-30	-28	-28	-28	-27	-26	-27	-27	-29	-28	-28	-28
4353.8	-28	-29	-26	-26	-25	-24	-22	-21	-21	-23	-24	-22	-19	-21	-23	-23	-26	-27	-24	-23	-23
4853.8	-34	-32	-27	-25	-27	-24	-19	-20	-22	-20	-20	-20	-17	-20	-18	-22	-20	-22	-22	-19	-24
5353.8	-33	-29	-27	-23	-24	-22	-23	-21	-19	-20	-19	-19	-17	-24	-20	-21	-19	-22	-19	-19	-24
5853.8	-34	-28	-27	-27	-25	-24	-21	-21	-15	-21	-19	-19	-22	-19	-23	-19	-20	-21	-20	-20	-20
6353.8	-34	-30	-30	-26	-25	-22	-25	-20	-21	-21	-21	-20	-17	-18	-19	-18	-18	-18	-21	-21	-22
6853.8	-33	-31	-29	-23	-26	-23	-20	-21	-21	-21	-18	-19	-19	-18	-19	-18	-20	-22	-24	-22	-19
7353.8	-35	-28	-30	-26	-23	-25	-23	-22	-19	-19	-20	-18	-19	-18	-20	-20	-22	-21	-21	-20	-20
7853.8	-34	-30	-28	-26	-26	-27	-24	-21	-20	-20	-18	-19	-23	-20	-21	-23	-21	-22	-22	-22	-21
8353.8	-36	-34	-30	-28	-27	-24	-24	-24	-21	-20	-21	-22	-23	-24	-23	-23	-24	-24	-23	-24	-24
8853.8	-37	-33	-31	-29	-27	-25	-24	-24	-23	-24	-25	-24	-24	-25	-26	-26	-26	-26	-26	-25	-26
9353.8	-36	-35	-32	-29	-27	-26	-27	-25	-26	-26	-26	-26	-27	-27	-28	-28	-29	-28	-28	-29	-30

LSM single system: β = 1.6 with similar predicted and observed values, and error minimisation



LSM single system: β = 1.6 with similar predicted and observed values, and error minimisation on 3D Surface map

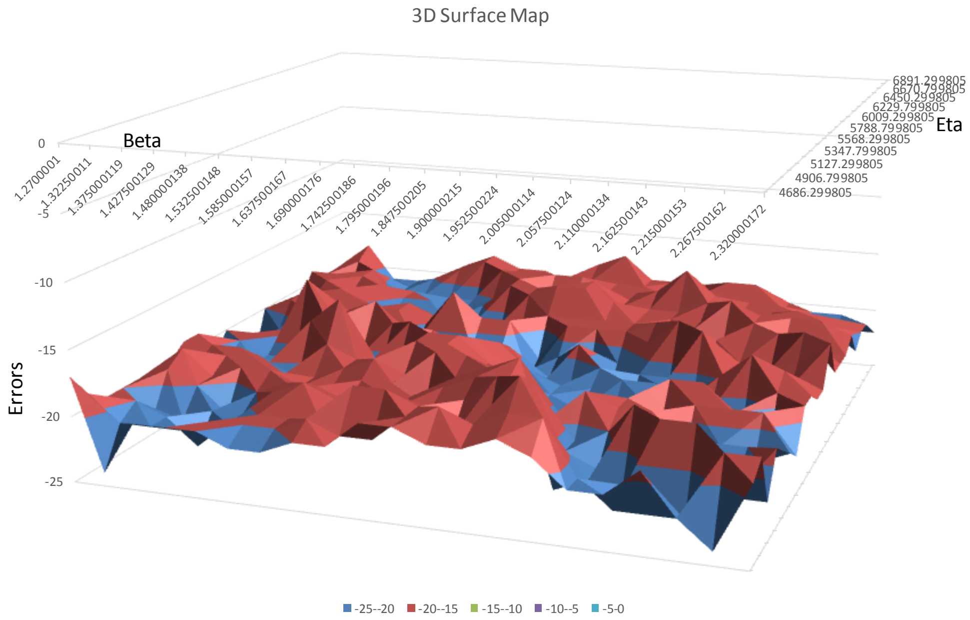


LSM single system: β = 1.6 with similar predicted and observed values, and error minimisation on Wireframe contour maps

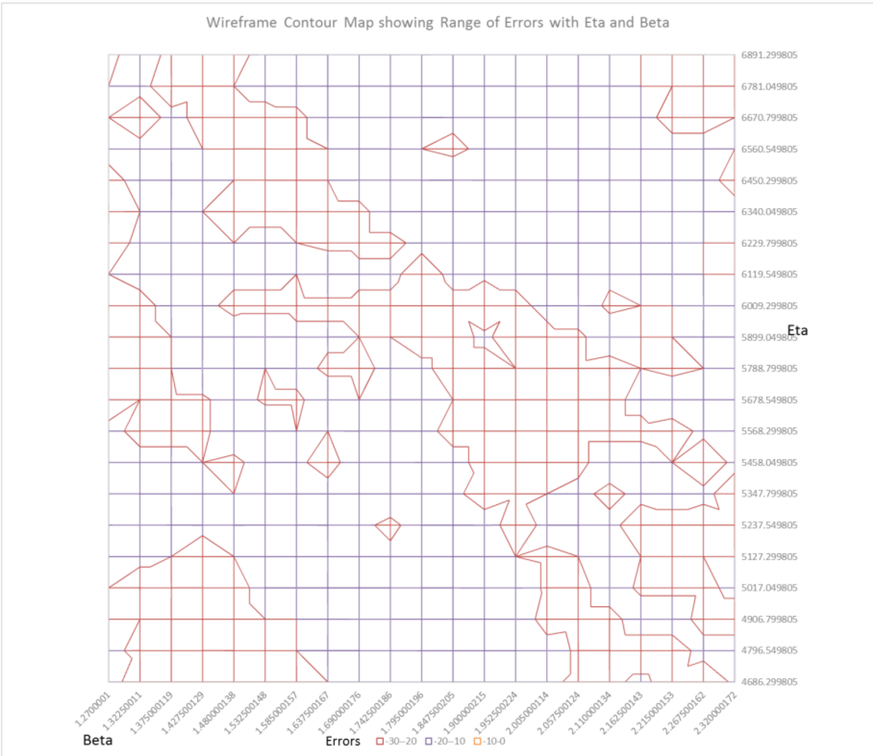
β

η	1.27	1.3225	1.375	1.4275	1.48	1.5325	1.585	1.6375	1.69	1.7425	1.795	1.8475	1.9	1.9525	2.005	2.0575	2.11	2.1625	2.215	2.2675	2.32
4686.3	-17	-24	-20	-20	-20	-21	-21	-20	-20	-18	-18	-19	-19	-18	-19	-21	-21	-19	-22	-24	-19
4796.55	-19	-21	-21	-21	-20	-20	-20	-19	-20	-20	-18	-17	-18	-17	-17	-21	-23	-23	-23	-18	-18
4906.8	-20	-20	-21	-23	-21	-20	-20	-20	-17	-17	-18	-20	-20	-15	-23	-22	-22	-17	-17	-22	-22
5017.05	-20	-22	-22	-21	-21	-19	-18	-19	-20	-19	-19	-18	-16	-16	-21	-22	-17	-21	-21	-21	-19
5127.3	-20	-19	-20	-22	-20	-19	-19	-20	-19	-19	-18	-17	-17	-20	-21	-20	-20	-20	-20	-20	-20
5237.55	-20	-18	-20	-19	-19	-20	-20	-19	-19	-21	-18	-17	-16	-24	-18	-19	-19	-22	-21	-22	-21
5347.8	-20	-20	-19	-19	-20	-20	-19	-18	-19	-17	-17	-18	-24	-21	-20	-19	-21	-19	-19	-19	-22
5458.05	-19	-19	-19	-20	-21	-18	-19	-22	-17	-17	-19	-19	-21	-21	-22	-21	-18	-18	-20	-23	-19
5568.3	-19	-21	-21	-21	-17	-15	-20	-20	-17	-17	-19	-21	-21	-22	-22	-21	-21	-21	-22	-19	-19
5678.55	-22	-20	-21	-21	-17	-21	-21	-17	-20	-20	-18	-20	-21	-21	-20	-20	-21	-19	-17	-18	-20
5788.8	-20	-20	-20	-15	-18	-20	-18	-21	-21	-19	-19	-22	-22	-20	-23	-21	-22	-20	-21	-20	-20
5899.05	-23	-21	-20	-19	-18	-17	-19	-19	-20	-20	-22	-22	-19	-23	-21	-21	-17	-20	-20	-19	-17
6009.3	-24	-21	-19	-19	-21	-21	-21	-21	-21	-21	-23	-21	-24	-21	-19	-17	-21	-20	-20	-17	-20
6119.55	-20	-19	-19	-19	-19	-19	-20	-17	-19	-19	-22	-19	-19	-19	-18	-19	-19	-19	-18	-20	-20
6229.8	-22	-19	-19	-19	-20	-19	-20	-21	-21	-21	-19	-19	-19	-19	-20	-19	-20	-18	-20	-20	-20
6340.05	-25	-20	-19	-20	-21	-21	-21	-21	-21	-18	-17	-17	-18	-19	-19	-19	-17	-18	-18	-18	-19
6450.3	-21	-19	-20	-19	-20	-20	-21	-20	-18	-18	-18	-17	-19	-19	-19	-18	-19	-19	-18	-19	-21
6560.55	-19	-19	-19	-20	-20	-21	-21	-20	-18	-20	-20	-21	-19	-18	-16	-18	-19	-19	-19	-19	-20
6670.8	-20	-22	-19	-21	-21	-21	-21	-18	-18	-18	-18	-19	-19	-19	-19	-19	-19	-19	-21	-21	-20
6781.05	-20	-19	-22	-21	-20	-19	-18	-19	-19	-19	-19	-19	-19	-20	-20	-18	-18	-20	-20	-20	-21
6891.3	-21	-18	-21	-21	-21	-19	-18	-19	-19	-20	-18	-17	-19	-19	-19	-19	-20	-20	-21	-22	-22

LSM single system: β = 1.6 with similar predicted and observed values, and realistic η and β with errors



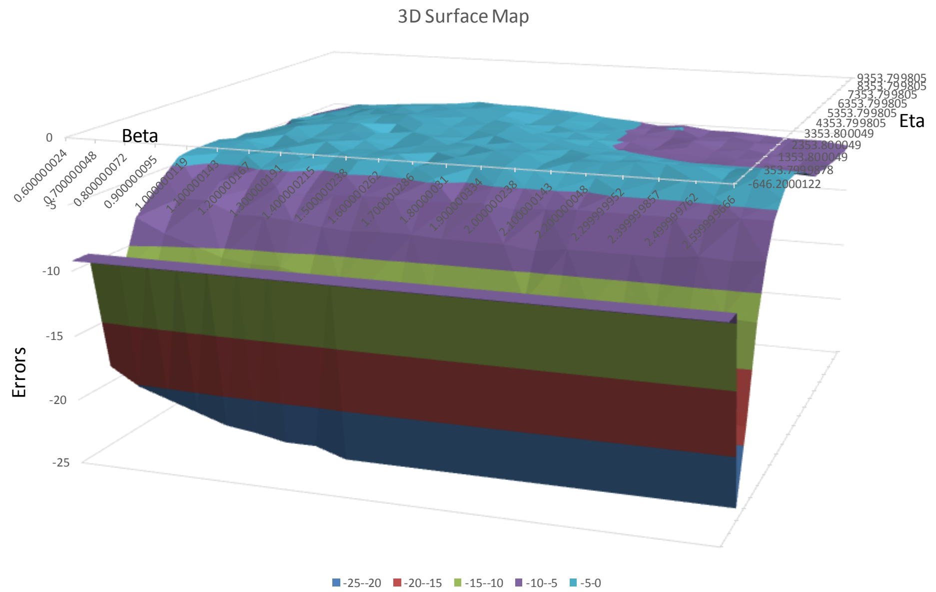
LSM single system: β = 1.6 with similar predicted and observed values, and realistic η and β with error values in 3D Surface map



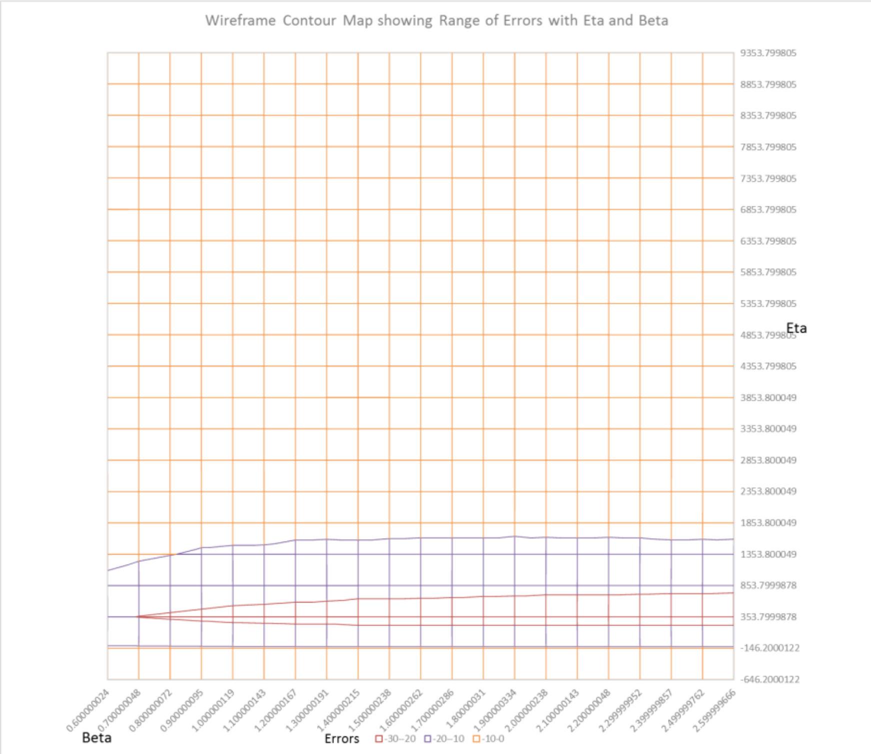
LSM single system: β = 1.6 with similar predicted and observed values, and realistic η and β with error values on Wireframe Contour map

η \ β	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6
-646.2	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9
-146.2	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9	-9
353.8	-19	-20	-21	-22	-22	-23	-23	-23	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24	-24
853.8	-12	-13	-14	-15	-16	-16	-16	-17	-17	-17	-17	-18	-18	-18	-18	-18	-18	-18	-19	-19	-19
1353.8	-8	-9	-10	-11	-11	-11	-12	-12	-12	-12	-12	-12	-12	-12	-12	-12	-12	-12	-12	-12	-12
1853.8	-7	-7	-7	-8	-8	-8	-8	-8	-8	-8	-8	-8	-8	-9	-8	-8	-8	-8	-8	-8	-8
2353.8	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6	-6
2853.8	-4	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5	-4
3353.8	-4	-4	-4	-5	-4	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
3853.8	-4	-4	-4	-4	-4	-4	-4	-4	-5	-4	-4	-4	-4	-4	-4	-3	-3	-3	-4	-3	-4
4353.8	-4	-4	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
4853.8	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5353.8	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5
5853.8	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-6
6353.8	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6
6853.8	-5	-4	-4	-4	-4	-3	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6
7353.8	-5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-5	-4	-5	-5	-5	-5	-5	-6	-6	-6	-6
7853.8	-5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6
8353.8	-5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6
8853.8	-5	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6
9353.8	-6	-5	-5	-5	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6

LSM multiple systems: β = 1.6 with similar predicted and observed values, and error minimisation



LSM multiple systems: β = 1.6 with similar predicted and observed values, error minimisation on 3D Surface map

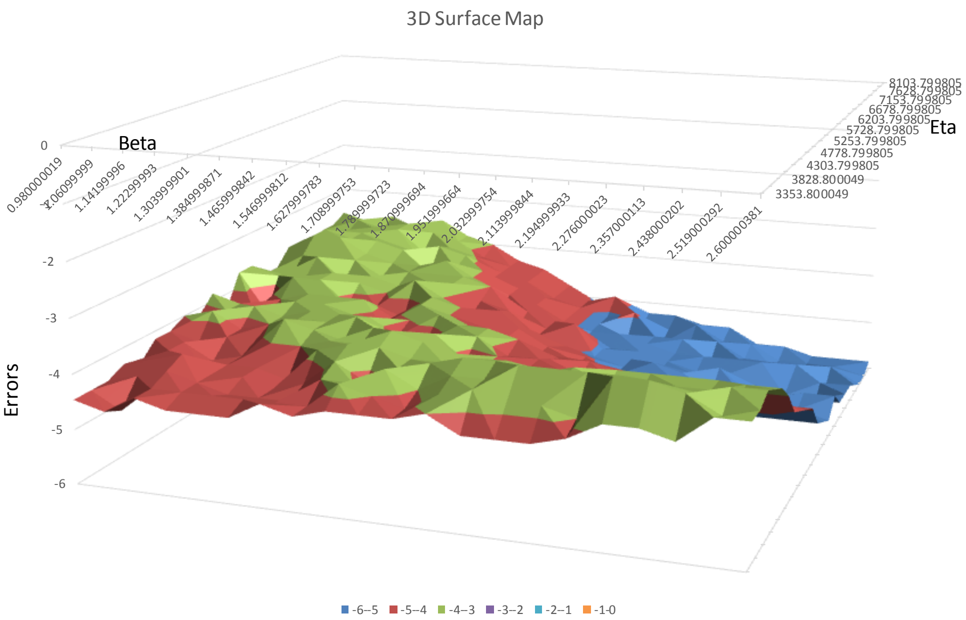


LSM multiple systems: β = 1.6 with similar predicted and observed values, error minimisation on Wireframe contour maps

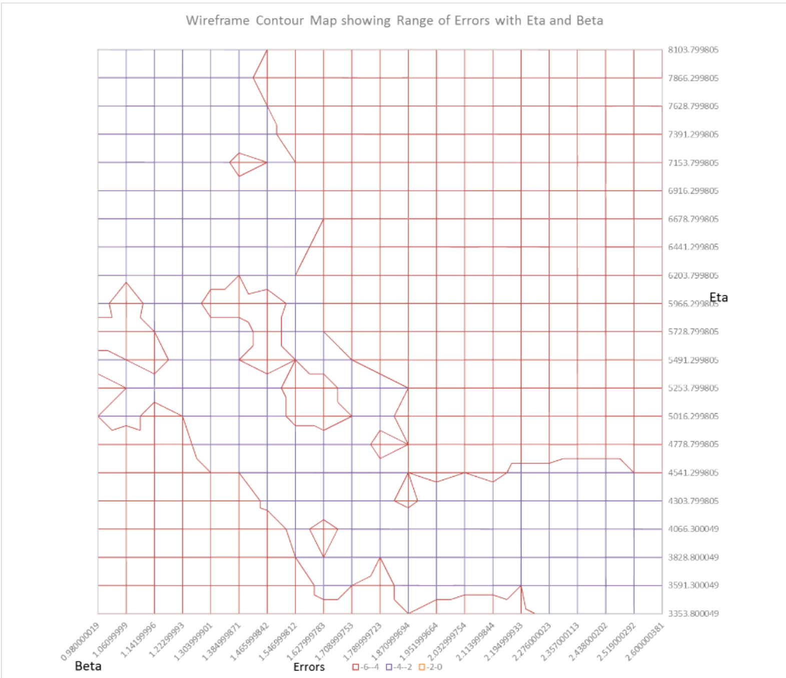
β

η	0.98	1.061	1.142	1.223	1.304	1.385	1.466	1.547	1.628	1.709	1.79	1.871	1.952	2.033	2.114	2.195	2.276	2.357	2.438	2.519	2.6
3353.8	-4	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
3591.3	-4	-5	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-3	-3	-3	-4	-4
3828.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-3	-3	-3	-3	-4	-4	-3	-3
4066.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
4303.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
4541.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
4778.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4
5016.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5
5253.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5
5491.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5
5728.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5
5966.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6
6203.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6
6441.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6	-5	-5
6678.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6
6916.3	-4	-3	-3	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6	-6
7153.8	-4	-3	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6
7391.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6	-6
7628.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-6	-6	-5	-6	-6	-6	-6	-6
7866.3	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6	-6
8103.8	-4	-4	-4	-4	-4	-4	-4	-4	-4	-5	-5	-5	-5	-5	-5	-5	-6	-6	-6	-6	-6

LSM multiple systems: β = 1.6 with similar predicted and observed values, and realistic η and β with error minimisation



LSM multiple systems: β = 1.6 with similar predicted and observed values, and realistic η and β with errors values on 3D Surface map



LSM multiple systems: β = 1.6 with similar predicted and observed values, and realistic η and β with errors Wireframe Contour map

Eta	Beta	Engine	Overhaul
4523.5	1.5	10015	Shop Visit (SV)

Predict Beta and Eta Parameters

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	1000	2500	3200	6000	8000	11000
Population 0	Number Off	36	32	24	20	8	3	1
	Overhaul Age		1000	2500	3200	6000	8000	11000
	% Failed		10%	34%	45%	78%	90%	98%
	Number of Failed parts (cum)		4	12	16	28	33	35
	Number of Failed parts (this)		4	8	4	12	5	2
Population 1	Number Off		4	3	3	1	1	0
	Overhaul Age			1500	2200	5000	7000	10000
	% Failed			17%	29%	69%	85%	96%
	Number of Failed parts (cum)			1	1	3	3	4
	Number of Failed parts (this)			1	0	2	0	1
Population 2	Number Off			9	8	5	2	1
	Overhaul Age				700	3500	5500	8500
	% Failed				6%	49%	74%	92%
	Number of Failed parts (cum)				1	4	7	8
	Number of Failed parts (this)				1	3	3	1
Population 3	Number Off				5	3	2	1
	Overhaul Age					2800	4800	7800
	% Failed					39%	66%	90%
	Number of Failed parts (cum)					2	3	4
	Number of Failed parts (this)					2	1	1
Population 4	Number Off					19	14	6
	Overhaul Age						2000	5000
	% Failed						25%	69%
	Number of Failed parts (cum)						5	13
	Number of Failed parts (this)						5	8
Population 5	Number Off						14	8
	Overhaul Age							3000
	% Failed							42%
	Number of Failed parts (cum)							6
	Number of Failed parts (this)							6
	Number Off							19

Cross check - number of parts fitted	36	36	36	36	36	36	36
Number of Failed Parts		4	9	5	19	14	19
Scrap Rate		11%	25%	14%	53%	39%	53%

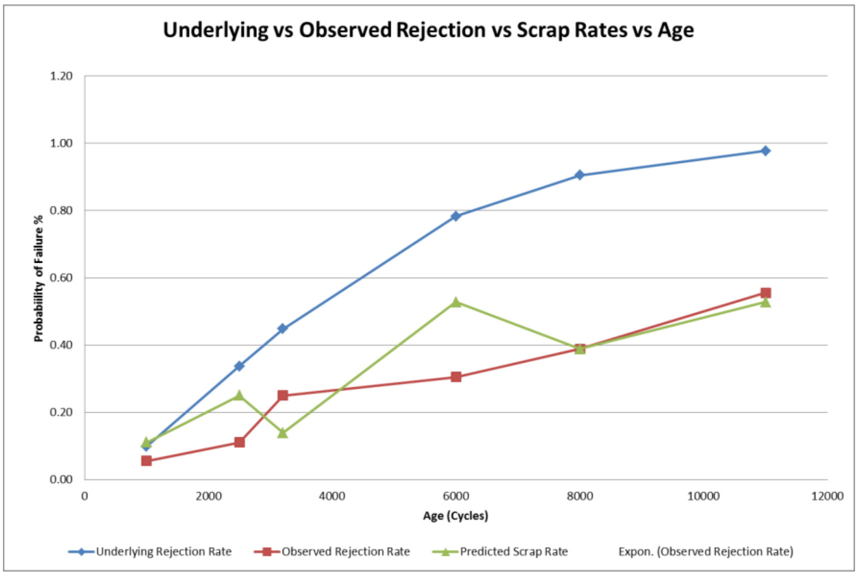
The Underlying Scrap Data Available

Underlying scrap rate		10%	34%	45%	78%	90%	98%

The Observed Scrap Data Available

Observed scrap number		2	4	9	11	14	20
Observed scrap rate		6%	11%	25%	31%	39%	56%
Engine age at Overhaul		1000	2500	3200	6000	8000	11000

MLE single system: β = 1.5 with similar predicted and observed values on Through-life prediction model

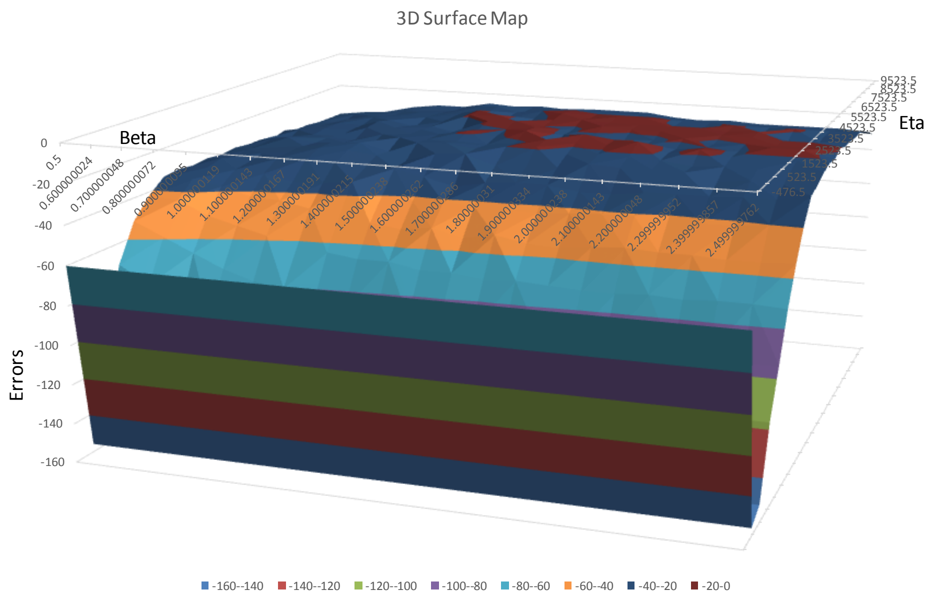


MLE single system: β = 1.5 with similar predicted and observed values on Probability of failure model

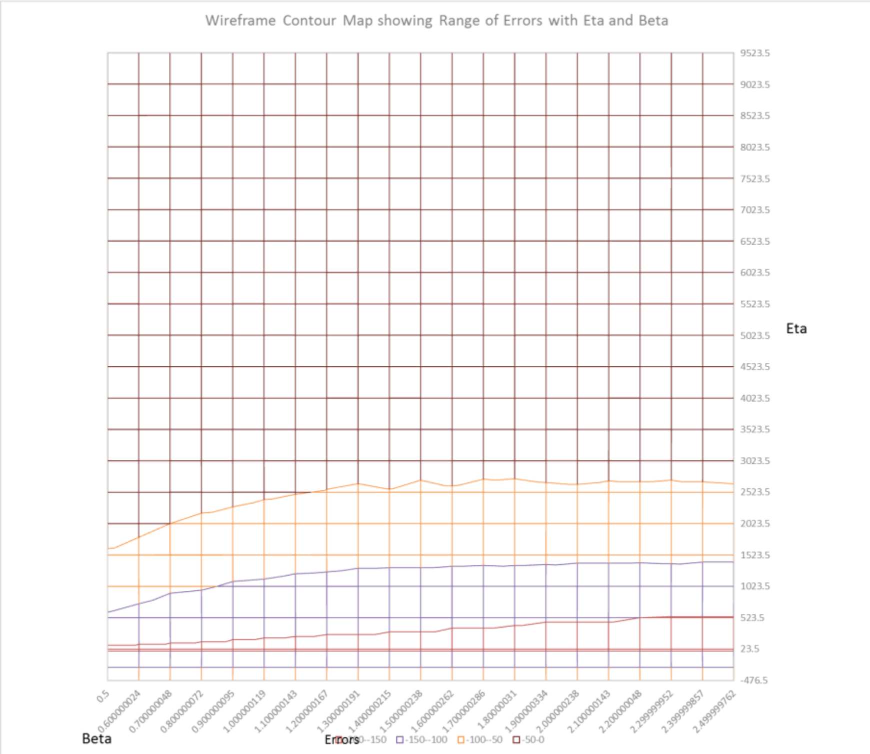
β

η	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5
-476.5	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60	-60
23.5	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156	-156
523.5	-106	-116	-125	-130	-136	-139	-141	-143	-143	-145	-145	-147	-147	-148	-149	-149	-149	-150	-151	-151	-151
1023.5	-71	-80	-93	-96	-104	-106	-110	-111	-115	-116	-116	-116	-116	-118	-118	-117	-117	-118	-118	-117	-117
1523.5	-52	-59	-66	-73	-78	-80	-85	-87	-89	-89	-89	-91	-92	-91	-92	-94	-94	-94	-93	-95	-95
2023.5	-42	-43	-50	-54	-58	-63	-64	-66	-66	-69	-69	-71	-70	-71	-72	-72	-71	-72	-71	-71	-72
2523.5	-35	-35	-38	-42	-43	-46	-49	-51	-53	-51	-55	-52	-55	-56	-54	-53	-54	-54	-55	-55	-54
3023.5	-34	-32	-32	-33	-36	-36	-34	-40	-42	-41	-42	-42	-43	-42	-41	-41	-43	-42	-42	-40	-39
3523.5	-35	-30	-31	-28	-27	-28	-30	-29	-32	-36	-33	-32	-32	-34	-34	-32	-32	-32	-31	-31	-28
4023.5	-34	-32	-29	-27	-24	-24	-26	-28	-23	-22	-27	-27	-26	-23	-24	-24	-24	-28	-26	-27	-26
4523.5	-35	-31	-29	-27	-24	-23	-27	-21	-20	-22	-20	-19	-22	-21	-21	-22	-24	-23	-23	-24	-23
5023.5	-34	-31	-26	-28	-27	-27	-22	-22	-22	-23	-21	-18	-19	-19	-16	-21	-18	-21	-21	-21	-21
5523.5	-35	-30	-29	-28	-28	-24	-23	-22	-19	-21	-17	-23	-17	-19	-21	-22	-20	-21	-18	-18	-22
6023.5	-35	-35	-30	-30	-24	-23	-23	-24	-21	-20	-18	-21	-21	-23	-21	-19	-21	-20	-20	-20	-19
6523.5	-37	-31	-29	-29	-23	-25	-24	-27	-19	-18	-20	-21	-18	-19	-19	-19	-19	-19	-20	-20	-21
7023.5	-35	-33	-29	-29	-25	-28	-24	-19	-18	-23	-19	-18	-19	-19	-19	-19	-20	-19	-23	-23	-21
7523.5	-37	-35	-29	-27	-26	-25	-24	-19	-23	-22	-18	-20	-18	-18	-21	-21	-19	-22	-19	-22	-22
8023.5	-37	-35	-32	-29	-27	-26	-24	-22	-22	-20	-19	-20	-20	-20	-21	-21	-22	-22	-23	-22	-22
8523.5	-38	-37	-32	-31	-28	-27	-24	-22	-24	-22	-21	-22	-24	-23	-24	-24	-24	-25	-25	-25	-24
9023.5	-38	-35	-33	-31	-30	-29	-25	-26	-24	-24	-25	-25	-25	-26	-26	-26	-27	-27	-26	-26	-27
9523.5	-38	-36	-35	-31	-29	-29	-26	-27	-26	-27	-26	-26	-26	-28	-29	-28	-29	-29	-30	-30	-31

MLE single system: β = 1.5 with similar predicted and observed values, and error minimisation



MLE single system: β = 1.6 with similar predicted and observed values, and error minimisation on 3D Surface map

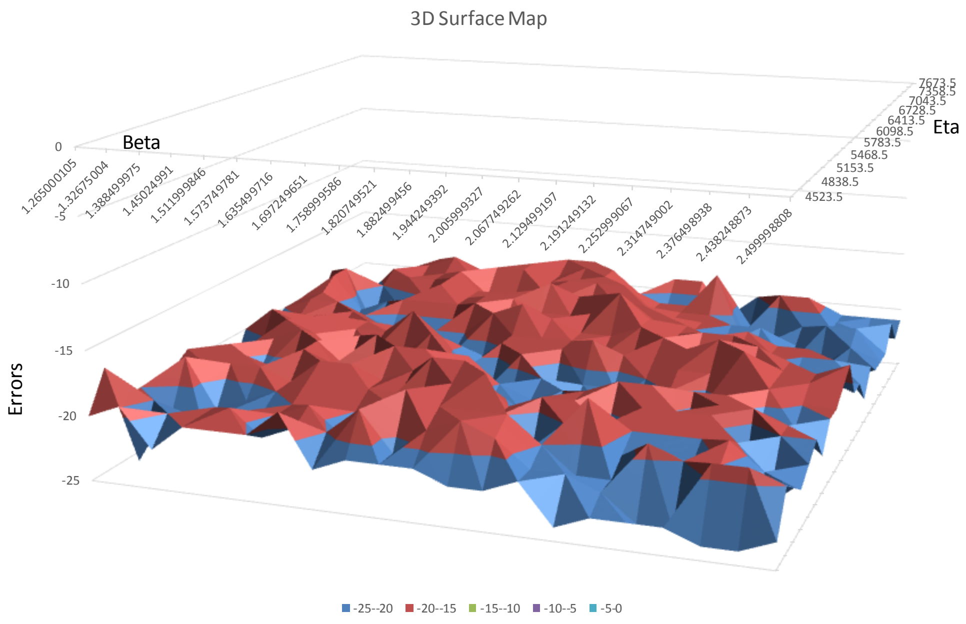


MLE single system: β = 1.5 with similar predicted and observed values, error minimisation on Wireframe Contour map

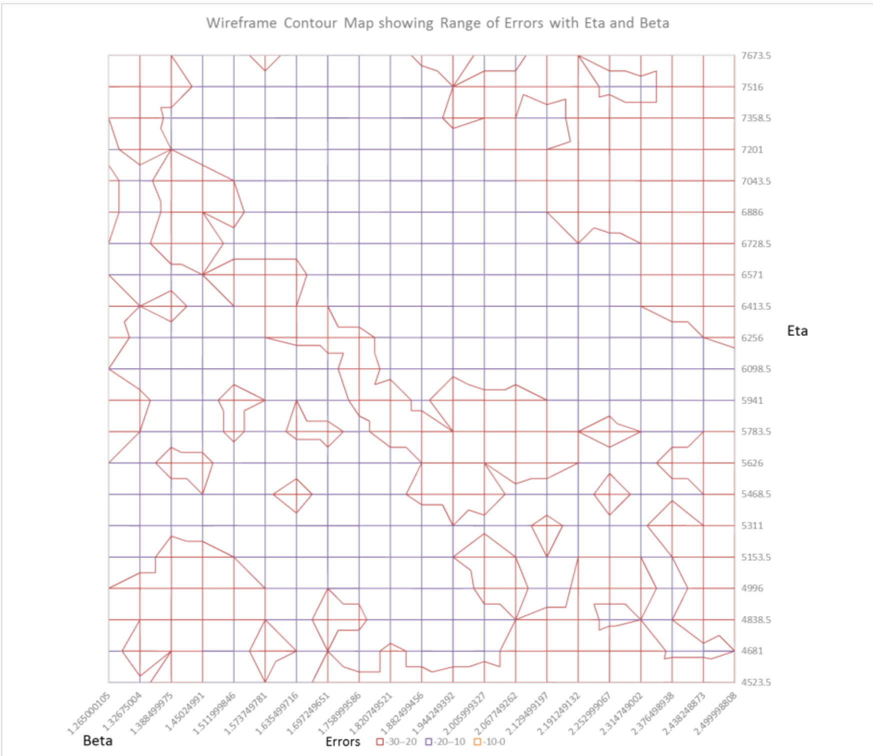
β

η	1.265	1.32675	1.3885	1.45025	1.512	1.57375	1.6355	1.69725	1.759	1.82075	1.882499	1.944249	2.005999	2.067749	2.129499	2.191249	2.252999	2.314749	2.376499	2.438249	2.499999
4523.5	-20	-19	-22	-20	-20	-20	-18	-22	-21	-21	-21	-22	-22	-21	-24	-23	-23	-23	-24	-24	-23
4681	-17	-24	-20	-20	-19	-21	-20	-20	-18	-21	-19	-18	-19	-21	-21	-22	-24	-24	-19	-19	-20
4838.5	-20	-20	-21	-20	-20	-20	-19	-21	-21	-17	-18	-18	-18	-20	-22	-22	-19	-20	-20	-23	-21
4996	-20	-22	-22	-21	-21	-20	-20	-20	-19	-19	-17	-16	-22	-22	-17	-21	-21	-21	-19	-21	-22
5153.5	-20	-18	-22	-21	-20	-19	-19	-19	-19	-16	-16	-20	-23	-20	-20	-20	-20	-20	-20	-23	-21
5311	-20	-19	-19	-19	-20	-18	-18	-19	-18	-18	-18	-20	-19	-19	-21	-19	-19	-19	-24	-20	-20
5468.5	-19	-19	-19	-20	-18	-19	-23	-17	-17	-19	-21	-21	-22	-19	-18	-18	-22	-19	-19	-20	-22
5626	-20	-19	-21	-21	-18	-20	-17	-19	-19	-18	-20	-21	-20	-22	-22	-20	-19	-19	-21	-21	-20
5783.5	-21	-20	-19	-18	-21	-18	-21	-21	-19	-22	-22	-20	-23	-22	-22	-20	-21	-20	-19	-20	-20
5941	-23	-21	-18	-19	-21	-20	-20	-18	-21	-22	-19	-23	-21	-21	-20	-19	-19	-17	-19	-19	-19
6098.5	-20	-18	-19	-18	-19	-19	-17	-19	-22	-19	-19	-19	-18	-19	-19	-18	-17	-20	-19	-19	-18
6256	-22	-19	-19	-20	-19	-20	-21	-21	-21	-19	-19	-19	-20	-20	-18	-20	-20	-18	-19	-20	-21
6413.5	-21	-20	-21	-19	-20	-20	-20	-20	-18	-17	-18	-19	-19	-18	-19	-18	-18	-20	-21	-21	-21
6571	-20	-19	-19	-20	-21	-21	-21	-18	-20	-20	-20	-18	-16	-18	-19	-19	-20	-20	-20	-20	-23
6728.5	-20	-19	-22	-22	-19	-19	-19	-18	-18	-19	-19	-17	-19	-19	-19	-20	-19	-20	-20	-22	-21
6886	-21	-18	-21	-20	-21	-18	-19	-19	-20	-17	-18	-19	-19	-19	-20	-21	-22	-22	-23	-23	-22
7043.5	-21	-18	-23	-21	-20	-18	-19	-19	-19	-19	-20	-19	-19	-20	-20	-20	-20	-23	-23	-21	-22
7201	-19	-22	-20	-19	-19	-18	-20	-20	-19	-18	-18	-18	-20	-20	-20	-21	-22	-22	-20	-20	-22
7358.5	-20	-23	-19	-20	-19	-19	-18	-18	-19	-19	-18	-21	-20	-20	-17	-22	-23	-21	-21	-21	-20
7516	-23	-22	-22	-19	-18	-19	-19	-18	-19	-18	-18	-20	-21	-21	-24	-22	-19	-19	-21	-22	-22
7673.5	-23	-21	-20	-19	-19	-21	-19	-19	-18	-18	-21	-22	-19	-19	-22	-20	-21	-22	-21	-21	-21

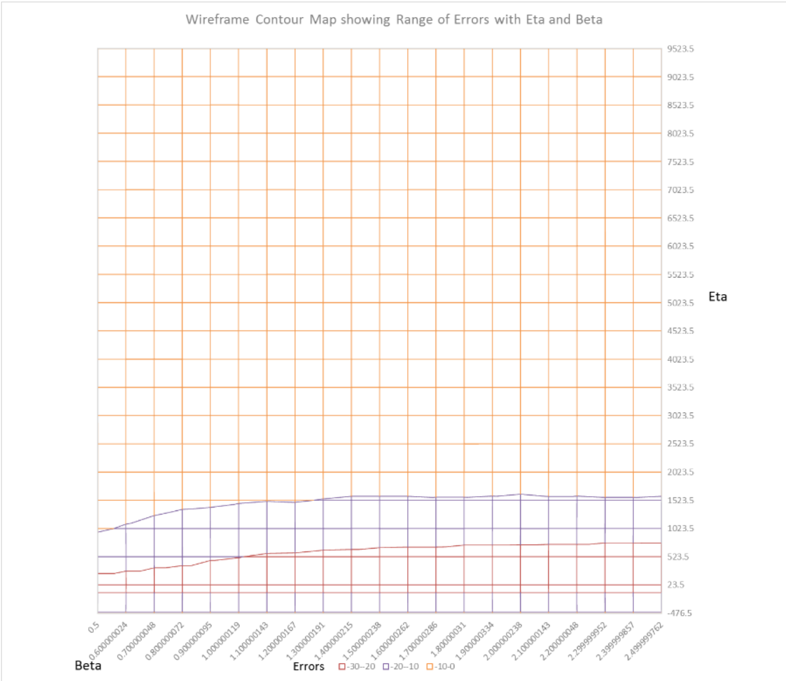
MLE single system: β = 1.5 with similar predicted and observed values, and realistic η and β with error minimisation



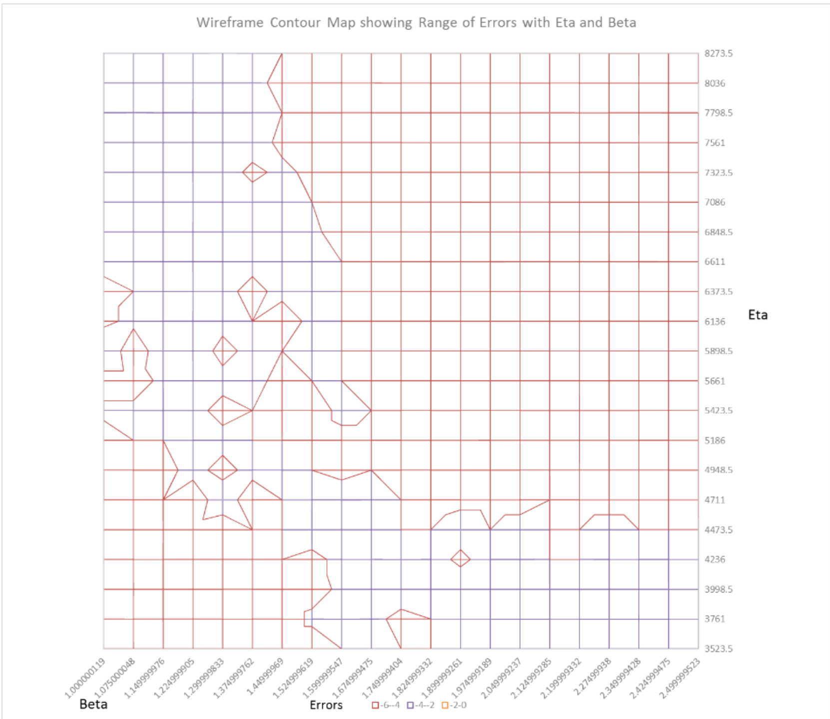
MLE single system: β = 1.5 with similar predicted and observed values, and realistic η and β with errors minimisation on 3D surface map



MLE single system: β = 1.6 with similar predicted and observed values, and realistic η and β with error minimisation on Wireframe Contour map



MLE multiple systems: β = 1.5 with similar predicted and observed values, and error minimisation on Wireframe contour map



MLE multiple systems: β = 1.5 with similar predicted and observed values, and realistic η and β with error values on Wireframe Contour map

Single stage turbine with new renewals of 6 overhauls for one engine

Eta	Beta	Engine	Overhaul	
6270	1.2	10015	Shop Visit (SV)	Predict Error Values

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	1000	2500	3200	6000	8000	11000
Population 0	Number Off	36	32	26	23	14	9	5
	Overhaul Age		1000	2500	3200	6000	8000	11000
	% Failed		10%	28%	36%	61%	74%	86%
	Number of Failed parts (cum)		4	10	13	22	27	31
	Number of Failed parts (this)		4	6	3	9	5	4
Population 1	Number Off		4	3	3	2	1	1
	Overhaul Age			1500	2200	5000	7000	10000
	% Failed			16%	25%	53%	68%	83%
	Number of Failed parts (cum)			1	1	2	3	3
	Number of Failed parts (this)			1	0	1	1	0
Population 2	Number Off			7	7	4	3	2
	Overhaul Age				700	3500	5500	8500
	% Failed				7%	39%	57%	76%
	Number of Failed parts (cum)				0	3	4	5
	Number of Failed parts (this)				0	3	1	1
Population 3	Number Off				3	2	1	1
	Overhaul Age					2800	4800	7800
	% Failed					32%	52%	73%
	Number of Failed parts (cum)					1	2	2
	Number of Failed parts (this)					1	1	0
Population 4	Number Off					14	11	7
	Overhaul Age						2000	5000
	% Failed						22%	53%
	Number of Failed parts (cum)						3	7
	Number of Failed parts (this)						3	4
Population 5	Number Off						11	7
	Overhaul Age							3000
	% Failed							34%
	Number of Failed parts (cum)							4
	Number of Failed parts (this)							4
	Number Off							13
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		4	7	3	14	11	13
	Scrap Rate		11%	19%	8%	39%	31%	36%

The Underlying Scrap Data Available

Underlying scrap rate		10%	28%	36%	61%	74%	86%

The Observed Scrap Data Available

Observed scrap number		2	4	9	11	14	20
Observed scrap rate		0.055555556	0.111111112	0.25	0.305555552	0.388888896	0.555555582
Engine age at Overhaul		1000	2500	3200	6000	8000	11000

LSM: Through-life model with overhaul times for the η and β parameters

Initial β 1.2

η 6270

	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2
1270	-50	-47	-50	-59	-69	-78	-86	-88	-93	-98	-98	-101	-102	-102	-103	-106	-105	-106	-105	-104	-105
1770	-50	-42	-43	-45	-51	-58	-63	-67	-71	-73	-76	-77	-78	-79	-80	-81	-80	-80	-82	-82	-84
2270	-48	-43	-39	-38	-38	-43	-48	-50	-53	-55	-58	-57	-59	-61	-62	-63	-63	-62	-62	-63	-63
2770	-46	-41	-37	-33	-33	-35	-38	-39	-42	-45	-44	-47	-47	-46	-48	-46	-46	-48	-47	-47	-48
3270	-50	-41	-38	-36	-31	-29	-30	-32	-32	-37	-37	-38	-37	-38	-37	-37	-38	-35	-38	-38	-34
3770	-49	-43	-38	-37	-31	-29	-28	-27	-26	-26	-27	-29	-28	-28	-31	-29	-29	-27	-29	-27	-27
4270	-50	-44	-37	-34	-33	-28	-28	-26	-26	-25	-21	-20	-24	-21	-22	-23	-20	-22	-21	-24	-27
4770	-49	-45	-37	-36	-34	-30	-25	-24	-27	-24	-16	-25	-20	-19	-21	-20	-18	-17	-19	-21	-23
5270	-50	-43	-38	-37	-33	-29	-27	-23	-25	-23	-23	-19	-19	-19	-18	-19	-18	-22	-19	-19	-19
5770	-52	-45	-38	-34	-34	-27	-26	-26	-25	-24	-21	-23	-19	-20	-18	-20	-18	-22	-20	-22	-20
6270	-51	-46	-40	-37	-33	-30	-30	-26	-25	-22	-24	-20	-19	-21	-21	-21	-19	-19	-20	-20	-18
6770	-52	-47	-40	-35	-32	-30	-28	-23	-24	-23	-21	-22	-22	-20	-18	-19	-19	-19	-20	-18	-20
7270	-52	-46	-40	-37	-34	-30	-27	-25	-23	-24	-23	-20	-20	-20	-20	-20	-18	-18	-21	-21	-22
7770	-51	-47	-40	-38	-34	-30	-28	-26	-26	-26	-21	-19	-20	-20	-18	-19	-20	-19	-19	-23	-21
8270	-52	-46	-43	-39	-37	-34	-29	-28	-26	-24	-24	-23	-21	-23	-20	-22	-23	-21	-23	-23	-24
8770	-51	-47	-42	-38	-37	-33	-31	-29	-27	-25	-24	-22	-23	-24	-24	-24	-24	-25	-25	-26	-26
9270	-52	-47	-43	-39	-36	-34	-31	-31	-29	-26	-27	-25	-26	-26	-26	-25	-27	-27	-27	-28	-28
9770	-51	-46	-44	-38	-37	-37	-31	-29	-29	-28	-26	-27	-27	-27	-28	-29	-28	-29	-29	-30	-31
10270	-51	-46	-44	-40	-38	-33	-34	-31	-29	-28	-28	-28	-29	-29	-30	-30	-31	-31	-33	-33	-33
10770	-51	-48	-42	-41	-38	-35	-34	-32	-29	-30	-30	-30	-30	-31	-31	-32	-33	-34	-35	-35	-36
11270	-52	-49	-42	-42	-37	-35	-34	-33	-31	-30	-30	-32	-32	-33	-33	-34	-35	-36	-36	-37	-37

LSM: a range of error values for the estimated η and β parameters

Optimised-ZoomIn **β 1.2**

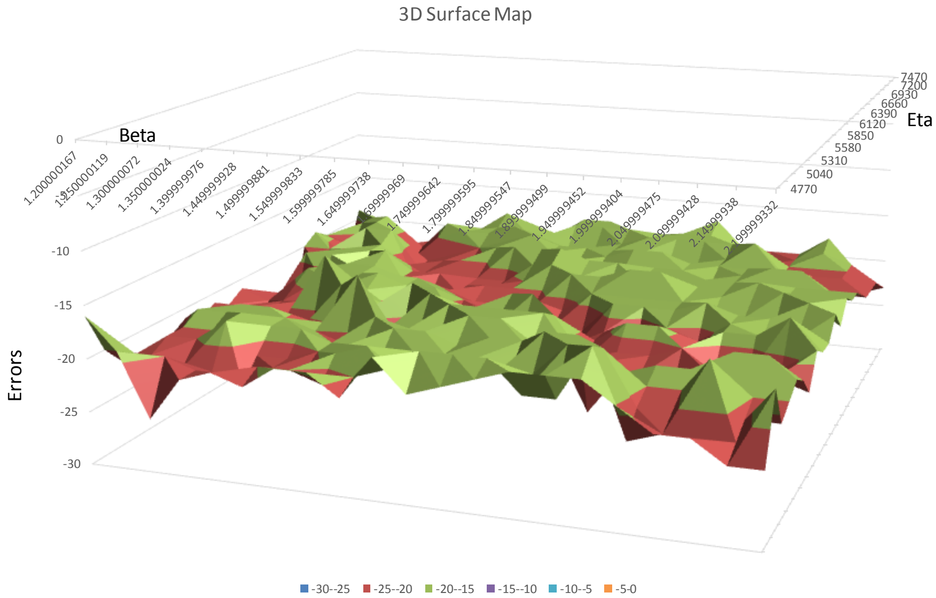
New NGV Replace	
η	β
7470	1.2
4770	2.2

η 6270

η	1.2	1.25	1.3	1.35	1.4	1.45	1.5	1.55	1.6	1.65
4770	-16	-19	-25	-21	-20	-21	-19	-19	-21	-17
4905	-20	-20	-20	-21	-21	-20	-20	-21	-20	-19
5040	-22	-21	-22	-22	-23	-21	-21	-19	-18	-20
5175	-22	-20	-20	-18	-21	-21	-20	-19	-20	-19
5310	-23	-20	-20	-18	-19	-19	-20	-20	-18	-18
5445	-22	-19	-19	-19	-19	-20	-21	-18	-19	-20
5580	-21	-20	-19	-19	-21	-20	-15	-20	-20	-17
5715	-22	-22	-20	-21	-21	-17	-19	-22	-17	-20
5850	-21	-21	-21	-20	-15	-18	-21	-17	-19	-19
5985	-22	-24	-21	-21	-19	-19	-21	-21	-21	-20
6120	-21	-22	-20	-19	-19	-18	-19	-19	-20	-21
6255	-24	-22	-19	-19	-19	-20	-19	-20	-21	-21
6390	-25	-25	-21	-19	-19	-20	-22	-21	-20	-20
6525	-27	-19	-19	-22	-18	-20	-20	-21	-21	-20
6660	-27	-21	-19	-19	-21	-21	-21	-21	-21	-19
6795	-20	-20	-23	-19	-21	-21	-20	-20	-18	-18
6930	-19	-21	-18	-18	-22	-21	-21	-19	-19	-19
7065	-20	-21	-18	-23	-22	-21	-20	-19	-18	-19
7200	-23	-19	-18	-23	-20	-19	-19	-18	-19	-20
7335	-23	-19	-22	-22	-19	-20	-19	-19	-20	-18
7470	-19	-20	-23	-22	-21	-20	-18	-19	-20	-18

η	1.7	1.75	1.8	1.85	1.899999	1.949999	1.999999	2.049999	2.099999	2.149999	2.199999
4770	-20	-19	-18	-17	-17	-17	-19	-21	-21	-23	-23
4905	-17	-17	-17	-20	-20	-15	-23	-22	-22	-22	-17
5040	-19	-19	-19	-19	-16	-16	-21	-21	-16	-21	-21
5175	-19	-19	-20	-16	-16	-21	-20	-20	-20	-20	-20
5310	-19	-18	-18	-18	-24	-20	-19	-19	-19	-19	-19
5445	-17	-17	-19	-19	-21	-21	-21	-21	-18	-18	-20
5580	-17	-17	-17	-21	-21	-22	-23	-21	-21	-21	-22
5715	-20	-20	-18	-22	-21	-21	-20	-22	-22	-21	-19
5850	-19	-17	-22	-21	-19	-19	-23	-19	-19	-17	-20
5985	-18	-21	-23	-21	-23	-20	-21	-19	-20	-20	-20
6120	-19	-22	-22	-19	-19	-19	-18	-19	-19	-19	-18
6255	-21	-21	-19	-19	-19	-19	-20	-20	-20	-18	-20
6390	-20	-18	-18	-17	-17	-19	-19	-19	-18	-18	-18
6525	-18	-19	-20	-19	-19	-19	-19	-18	-19	-19	-19
6660	-17	-18	-18	-19	-19	-19	-19	-19	-19	-19	-19
6795	-19	-20	-19	-19	-19	-20	-19	-18	-18	-20	-20
6930	-20	-19	-18	-18	-19	-19	-19	-19	-21	-21	-21
7065	-19	-19	-19	-20	-20	-19	-17	-20	-20	-20	-21
7200	-20	-19	-18	-18	-18	-18	-20	-20	-20	-20	-21
7335	-18	-18	-19	-18	-18	-21	-21	-20	-19	-20	-22
7470	-18	-19	-19	-19	-17	-20	-20	-20	-18	-24	-23

LSM: a range of error values for the estimated η and β parameters



LSM: 3D surface map of error values of refined estimated parameters

Single stage turbine with new and repair renewals of 6 overhauls for one engine

Eta	Beta	Engine	Overhaul
6270	1.2	10015	Shop Visit (SV)
4968	1.5		
Repair	0.9		

Predict Error Values

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	1000	2500	3200	6000	8000	11000
Population 0	Number Off	36	32	26	23	14	9	5
	Overhaul Age		1000	2500	3200	6000	8000	11000
	% Failed		10%	28%	36%	61%	74%	86%
	Number of Failed parts (cum)		4	10	13	22	27	31
	Number of Failed parts (this)		4	6	3	9	5	4
Population 1	Number Off		4	3	3	2	1	0
	Overhaul Age			1350	1980	4500	6300	9000
	% Failed			13%	22%	58%	76%	91%
	Number of Failed parts (cum)			1	1	2	3	4
	Number of Failed parts (this)			1	0	1	1	1
Population 2	Number Off			7	7	4	3	1
	Overhaul Age				630	3150	4950	7650
	% Failed				4%	40%	63%	85%
	Number of Failed parts (cum)				0	3	4	6
	Number of Failed parts (this)				0	3	1	2
Population 3	Number Off				3	2	1	1
	Overhaul Age					2520	4320	7020
	% Failed					30%	56%	81%
	Number of Failed parts (cum)					1	2	2
	Number of Failed parts (this)					1	1	0
Population 4	Number Off					14	11	6
	Overhaul Age						1800	4500
	% Failed						20%	58%
	Number of Failed parts (cum)						3	8
	Number of Failed parts (this)						3	5
Population 5	Number Off						11	7
	Overhaul Age							2700
	% Failed							33%
	Number of Failed parts (cum)							4
	Number of Failed parts (this)							4
	Number Off							16
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		4	7	3	14	11	16
	Scrap Rate		11%	19%	8%	39%	31%	44%

The Underlying Scrap Data Available

Underlying scrap rate		10%	28%	36%	61%	74%	86%

The Observed Scrap Data Available

Observed scrap number		4	7	3	14	11	13
Observed scrap rate		0.111111111	0.194444444	0.083333333	0.388888889	0.305555556	0.361
Engine age at Overhaul		1000	2500	3200	6000	8000	11000

LSM: Through-life model with repaired component replacement

Multiple stages turbine with new renewals of 6 overhauls

Eta	Beta	Engine		Overhaul
205	2.7	10015		Shop Visit (SV)

Predict Beta and Eta Parameters

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	8	21	27	50	67	92
Population 0	Number Off	36	36	36	36	35	34	32
	Overhaul Age		8	21	27	50	67	92
	% Failed		0%	0%	0%	2%	5%	11%
	Number of Failed parts (cum)		0	0	0	1	2	4
	Number of Failed parts (this)		0	0	0	1	1	2
Population 1	Number Off		0	0	0	0	0	0
	Overhaul Age			13	19	42	59	84
	% Failed			0%	0%	1%	3%	9%
	Number of Failed parts (cum)			0	0	0	0	0
	Number of Failed parts (this)			0	0	0	0	0
Population 2	Number Off			0	0	0	0	0
	Overhaul Age				6	29	46	71
	% Failed				0%	1%	2%	6%
	Number of Failed parts (cum)				0	0	0	0
	Number of Failed parts (this)				0	0	0	0
Population 3	Number Off				0	0	0	0
	Overhaul Age					23	40	65
	% Failed					0%	1%	4%
	Number of Failed parts (cum)					0	0	0
	Number of Failed parts (this)					0	0	0
Population 4	Number Off					1	1	1
	Overhaul Age						17	42
	% Failed						0%	1%
	Number of Failed parts (cum)						0	0
	Number of Failed parts (this)						0	0
Population 5	Number Off						1	1
	Overhaul Age							25
	% Failed							0%
	Number of Failed parts (cum)							0
	Number of Failed parts (this)							0
	Number Off							2
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		0	0	0	1	1	2
	Scrap Rate		0%	0%	0%	3%	3%	6%

The Underlying Scrap Data Available

Underlying scrap rate		0%	0%	0%	2%	5%	11%

The Observed Scrap Data Available

Observed scrap number	2	4	9	11	14	20
Observed scrap rate	6%	11%	25%	31%	39%	56%
Engine age at Overhaul	8	21	27	50	67	92

Through-life prediction model for a single row with a shape factor of 2.7

New NGV Replace	
η	β
261.25	1.7
205	2.2

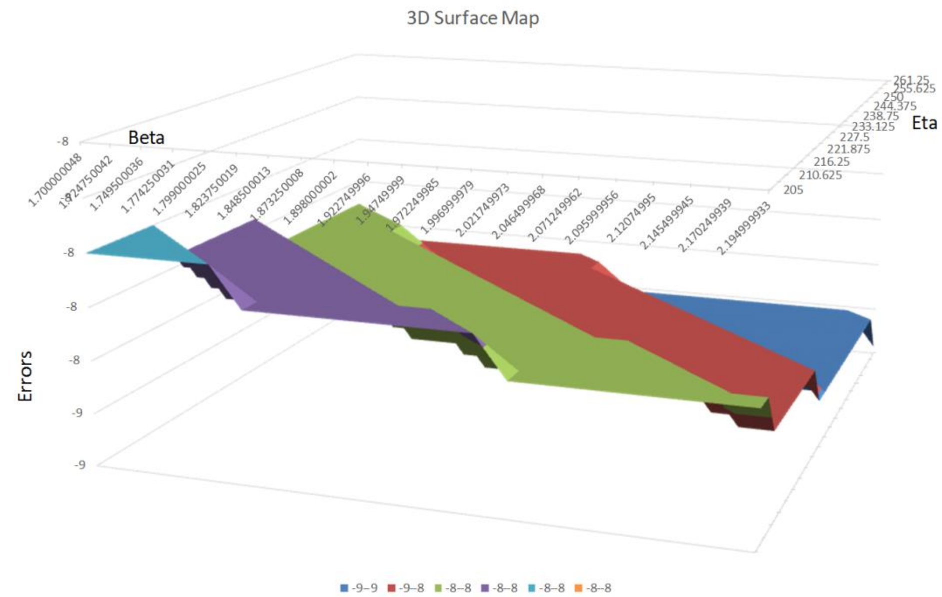
Optimised-ZoomIn

β 2.7

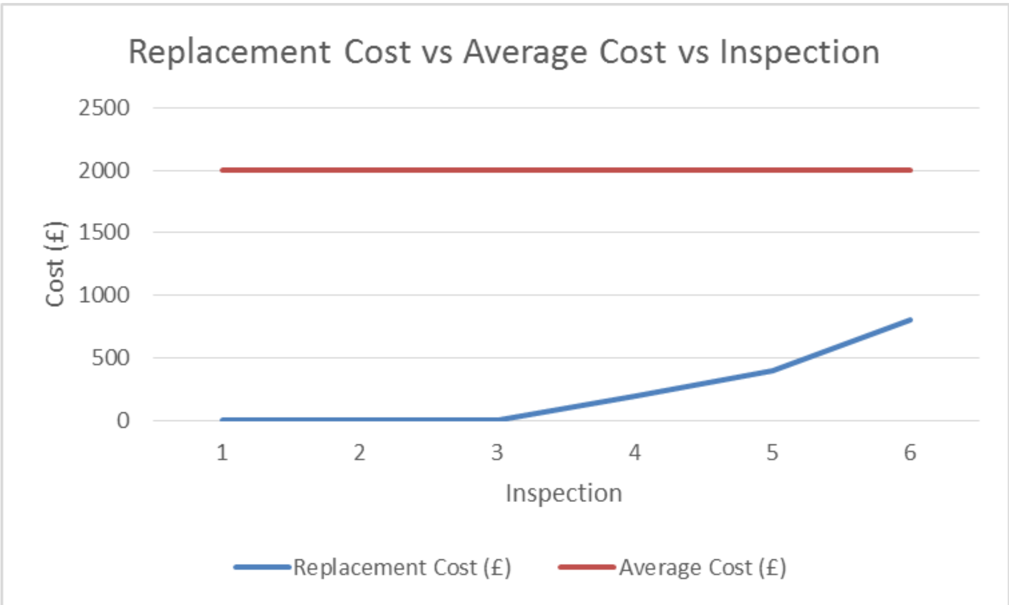
η 205

η \ β	1.7	1.72475	1.7495	1.77425	1.799	1.82375	1.8485	1.87325	1.898	1.92275	1.9475	1.97225	1.997	2.02175	2.0465	2.07125	2.096	2.12075	2.1455	2.17025	2.195
205	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54
207.8125	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-54
210.625	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55
213.4375	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55
216.25	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55
219.0625	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55
221.875	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55
224.6875	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55
227.5	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55
230.3125	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56
233.125	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56
235.9375	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56
238.75	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56
241.5625	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56
244.375	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56	-56
247.1875	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56	-56	-56
250	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56	-56	-56	-56
252.8125	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56	-56	-56	-56	-56
255.625	-54	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56	-56	-56	-56	-56	-56
258.4375	-54	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56	-56	-56	-56	-56	-56
261.25	-54	-55	-55	-55	-55	-55	-55	-55	-55	-55	-56	-56	-56	-56	-56	-56	-56	-56	-56	-56	-57

Error values with a shape factor of 2.7



Error values on 3D surface map with a shape factor of 2.7



Cost threshold model for a single engine with a shape factor of 2.7

Eta	Beta	Engine	Overhaul
179	2.6	10015	Shop Visit (SV)

Predict Beta and Eta Parameters

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	8	21	27	50	67	92
Population 0	Number Off	36	36	36	36	35	33	30
	Overhaul Age		8	21	27	50	67	92
	% Failed		0%	0%	1%	4%	7%	16%
	Number of Failed parts (cum)		0	0	0	1	3	6
	Number of Failed parts (this)		0	0	0	1	2	3
Population 1	Number Off		0	0	0	0	0	0
	Overhaul Age			13	19	42	59	84
	% Failed			0%	0%	2%	5%	13%
	Number of Failed parts (cum)			0	0	0	0	0
	Number of Failed parts (this)			0	0	0	0	0
Population 2	Number Off			0	0	0	0	0
	Overhaul Age				6	29	46	71
	% Failed				0%	1%	3%	9%
	Number of Failed parts (cum)				0	0	0	0
	Number of Failed parts (this)				0	0	0	0
Population 3	Number Off				0	0	0	0
	Overhaul Age					23	40	65
	% Failed					0%	2%	7%
	Number of Failed parts (cum)					0	0	0
	Number of Failed parts (this)					0	0	0
Population 4	Number Off					1	1	1
	Overhaul Age						17	42
	% Failed						0%	2%
	Number of Failed parts (cum)						0	0
	Number of Failed parts (this)						0	0
Population 5	Number Off						2	2
	Overhaul Age							25
	% Failed							1%
	Number of Failed parts (cum)							0
	Number of Failed parts (this)							0
	Number Off							3
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		0	0	0	1	2	3
	Scrap Rate		0%	0%	0%	3%	6%	8%
	The Underlying Scrap Data Available							
	Underlying scrap rate		0%	0%	1%	4%	7%	16%
	The Observed Scrap Data Available							
	Observed scrap number		2	4	9	11	14	20
	Observed scrap rate		6%	11%	25%	31%	39%	56%
	Engine age at Overhaul		8	21	27	50	67	92

Through-life prediction model with a shape factor of 2.6 for row 2 blades

New NGV Replace	
η	β
224	1.6
179	2.2

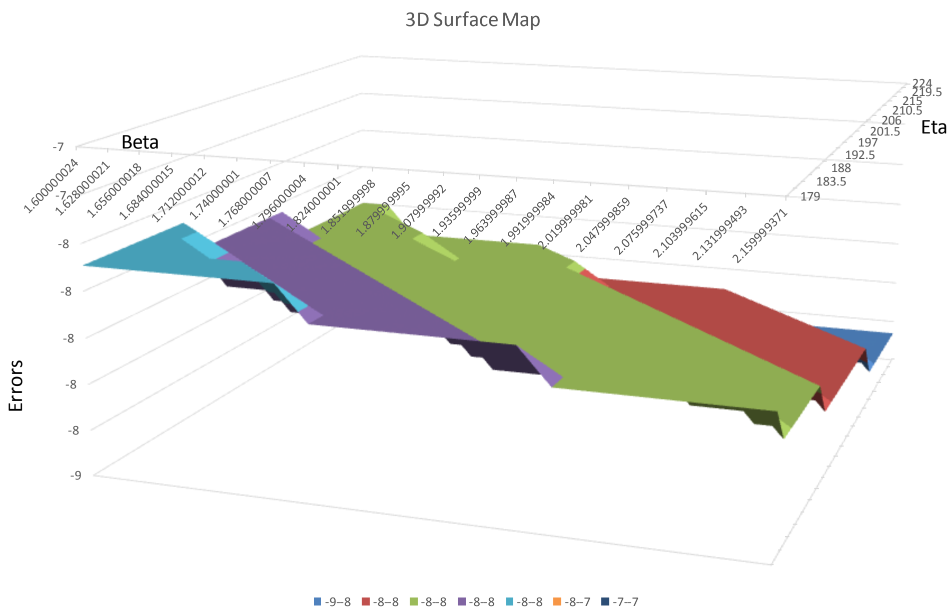
Optimised-ZoomIn

β 2.6

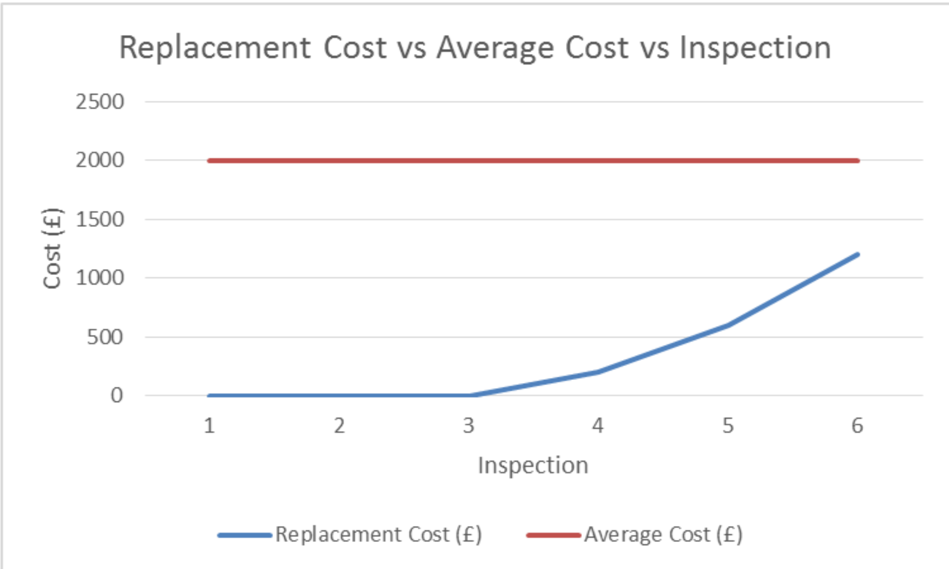
η 179

	1.6	1.628	1.656	1.684	1.712	1.74	1.768	1.796	1.824	1.852	1.88	1.908	1.936	1.964	1.992	2.02	2.048	2.076	2.104	2.131999	2.159999
179	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52
181.25	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-52	-53
183.5	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-52	-53	-53
185.75	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53
188	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53
190.25	-50	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53
192.5	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53
194.75	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54
197	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54
199.25	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54
201.5	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54
203.75	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54
206	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54
208.25	-51	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54
210.5	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54
212.75	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55
215	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55
217.25	-52	-52	-52	-52	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55
219.5	-52	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55
221.75	-52	-52	-53	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55
224	-52	-52	-53	-53	-53	-53	-53	-53	-54	-54	-54	-54	-54	-54	-54	-55	-55	-55	-55	-55	-55

Error values with a shape factor of 2.6



Error values on 3D surface map with a shape factor of 2.6



Cost threshold model for a single engine with a shape factor of 2.6

Eta	Beta	Engine		Overhaul	
163	2.5	10015		Shop Visit (SV)	Predict Beta and Eta Parameters

		New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	8	21	27	50	67	92
Population 0	Number Off	36	36	36	36	34	32	28
	Overhaul Age		8	21	27	50	67	92
	% Failed		0%	1%	1%	5%	10%	21%
	Number of Failed parts (cum)		0	0	0	2	4	8
	Number of Failed parts (this)		0	0	0	2	2	4
Population 1	Number Off		0	0	0	0	0	0
	Overhaul Age			13	19	42	59	84
	% Failed			0%	0%	3%	8%	17%
	Number of Failed parts (cum)			0	0	0	0	0
	Number of Failed parts (this)			0	0	0	0	0
Population 2	Number Off			0	0	0	0	0
	Overhaul Age				6	29	46	71
	% Failed				0%	1%	4%	12%
	Number of Failed parts (cum)				0	0	0	0
	Number of Failed parts (this)				0	0	0	0
Population 3	Number Off				0	0	0	0
	Overhaul Age					23	40	65
	% Failed					1%	3%	10%
	Number of Failed parts (cum)					0	0	0
	Number of Failed parts (this)					0	0	0
Population 4	Number Off					2	2	2
	Overhaul Age						17	42
	% Failed						0%	3%
	Number of Failed parts (cum)						0	0
	Number of Failed parts (this)						0	0
Population 5	Number Off						2	2
	Overhaul Age							25
	% Failed							1%
	Number of Failed parts (cum)							0
	Number of Failed parts (this)							0
	Number Off							4
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		0	0	0	2	2	4
	Scrap Rate		0%	0%	0%	6%	6%	11%

The Underlying Scrap Data Available

Underlying scrap rate		0%	1%	1%	5%	10%	21%

The Observed Scrap Data Available

Observed scrap number		2	4	9	11	14	20
Observed scrap rate		0.055555556	0.111111112	0.25	0.305555552	0.388888896	0.555555582
Engine age at Overhaul		8	21	27	50	67	92

Through-life prediction model for shape factor of 2.5 for row 3 blades

Optimised-ZoomIn

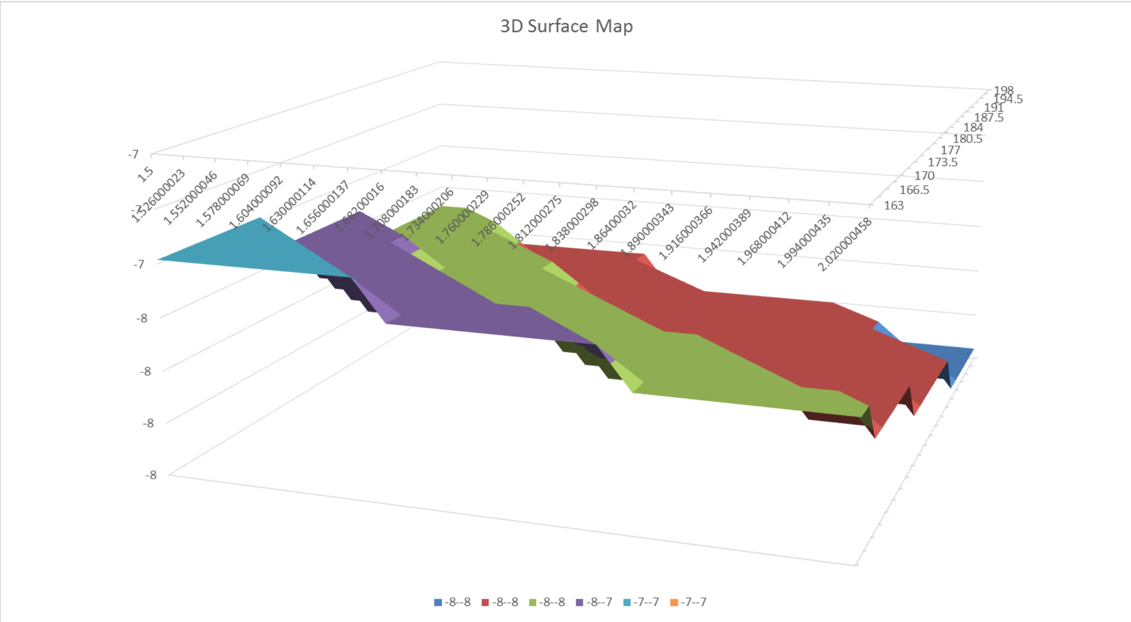
β 2.5

New NGV Replace	
η	β
198	1.5
163	2.0

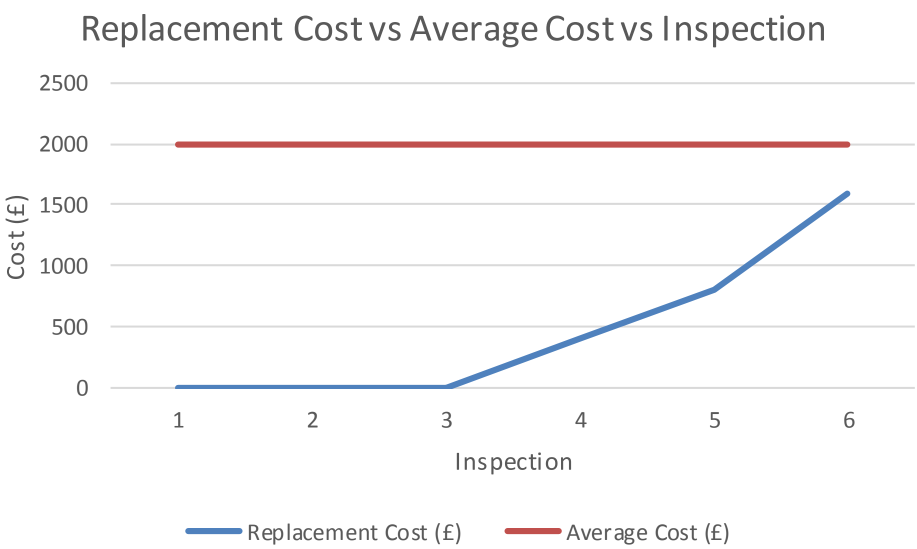
η 163

	1.5	1.526	1.552	1.578	1.604	1.63	1.656	1.682	1.708	1.734	1.76	1.786	1.812	1.838	1.864	1.89	1.916	1.942	1.968	1.994	2.02
163	-48	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50
164.75	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-50
166.5	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-50	-51
168.25	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51
170	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51
171.75	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51
173.5	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51
175.25	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-51
177	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-51	-52
178.75	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-51	-52	-52
180.5	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52
182.25	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52
184	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52
185.75	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52
187.5	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52
189.25	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53
191	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53
192.75	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53
194.5	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53
196.25	-50	-50	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53
198	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52	-53	-53	-53	-53	-53

Error values with a shape factor of 2.5



Error values on 3D surface map with a shape factor of 2.5



Cost threshold model for a single engine with a shape factor of 2.5

Eta	Beta	Engine	Overhaul
159	2.4	10015	Shop Visit (SV)

Predict Beta and Eta Parameters

Population	Item	New	Overhaul 1	Overhaul 2	Overhaul 3	Overhaul 4	Overhaul 5	Overhaul 6
	Cycles	0	8	21	27	50	67	92
Population 0	Number Off	36	36	36	35	34	32	28
Population 0	Overhaul Age		8	21	27	50	67	92
Population 0	% Failed		0%	1%	1%	6%	12%	24%
Population 0	Number of Failed parts (cum)		0	0	1	2	4	8
Population 0	Number of Failed parts (this)		0	0	1	1	2	4
Population 1	Number Off		0	0	0	0	0	0
Population 1	Overhaul Age			13	19	42	59	84
Population 1	% Failed			0%	1%	4%	9%	19%
Population 1	Number of Failed parts (cum)			0	0	0	0	0
Population 1	Number of Failed parts (this)			0	0	0	0	0
Population 2	Number Off			0	0	0	0	0
Population 2	Overhaul Age				6	29	46	71
Population 2	% Failed				0%	2%	5%	13%
Population 2	Number of Failed parts (cum)				0	0	0	0
Population 2	Number of Failed parts (this)				0	0	0	0
Population 3	Number Off				1	1	1	1
Population 3	Overhaul Age					23	40	65
Population 3	% Failed					1%	4%	11%
Population 3	Number of Failed parts (cum)					0	0	0
Population 3	Number of Failed parts (this)					0	0	0
Population 4	Number Off					1	1	1
Population 4	Overhaul Age						17	42
Population 4	% Failed						0%	4%
Population 4	Number of Failed parts (cum)						0	0
Population 4	Number of Failed parts (this)						0	0
Population 5	Number Off						2	2
Population 5	Overhaul Age							25
Population 5	% Failed							1%
Population 5	Number of Failed parts (cum)							0
Population 5	Number of Failed parts (this)							0
	Number Off							4
	Cross check - number of parts fitted	36	36	36	36	36	36	36
	Number of Failed Parts		0	0	1	1	2	4
	Scrap Rate		0%	0%	3%	3%	6%	11%

The Underlying Scrap Data Available

Underlying scrap rate	0%	1%	1%	6%	12%	24%

The Observed Scrap Data Available

Observed scrap number	2	4	9	11	14	20
Observed scrap rate	6%	11%	25%	31%	39%	56%
Engine age at Overhaul	8	21	27	50	67	92

Through-life prediction model for shape factor of 2.4 for row 4 blades

New NGV Replace	
η	β
194	1.4
159	1.9

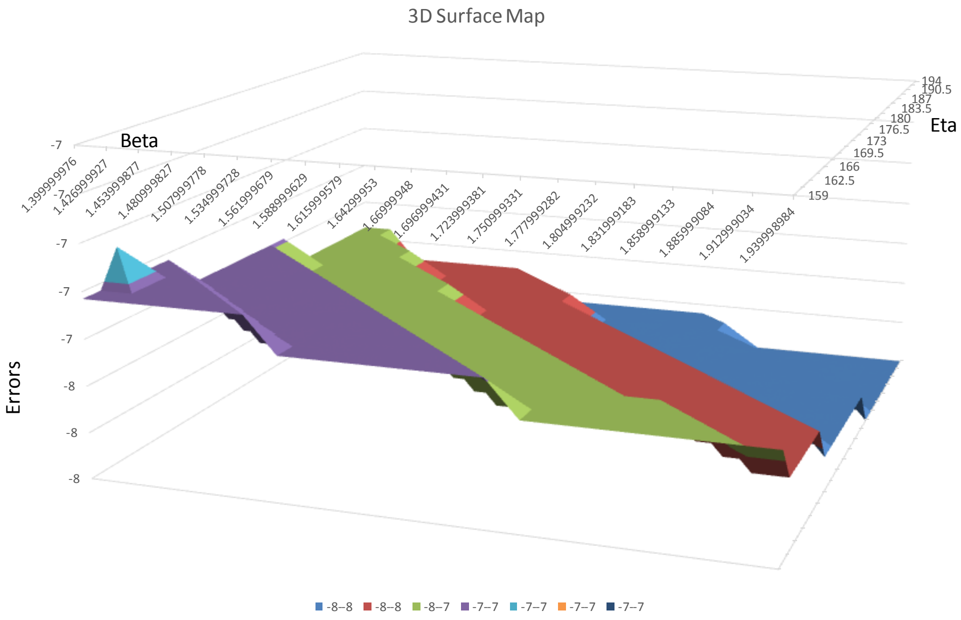
Optimised-ZoomIn

β 2.4

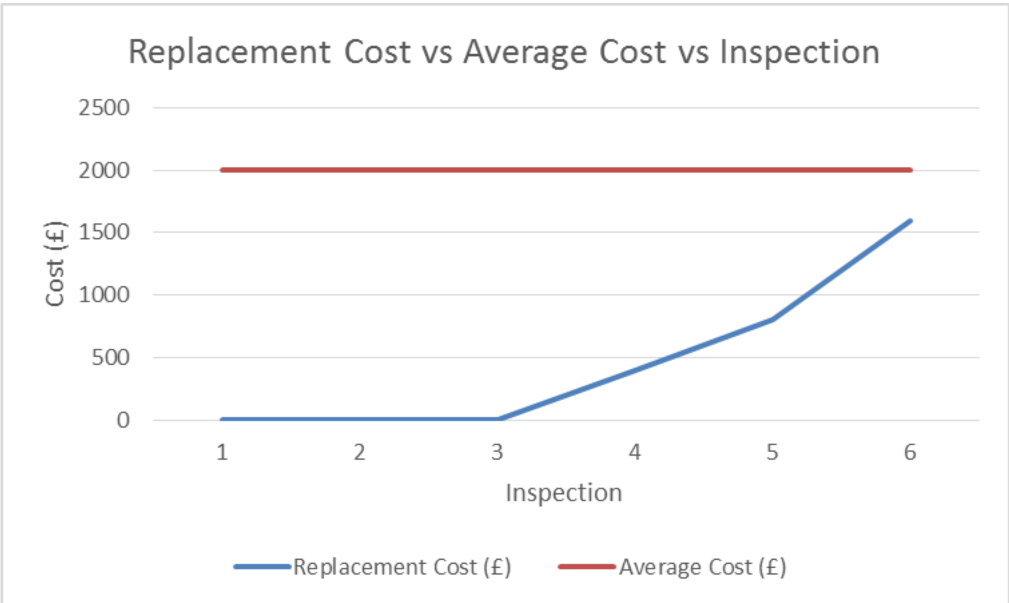
η 159

η	1.4	1.427	1.454	1.481	1.508	1.535	1.562	1.589	1.616	1.643	1.669999	1.696999	1.723999	1.750999	1.777999	1.804999	1.831999	1.858999	1.885999	1.912999	1.939999
159	-47	-47	-46	-46	-45	-46	-48	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-49
160.75	-47	-46	-46	-45	-46	-48	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-50	-50
162.5	-47	-46	-46	-45	-48	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-50	-50	-50
164.25	-47	-46	-46	-47	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50
166	-47	-46	-46	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50
167.75	-47	-47	-48	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50
169.5	-47	-47	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51
171.25	-47	-47	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51
173	-48	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51
174.75	-48	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51
176.5	-48	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51
178.25	-48	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51
180	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51
181.75	-48	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52
183.5	-49	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52
185.25	-49	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52
187	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52
188.75	-49	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52
190.5	-49	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52
192.25	-49	-49	-50	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52
194	-49	-49	-50	-50	-50	-50	-50	-51	-51	-51	-51	-51	-51	-51	-52	-52	-52	-52	-52	-52	-52

Error values with a shape factor of 2.4



Error values on 3D surface map with a shape factor of 2.4



Cost threshold model for a single engine with a shape factor of 2.4

New NGV Replace	
η	β
66.4502	1.3
45.2002	2.3

Optimised-ZoomIn

β 1.7

η 45.2

	1.26	1.314	1.368	1.421999	1.475999	1.529999	1.583999	1.637999	1.691999	1.745999
45.2002	-17	-20	-20	-19	-20	-21	-19	-18	-19	-17
46.2627	-19	-21	-19	-21	-19	-18	-20	-20	-16	-17
47.3252	-22	-18	-21	-21	-15	-21	-20	-17	-17	-19
48.3877	-21	-21	-20	-15	-21	-20	-16	-19	-18	-19
49.4502	-20	-21	-20	-19	-21	-21	-19	-19	-19	-20
50.5127	-22	-21	-20	-19	-20	-21	-21	-21	-18	-23
51.5752	-21	-21	-19	-19	-19	-19	-20	-17	-21	-22
52.6377	-22	-19	-19	-21	-20	-20	-17	-21	-22	-22
53.7002	-21	-20	-17	-19	-20	-20	-20	-20	-19	-18
54.7627	-19	-19	-21	-20	-20	-21	-21	-18	-18	-19
55.8252	-21	-19	-21	-21	-21	-21	-17	-20	-18	-17
56.8877	-20	-22	-21	-21	-20	-19	-18	-18	-19	-19
57.9502	-21	-18	-21	-22	-21	-19	-18	-19	-18	-19
59.0127	-21	-18	-23	-21	-19	-19	-19	-19	-19	-18
60.0752	-19	-22	-21	-19	-19	-19	-19	-19	-20	-19
61.1377	-18	-23	-20	-19	-20	-19	-19	-18	-18	-17
62.2002	-20	-23	-21	-20	-20	-18	-19	-19	-18	-19
63.2627	-23	-23	-21	-20	-18	-19	-21	-19	-17	-18
64.3252	-23	-19	-20	-20	-19	-21	-21	-18	-19	-19
65.3877	-23	-20	-20	-19	-19	-22	-18	-18	-19	-19
66.4502	-23	-22	-22	-19	-19	-22	-19	-20	-19	-19

	1.799999	1.853999	1.907999	1.961998	2.015998	2.069998	2.123998	2.177998	2.231998	2.285998	2.339998
45.2002	-17	-21	-20	-21	-19	-21	-21	-20	-20	-20	-21
46.2627	-22	-21	-21	-21	-22	-20	-19	-18	-19	-18	-18
47.3252	-20	-20	-21	-21	-20	-19	-19	-19	-17	-18	-20
48.3877	-20	-22	-22	-20	-19	-22	-22	-20	-20	-20	-19
49.4502	-22	-23	-19	-20	-21	-21	-17	-20	-18	-17	-17
50.5127	-23	-21	-20	-19	-18	-17	-19	-17	-17	-17	-18
51.5752	-16	-19	-19	-19	-17	-19	-18	-18	-18	-20	-20
52.6377	-19	-17	-17	-16	-19	-17	-17	-17	-18	-19	-19
53.7002	-18	-17	-18	-19	-18	-18	-19	-18	-18	-19	-20
54.7627	-20	-19	-18	-16	-16	-18	-19	-19	-18	-20	-20
55.8252	-18	-19	-19	-17	-19	-19	-19	-19	-21	-19	-19
56.8877	-19	-19	-17	-18	-19	-18	-18	-20	-20	-20	-22
57.9502	-18	-16	-19	-19	-19	-19	-20	-21	-19	-20	-20
59.0127	-19	-17	-19	-19	-17	-20	-20	-20	-20	-20	-23
60.0752	-16	-18	-18	-18	-17	-20	-20	-21	-20	-22	-20
61.1377	-18	-18	-18	-18	-21	-20	-19	-20	-22	-21	-21
62.2002	-19	-19	-17	-20	-20	-20	-21	-22	-21	-19	-19
63.2627	-18	-18	-21	-21	-21	-21	-22	-22	-20	-19	-19
64.3252	-18	-18	-21	-19	-19	-19	-22	-20	-20	-21	-21
65.3877	-20	-19	-20	-20	-21	-23	-21	-21	-21	-21	-22
66.4502	-20	-20	-21	-20	-21	-22	-22	-22	-22	-22	-22

Optimised error values with estimated parameters for all row blades with a 1.7 shape factor

Appendix M **Validation and Verification of Technique**

This appendix presents the questionnaire for the validation and verification of the approach used in the framework development.

Validation and Verification (V&V) of the Technique for the Part Deterioration and Remaining Useful Life Prediction Tool

Project Title	**Part Deterioration and Remaining Useful Life of Gas Turbine Component**
Researcher	Caxton Okoh
Supervisors	Prof Rajkumar Roy, Dr. Jorn Mehnen
Industrial Supervisor	Andrew Harrison
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Address	Building 30, Through-life Engineering Services, Manufacturing Department, School of Aerospace, Transport and Manufacturing, Cranfield University, Bedfordshire, MK43 0AL

The research relates to the presence of assembly level failure data, with no trace of component level records. Designers assumed life at design stage and need realistic basis of their assumptions. The scope is to optimise a predictive maintenance strategy for part deterioration and remaining useful life of the gas turbine mechanical component. The tool aims to provide a predictive modelling of part deterioration and remaining useful prediction of reject, replace and reused of new and repaired Nozzle Guide Vanes (NGVs) of a single stage turbine.

The objective of the tool is to estimate an average failure rate at component level, given only the failure at the assembly level

The objectives of this validation and verification sheet are to ensure that the model:

i. Meets the specifications and the purpose it was built;
ii. Interpret the list of requirements and assumptions to accurately estimate remaining useful life;
iii. Perform accurate under various types of gas turbine engine;
iv. Meets the required usability level;
v. The input data to the model were considered accurate, from valid and reliable sources.

A. General:

The following list of questions aims to ascertain the current level maturity of the tool. Please fill the heading with your personal information and then complete the questionnaire. This questionnaire will be anonymous.

Date: / /

Personal Information	
Name and Surname	
Company Name	
Industry Sector	
Job Role	
Years of Relevant Experience	
Email	

B. Logic

1. How logical is the predictive modelling considered in the framework (Put a tick in the suitable number)

1	2	3	4	5	6	7	8	9	10
Illogical	Logical with major deficiencies				Logical with minor deficiencies				logical

If any, please explain why
…………………………………………………………………………………

2. Is the framework logic suitable for predictive modelling of part deterioration?

1	2	3	4	5	6	7	8	9	10
Very Unsuitable	Suitable with major deficiencies				Suitable with minor deficiencies				Very Suitable

If any, please explain why
…………………………………………………………………………………
3. Can the framework be applied in another scenario for predictive modelling? Yes ☐ No ☐

If yes, please specify
…………………….....…………………………………………………………………

C. Generality

1. Please comment on the generality of this framework in the aerospace industry

………
2. Please comment on the generality of this framework in other industries (e.g. Power generation)?

……...
3. What other problem recognition is applicable to the types of similar applications (e.g. blades)?

……...
D. Responsibility

1. Who should use the framework within the industry? (E.g. Only policymakers, designers, manufacturers (OEM), or maintenance personnel) Why and How?

……...
2. What team or department should have ownership or responsibility of the model within the organisation?

……...
E. Benefits of using the framework

1. How would the framework benefit the organisation?

……...
F. Limitations of the framework

1. What are the potential limitations in using and implementing this tool?

……...
2. What are the potential limitations that may arise in using this software tool?

……...

3. How could the output of this tool be affected by the background of people putting the input?

………...

G. Usability of the software prototype

1. Assess the features in terms of usability of the tool

a. What are the strongest features? Please suggest any possible improvement

……

b. What are the weakest features? Please suggest any possible improvement

……

2. Does this tool offer an adequate level of information to guide a user? Yes / No

If no, please explain: ……………………………………………………………………………………

3. Assess this time required to populate the tool for implementation of a project

……

4. Please assess the following facets of the tool [1-5]

a. Layout ………………………………….

b. Use of colour ...…………………...……………

c. Ease of navigation ...…………………

c. Level of awareness.…………………………

5. Is this tool flexible enough to be applied to different levels of information available?

……

H. Assessment of the framework

Please assess the completeness/suitability of the framework using the following questions

a. The presentation of the data for input

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons……………………………………………………………………

b. The approach to parameter estimation of the failure time data

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons: ………………………..…………………………………………

c. The prognostic modelling and simulation of the estimated parameters with the failure time data

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons: ……….………………………………………………………

d. The comparison of the predicted data and the presented data in (a)

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons: ……………………………………………………………………………

e. The approach for realistic estimated parameters with errors in the prediction

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons:……………………………………………… ……………………………

f. The conversion of the realistic predictions of unreliability distribution

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons: ……………………………………………………………………………

g. The transformation of the unreliability distribution to survival distribution

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons: …………………………………………………………………………

h. The prediction of the remaining useful life of components in an assembly using survival distribution

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons: ………………………………………………………………………

i. The use of cost to predict the overhaul stage to scrap an entire assembly

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons: ..………………………………………………………………………

j. The iterative process to predict the number of rejections for a multiple stage turbine

1	2	3	4	5	6	7	8	9	10
Very incomprehensible	Comprehensible with major deficiencies				Comprehensible with minor deficiencies				Very comprehensible

If any, please explain the reasons…………………………………………………………………………

I. Quality of the Results

a. How realistic is the result after running this tool?

1	2	3	4	5	6	7	8	9	10
Very Unrealistic	Realistic with major deficiencies				Realistic with minor deficiencies				Very Realistic

If any, please explain the reasons: …………………………………………………………………………

b. How significant do the results compare to the understandings of similar components?

1	2	3	4	5	6	7	8	9	10
Very Insignificant	Significant with major deficiencies				Significant with minor deficiencies				Very significant

c. Please, state potential weakness of the results ……………………………………………

……………………………………………………………………………..…………………………

d. Is the visual representation of the output of this tool clear? Yes ☐ No ☐

If no, please suggest improvements……………………………………………………………..

……………………………………………………………………………..………………………………

e. Please suggest any improvement on the overall framework...…………………………

Appendix N **User Manual**

User Manual of the Predictive Tool for Assessment and Simulation of the Part Deterioration and Remaining Useful Life

Abstract

This User Manual, produced by the TES centre for the project at Cranfield University, offers provision and the guidelines to use the Predictive Tool for Assessment and Simulation of the Part Deterioration and Remaining Useful Life. The tool has been designed and developed as a result of the challenges that are encountered with analysing historical data gathered from conventional maintenance to determine part deterioration and RUL. The focus of the tool forecast upcoming maintenance and the number of parts to be rejected, replace and reused. The key feature of the predictive tool includes data preparation, update failure data, single engine, multiple engine; through-life modelling and simulation, predicted rejection values, observed rejection values; back-fitting, Zoomin, Zoomout and resolve with low, medium and high sensitivity of the errors. The errors from the back-fitting of the Eta and Beta are simulated for decision making through Weibull distribution.

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Address	Building 30, Through-life Engineering Services, Manufacturing Department, School of Aerospace, Transport and Manufacturing, Cranfield University, Bedfordshire, MK43 0AL

Overview of Predictive Tool for Assessment and Simulation of the Part Deterioration and Remaining Useful Life

The research tends to generate an approach to convert observed rejection historical data into an understanding of the underlying component degradation rate towards a rejection threshold by modelling the Through-life performance to forecast the rejections (number of degraded components), replacement (new components) and reuse (existing component) (R-Cube). An approach to automatically back-fitting an observed rejection rate that obtains an estimated underlying rejection rate, thereby predicting the remaining useful of the component was presented.

The predictive tool is known as WTPPM described in Figure 1. This User Manual follows the architecture to cover the main features of the tool.

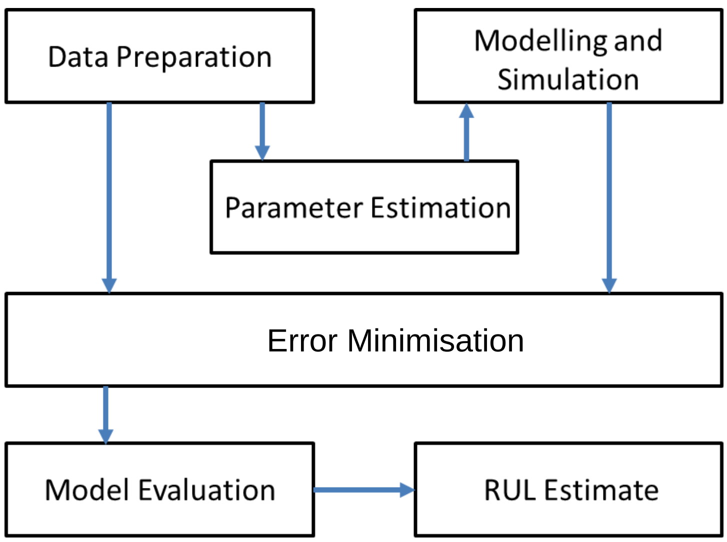


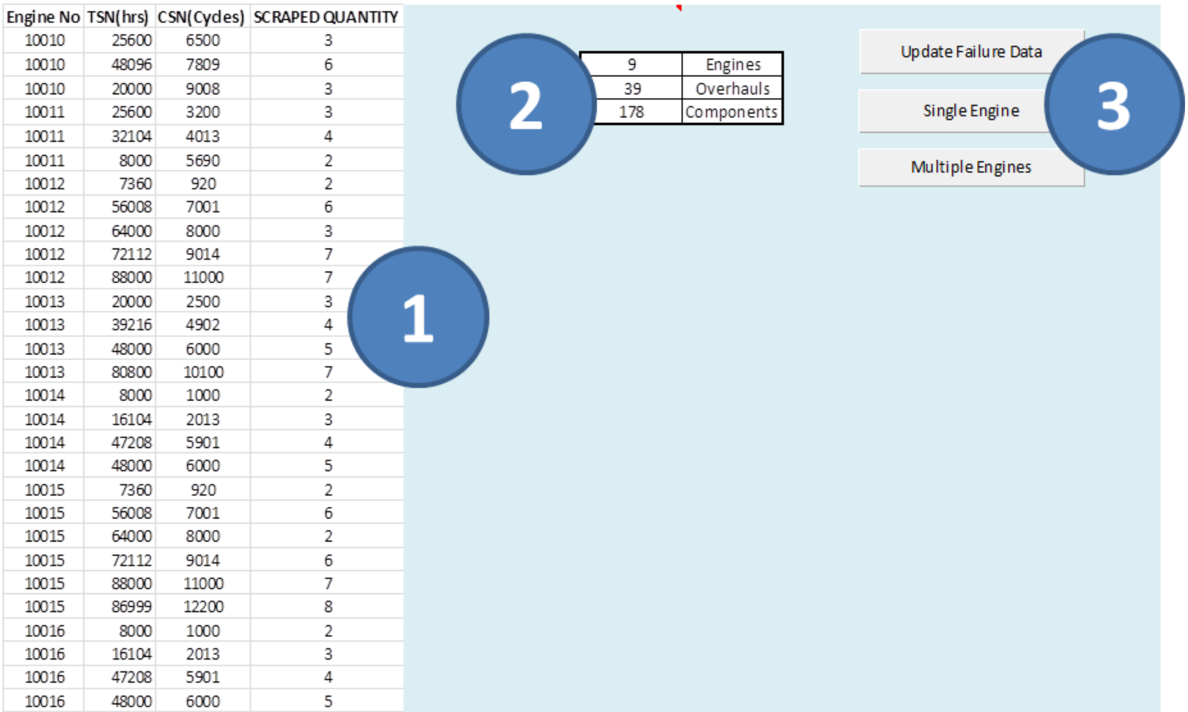
Figure 1 Overview of the predictive modelling

The data preparation module focuses on the type of data and format to produce the data.
The parameter estimation concentrates on the calculating the two values required for the next stage. The modelling and simulation module focuses on the predictive analysis to forecast the component rejected, replace and reused. The error minimisation segment calls predicted and observed values based on the estimate from the initial parameters. The model evaluation module uses the Monte Carlo method to generate data to simulate the Weibull distribution function.

To run the application, set the data into specified rows and columns, set design life, enter Eta and Beta parameters and adjust focus to either low, medium or high. Click Analyse Data to generate the Weibull distribution.

Figure 2 performs the following in a data preparation module

1. The structure of how the historical data should be presented as input. The engine number, the Time Since New, the Cycle Since New and the number of rejected parts
2. The result of the number of engines, overhauls and components being analysed
3. Update failure data checks and adds new data to 1. The Single engine splits the failure data based on the presented data in terms of engine and overhauls. The multiple engines send the entire data through the WTPPM



Engine No	TSN(hrs)	CSN(Cycles)	SCRAPED QUANTITY
10010	25600	6500	3
10010	48096	7809	6
10010	20000	9008	3
10011	25600	3200	3
10011	32104	4013	4
10011	8000	5690	2
10012	7360	920	2
10012	56008	7001	6
10012	64000	8000	3
10012	72112	9014	7
10012	88000	11000	7
10013	20000	2500	3
10013	39216	4902	4
10013	48000	6000	5
10013	80800	10100	7
10014	8000	1000	2
10014	16104	2013	3
10014	47208	5901	4
10014	48000	6000	5
10015	7360	920	2
10015	56008	7001	6
10015	64000	8000	2
10015	72112	9014	6
10015	88000	11000	7
10015	86999	12200	8
10016	8000	1000	2
10016	16104	2013	3
10016	47208	5901	4
10016	48000	6000	5

9	Engines
39	Overhauls
178	Components

Figure 2 Data presentation, Numbers of engines, overhauls and components

Split Failure Data into Individual Engine

4

The function 4 in Figure 3 shows the input to solve through-life performance for a single engine. Enter the item number and click transfer data. The estimated parameters are used to calculate the number of rejections.

Split Failure Data into Individual Engine

Select Engine to Analyse: 4

Click to Transfer Data

4

Engine Number	10010	10010	10010			
Scrap Quantity	3	6	3			
Scrap Rate	0.083333336	0.166666672	0.083333336			
Cycles Since New	6500	7809	9008			
Engine Number	10011	10011	10011			
Scrap Quantity	3	4	2			
Scrap Rate	0.083333336	0.111111112	0.055555556			
Cycles Since New	3200	4013	5690			
Engine Number	10012	10012	10012	10012	10012	
Scrap Quantity	2	6	3	7	7	
Scrap Rate	0.055555556	0.166666672	0.083333336	0.194444448	0.194444448	
Cycles Since New	920	7001	8000	9014	11000	
Engine Number	10013	10013	10013	10013		
Scrap Quantity	3	4	5	7		
Scrap Rate	0.083333336	0.111111112	0.138888896	0.194444448		
Cycles Since New	2500	4902	6000	10100		
Engine Number	10014	10014	10014	10014	10014	10014
Scrap Quantity	2	3	4	5	4	8
Scrap Rate	0.055555556	0.083333336	0.111111112	0.138888896	0.111111112	0.222222224
Cycles Since New	1000	2013	5901	6000	8000	11000

Figure 3 Split data for Single engine

Through-life performance Model Analysis

The through-life performance model analyses as seen in Figure 4 are presented with inputs, processes and outputs.

5. The Eta and Beta are input parameters required for assessing the through-life performance of component degradation in an assembly
6. The number of components starting at initiation e.g. 36. This is another input for the model
7. Another input is the overhaul in cycles. The overhaul is a maximum of six stages
8. The initial outputs are used as input in the further different stages of the population
9. The outcome of the different stages of the entire Through-life performance model. The total number of the components at each stage and the scrap rate
10. The cumulative failure rate is the underlying scrap rate across all six stages
11. The observed scrap rate data from the historical data are required to compare with the outcome of the predicted rejections from number 9.

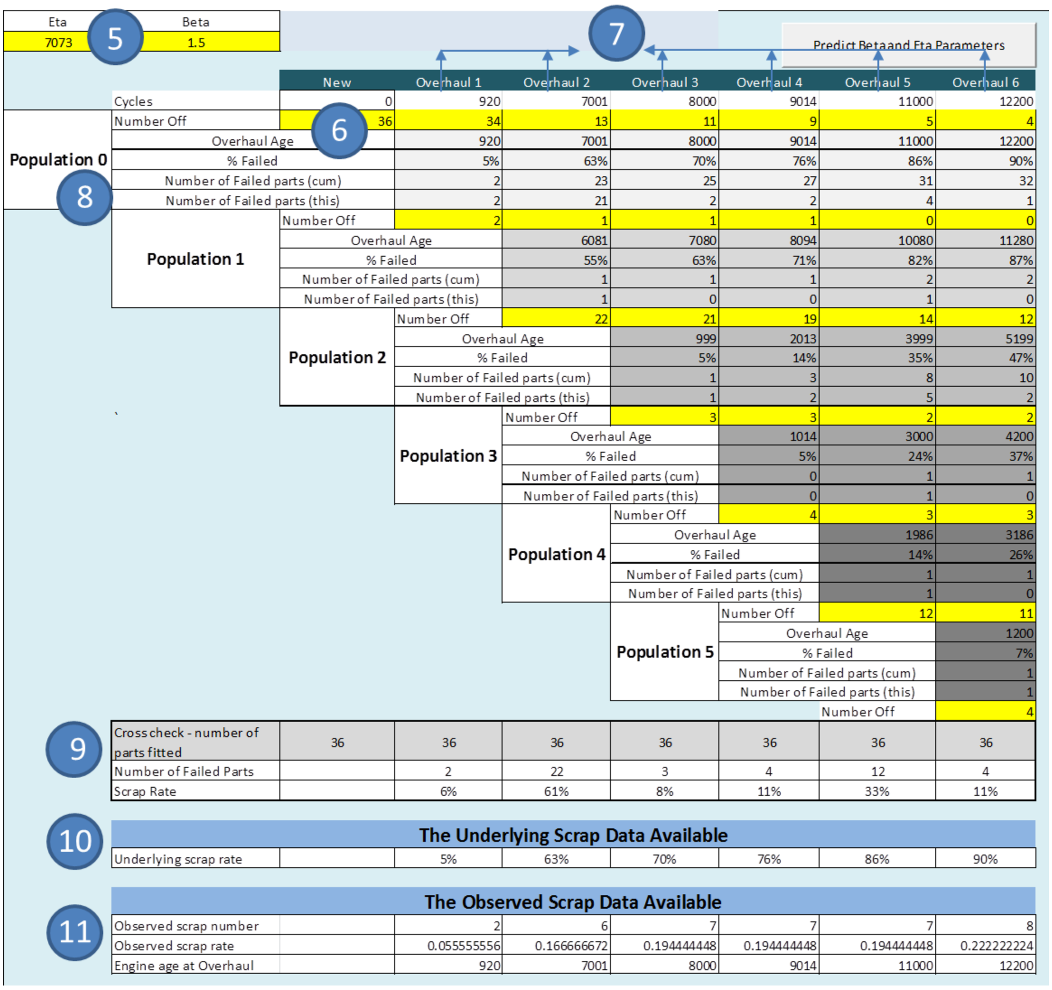
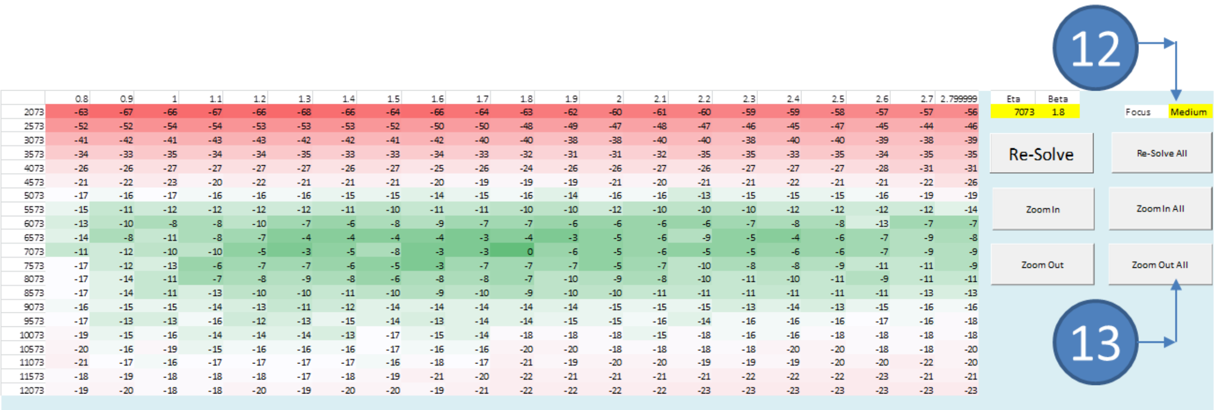


Figure 4 Through-life performance model

12 The selection of low, medium and high

13 The different buttons are used for single and multiple engines to drill-in or zoom-in. The zoom-in recalculates the shape factor and the characteristic life and represented the error values in Figure 5. The Re-Solve recalculates the error anytime the focus is changed.



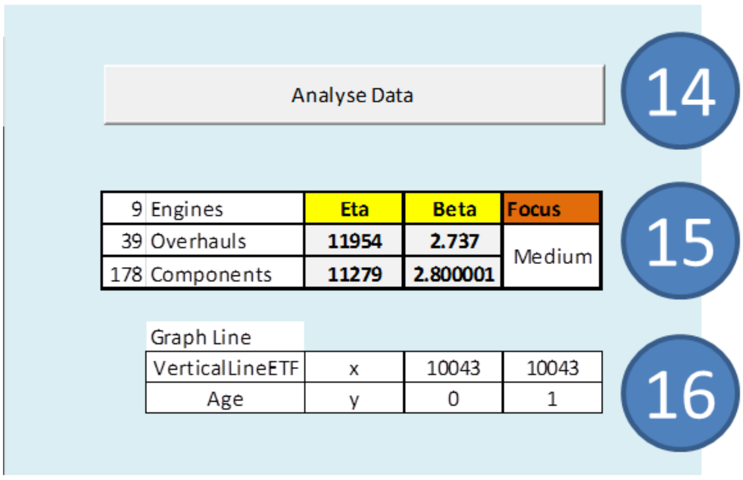
	0.8	0.9	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.799999
2073	-63	-67	-66	-67	-66	-68	-66	-64	-66	-64	-63	-62	-60	-61	-60	-59	-59	-58	-57	-57	-56
2573	-52	-52	-54	-54	-53	-53	-53	-52	-50	-50	-48	-49	-47	-48	-47	-46	-45	-47	-45	-44	-46
3073	-41	-42	-41	-43	-43	-42	-42	-41	-42	-40	-40	-38	-38	-40	-40	-38	-40	-40	-39	-38	-39
3573	-34	-33	-35	-34	-34	-35	-33	-33	-34	-33	-32	-31	-31	-32	-35	-35	-33	-35	-34	-35	-35
4073	-26	-26	-27	-27	-27	-27	-26	-27	-25	-26	-24	-26	-26	-27	-26	-27	-27	-27	-28	-31	-31
4573	-21	-22	-23	-20	-22	-21	-21	-21	-20	-19	-19	-19	-21	-20	-21	-21	-22	-21	-21	-22	-26
5073	-17	-16	-17	-16	-16	-16	-15	-15	-14	-15	-16	-14	-16	-16	-13	-15	-15	-15	-16	-19	-19
5573	-15	-11	-12	-12	-12	-12	-11	-10	-11	-11	-10	-10	-12	-10	-10	-10	-12	-12	-12	-12	-14
6073	-13	-10	-8	-8	-10	-7	-6	-8	-9	-7	-7	-6	-6	-6	-6	-7	-8	-8	-13	-7	-7
6573	-14	-8	-11	-8	-7	-4	-4	-4	-4	-3	-4	-3	-5	-6	-9	-5	-4	-6	-7	-9	-8
7073	-11	-12	-10	-10	-5	-3	-5	-8	-3	-3	0	-6	-5	-6	-5	-5	-6	-6	-7	-9	-9
7573	-17	-12	-13	-6	-7	-7	-6	-5	-3	-7	-7	-7	-5	-7	-10	-8	-8	-9	-11	-11	-9
8073	-17	-14	-11	-7	-8	-9	-8	-6	-8	-8	-7	-10	-9	-8	-10	-11	-10	-11	-9	-11	-11
8573	-17	-14	-11	-13	-10	-10	-11	-10	-9	-10	-9	-10	-10	-11	-11	-11	-11	-11	-11	-13	-13
9073	-16	-15	-15	-14	-13	-11	-12	-14	-14	-14	-14	-14	-15	-15	-15	-13	-14	-13	-15	-16	-16
9573	-17	-13	-13	-16	-12	-13	-15	-14	-13	-14	-14	-15	-15	-16	-14	-16	-16	-16	-17	-16	-18
10073	-19	-15	-16	-14	-14	-14	-13	-17	-15	-14	-18	-18	-18	-15	-18	-16	-16	-18	-18	-18	-18
10573	-20	-16	-19	-15	-16	-16	-16	-17	-16	-16	-20	-20	-18	-18	-18	-18	-20	-20	-18	-18	-20
11073	-21	-17	-16	-17	-17	-17	-17	-16	-18	-17	-21	-19	-20	-20	-19	-19	-19	-20	-20	-22	-20
11573	-18	-19	-18	-18	-18	-17	-18	-19	-21	-20	-22	-21	-21	-21	-21	-22	-22	-22	-23	-21	-21
12073	-19	-20	-18	-18	-20	-19	-20	-20	-19	-21	-22	-22	-22	-22	-23	-23	-23	-23	-23	-23	-23

Figure 5 Estimated Eta and Beta to generate errors

14 This is the single button that calculates and spools the outcome. When the button is pressed, the failure data are passed to the Through-life performance prediction model, back-fitting is solved and the output presented in Figure 6

15 The Zoom-in estimated parameters are selected and recalculated. It shows the selected focus and the total Engines,overhauls stages and components being analysed.

16 The x and y are the vertical and horizontal coordinate to depict the exact location of the values.



		Eta	Beta	Focus
9	Engines	Eta	Beta	Focus
39	Overhauls	11954	2.737	Medium
178	Components	11279	2.800001	

Graph Line			
VerticalLineETF	x	10043	10043
Age	y	0	1

Figure 6 Analyse Data

Through-life performance Output

The output for the probability of failure, and remaining useful life are presented in Figure 7.

Figure 7 Output for probability of failure and RUL