NTNU – Trondheim
Norwegian University of
Science and Technology

Use of Technical Condition Indicators as Basis for Residual Useful Life Assessments

Bin Lu

Reliability, Availability, Maintainability and Safety (RAMS)
Submission date: June 2014
Supervisor: Jørn Vatn, IPK
Co-supervisor: Thor Inge Bernhardsen, Statoil

Norwegian University of Science and Technology
Department of Production and Quality Engineering

RAMS

Reliability, Availability,
Maintainability and Safety

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June 2014, Trondheim

Master Thesis

Departement of Production and Quality Engineering

Norwegian University of Science and Technology

Responsible Supervisor: Professor Jørn Vatn

Supervisor at the company: Thor Inge Bernhardsen

MASTER THESIS

Spring 2014

for stud. techn. Bin Lu

Use of technical condition indicators as basis for residual useful life assessments

To ensure that an installation is able to provide sufficient performance on various criteria such as production regularity, safety and maintenance cost it is required to know the technical condition of it's parts, components and systems. The use of technical condition indicators may be one starting point to access residual useful life (RUL) for these pars, components and systems. RUL assessment is considered to be a critical aspect of aging and life extension management. In this master thesis work the candidate shall follow a research and development (R&D) project sponsored by Statoil and executed by SINTEF/NTNU. The following tasks are initially seen as the contribution from the master student as part of the R&D project:

1. Review the literature regarding various use of the term residual useful life as a basis for giving an explicit definition to be used through the work.
2. Identify two to three classes of critical equipment types as a basis for case studies. Such classes could be rotating equipment, static equipment and safety systems.
3. For each of the identified classes the literature shall be revived with respect to which deterministic, probabilistic and combined models are proposed to link technical condition indicators and other degradation measures to residual useful life (RUL).
4. Select one or two cases where models, methods and real condition data could be applied in the aging and life extension management.
5. The case studies shall demonstrate how the maintenance program will affect the technical condition on the equipment, and how to balance maintenance effort with other measures such as upgrading projects, renewal and modification.

The assignment solution must be based on any standards and practical guidelines that already exist and are recommended. This should be done in close cooperation with supervisors and any other responsibilities involved in the assignment. In addition it has to be an active interaction between all parties.

Within three weeks after the date of the task handout, a pre-study report shall be prepared. The report shall cover the following:

- An analysis of the work task's content with specific emphasis of the areas where new knowledge has to be gained.
- A description of the work packages that shall be performed. This description shall lead to a clear definition of the scope and extent of the total task to be performed.
- A time schedule for the project. The plan shall comprise a Gantt diagram with specification of the individual work packages, their scheduled start and end dates and a specification of project milestones.

The pre-study report is a part of the total task reporting. It shall be included in the final report. Progress reports made during the project period shall also be included in the final report.

The report should be edited as a research report with a summary, table of contents, conclusion, list of reference, list of literature etc. The text should be clear and concise, and include the necessary references to figures, tables, and diagrams. It is also important that exact references are given to any external source used in the text.

Equipment and software developed during the project is a part of the fulfilment of the task. Unless outside parties have exclusive property rights or the equipment is physically non-moveable, it should be handed in along with the final report. Suitable documentation for the correct use of such material is also required as part of the final report.

The candidate shall follow the work regulations at the company's plant. The candidate may not intervene in the production process in any way. All orders for specific intervention of this kind should be channelled through company's plant management.

The student must cover travel expenses, telecommunication, and copying unless otherwise agreed.

If the candidate encounters unforeseen difficulties in the work, and if these difficulties warrant a reformation of the task, these problems should immediately be addressed to the Department.

The assignment text shall be enclosed and be placed immediately after the title page.

Deadline: 10 June 2014.

Two bound copies of the final report and one electronic (pdf-format) version are required according to the routines given in DAIM. Please see http://www.ntnu.edu/ivt/master-s-thesis-regulations regarding master thesis regulations and practical information, inclusive how to use DAIM.

Responsible supervisor: Jørn Vatn
E-mail: jorn.vatn@ntnu.no
Telephone: 41473730

Supervisor(s) at the Company: Thor Inge Bernhardsen
E-mail: thib@statoil.com
Telephone:

DEPARTMENT OF PRODUCTION AND QUALITY ENGINEERING

Per Schjølberg

Per Schjølberg
Associate Professor/Head of Department

Jørn Vatn

Jørn Vatn
Responsible Supervisor

Preface

This master thesis is carried out at Department of Production and Quality Engineering, NTNU and is cooperated with the company Statoil. The thesis is a part of education plan in the Master Program RAMS (Reliability, Availability, Maintainability and Safety) Engineering. It is performed during the spring semester of 2014. The topic was put forward in January 2014 by Professor Jørn Vatn. It is extended from the specialization project “Life extension and maintenance optimization in the oil and gas industry”.

The report is written for readers with some background of maintenance engineering and statistical theory. It is also assumed that the reader has a number of knowledge regarding signal processing techniques. Besides, several technical terms are less familiar to readers, hence it is recommended to view technical background in the appendix and consult relevant professional books. Mathematical details could not be interpreted in the thesis due to limits on the page.

Trondheim, 2014-06-10

Bin Lu

Acknowledgments

I would like to express my sincere thanks to my supervisor Professor Jørn Vatn at NTNU for guidance as well as the patient teaching and providing me with knowledge about maintenance engineering and statistical models. I also appreciate every other help that were given by Professor Jørn Vatn during my period of study at IPK, NTNU.

Many thanks are also given to my co-supervisor at Statoil, Thor Inge Bernhardsen, for his support and guidance in the project, and comments on the report. I also wish to show my gratitude to Trond Østerås, project manager of 'Kristin Regularity', for his patient explanations concerning project details. Besides, I want to thank Harald Rødseth, who provides me sources regarding technical condition indicator.

Finally, I would like to acknowledge my family members and friends. Thank their love, encouragement and support.

B. L.

Summary and Conclusions

This thesis is of service to realize residual useful life assessment. Everything in the world deteriorates over time. To know the residual useful life of a piece of equipment contributes to optimal decision-making on its usage time and discards. The rewarding also lies in reduced maintenance cost.

For the application of industry process, a novel approach is proposed to define the term residual useful life, making efforts to satisfy diverse criterion on evaluation of equipment usefulness. In current research findings the definition of residual useful life varies. For maintenance purposes, residual useful life is explained by using diagnostics and prognostics, which are critical elements in condition based maintenance. In the domain of reliability, residual useful life is interpreted with probability theory, where mean residual life and conditional survival probability are frequently utilized.

Rotating equipment is concentrated in which state-of-the-art models and methods for residual useful life assessment are investigated in this thesis. Residual useful life assessment techniques are dependent on deterministic, probabilistic and combined models in representing deterioration behaviors on various types of equipment. Apart from statistical theory, vibration signals, lubrication oil condition and acoustic noise signals are principal elements for the assessment. A stereotyped residual useful life assessment procedure consists of two interdependent stages, off-line deterioration model learning and on-line prognostic model training. In the best of circumstances, the sufficient raw data for the assessment are acquired through run-to-failure tests.

The targeted systems for case study are AC generators and gas turbines served for oil and gas production in Kristin field. Statistical techniques are employed to process and analyze notification data of generators. The regression analysis shows an unimportant relationship between notification date and failure impact. Statistical trend tests do not verify the existence of any monotonic rate of occurrence of failures on AC generators. Vibration data analysis of the gas turbine does not provide monotonic information where residual useful life assessment models could be applied for. The notifications are not demonstrating a systematic pattern. Failures of AC generators and gas turbines are tend to be random. Challenges and recommendations are pointed out for Statoil to execute residual useful life assessment based on current situations. Lubrication oil condition monitoring is strongly recommended in this aspect.

Procedures to realize maintenance optimization are demonstrated as a theoretical case study. Markov state model with inspection and block replacement policy are employed to construct cost models on maintenance optimization. With assumed cost elements, an optimal maintenance program is proposed. The analytic process is practically valuable to verify whether the regular inspection is the optimum maintenance strategy.

Contents

Nomenclature

	Abbreviation
AD	Anderson-Darling
BRP	Block replacement policy
CBM	Condition based maintenance
CWT	Continuous wavelet transform
DFT	Discrete Fourier Transform
DWT	Discrete wavelet transform
FFT	Fast Fourier Transform
HPP	Homogeneous Poisson process
MTTF	Mean time to failure
NCS	Norwegian Continental Shelf
NHPP	Nonhomogeneous Poisson process
OREDA	Offshore Reliability Data
O&G	Oil and gas
PCA	Principal Component Analysis
PHM	Prognostics and health monitoring
PI	Statoil condition monitoring system
RUL	Residual (Remaining) useful life
R&D	Research and development
RP	Renewal process
RMS	Root mean square
ROCOF	Rate of occurrence of failures
SAP	Statoil Computer-aided Maintenance Management System
SVR	Support vectors regression
STFT	Short-time Fourier Transform
TCI	Technical condition indicator
WPT	Wavelet packet transform
WT	Wavelet transform

	Notation
T	Lifetime random variable, time to failure of a component or system
t	A specific point in time irrespective of global time and local time

f	Frequency composition of a time-series signal
υ	Scale parameter in the wavelet function
ω	Translation parameter in the wavelet function
τ	Maintenance interval/Inspection interval
l	Maintenance limit
$\lambda_E(\tau)$	Effective failure rate
$rr(\tau, l)$	Renewal rate
T_u	Residual(Remaining) useful life, nonnegative random variable
T_M	Static mean life
T_A	Actual used life
T_C	Current time
T_F	The time where a critical failure occurs
T_L	The time where the equipment reaches the threshold value
$C(\tau)$	Total cost per unit time
$x(t)$	Time series signal
$\psi(t)$	Wavelet function
$X(f)$	Fourier transform of a time-series signal
$F(t)$	Cumulative distribution function (Cdf) of a lifetime random variable
$f(t)$	Probability distribution function (Pdf) of a lifetime random variable
$R(t)$	Reliability function
$RUL(t)$	Residual (remaining) useful life as a function of time
$MRUL(t)$	Mean residual (remaining) useful life as a function of time
$z(t)$	Failure rate function
$\mu(t)$	Mean residual useful life
$S(t)$	Degradation level or state
$d(t) = \triangle S(t)/\triangle t$	Degradation rate
$\lambda(x) = z(t+x)$	RUL failure rate function

Chapter 1 Introduction

This chapter demonstrates the background, problem description, objectives, limitations, approach and the structure of the report for the thesis.

1.1 Background

The oil and gas operators on the Norwegian Continental Shelf (NCS) are facing considerable challenges as facilities are entering the tail-end production phase. Several oil and gas (O&G) facilities were built in the 70's and 80's, with a design lifetime typically of 20-30 years, and are now approaching or have reached their design lifetime, see figure 1 (Ersdal et al., 2008). This challenge also applies to operators worldwide due to 30% of more than 6,700 operating platforms have been in operation for more than 20 years (Nabavian et al 2010). With the application of new advanced technology, the recovery factors have been gradually increased over many years, for example from 20 to 50%. The recovery of the oil and gas resources offshore Norway contributes to approximately 25% of Norway's GNP, 35% of the state income, 20% of all investments and 50% of the export value (Ersdal et al. , 2010). The improvements in extraction technologies as well as high energy prices have led to opportunities for extending the operation beyond the intended lifetime.

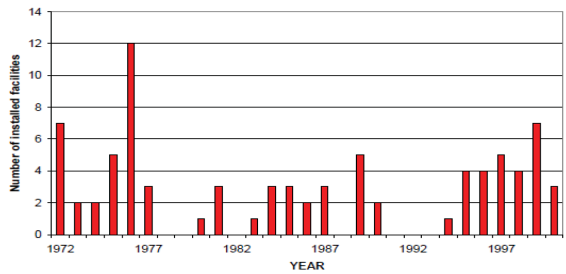


Figure 1 Age distribution of existing installations on the NCS (Ersdal et al., 2008)

The effectiveness of O&G industrial performance is determined by the reliability, availability and safety of a system. To ensure that an installation is able to provide sufficient performance on various criteria such as production regularity, safety and maintenance cost it is required to know the technical condition of its parts, components and systems. The residual useful life (RUL) assessment attracts strong interests in industry since it has critical impacts on planning of maintenance activities; spare parts management, functional performance assurance as well as profits obtained from the installation. RUL assessment is also considered to be a critical aspect of aging and life extension management.

1.2 Problem Description

A main challenge when extending the life of an ageing infrastructure or system is to achieve a longer period of economic benefit while ensuring that safety and integrity are maintained. Key factors to consider are the physical deterioration, operation, and maintenance of the system, although less obvious factors may also have an important impact on safety, such as the obsolescence of equipment and changes in the organization. Operating beyond the original design lifetime is known as life extension (LE). Ageing is related to deterioration and may pose a serious risk to the safety of the infrastructure, the personnel, and the environment as the equipment becomes less reliable, obsolete or no longer fit for service, reducing the reliability of safety systems.

The gained knowledge of RUL assessment would lead to the development of cost-effective and lifetime-optimized operation of an installation. The use of technical condition indicators may be one starting point to assess residual useful life (RUL) for these parts, components and systems. For this thesis work, it follows a research and development (R&D) project sponsored by Statoil and executed by SINTEF/NTNU. The contribution from the master thesis as part of the R&D project is shown in chapter 5.

1.3 Objectives

The scope of the master thesis will concentrate on methods, models and approaches to realize RUL assessment. The following objectives will be achieved through the thesis work:

1. Review the literature regarding various use of the term residual useful life as a basis for giving an explicit definition to be used through the work.
2. Identify two to three classes of critical equipment types as a basis for case studies. Such classes could be rotating equipment, static equipment and safety systems.
3. For each of the identified classes the literature shall be revived with respect to which deterministic, probabilistic and combined models are proposed to link technical condition indicators and other degradation measures to residual useful life (RUL).
4. Select one or two cases where models, methods and real condition data could be applied in the aging and life extension management.
5. The case studies shall demonstrate how the maintenance program will affect the technical condition on the equipment, and how to balance maintenance effort with other measures such as upgrading projects, renewal and modification.

1.4 Limitations

The thesis is subject to available methods, models and approaches of dealing with ageing facilities and RUL assessment presented in the literature review and extended work on account of the time limit and complexity. Another limitation lies in available technical and maintenance data supported by Statoil within limited time. Practical RUL assessment is relied on sufficient data and proper prognostics models. Within this thesis, the relatively small amount and few types of real condition data is a major limitation, leading to marginally application of various RUL assessment techniques and RUL estimation models.

1.5 Approach

The main approach of this thesis is based on literature review and discussions with expertise in the project team 'Kristin Regularity'. The first objective is performed by reviewing the research work that gives the term residual useful life survival. It also contains an extensive review of RUL assessment techniques up to now, by the use of database Engineering Village and Science Direct. Objective two follows the R&D project. The SINTEF project team outlines the production-critical equipment that is analyzed in the thesis. The third objective is achieved by a revived literature review. Objective four considers a specific case study and applies real condition data that is supported by Statoil. The fifth purpose is accomplished by a further work considering an establishment of maintenance program based on the result of RUL assessment.

1.6 Structure of the Report

The thesis mainly consists of three parts. The first part, chapter 2 and 3, is centered on presenting explicit understanding and interpretation of the term RUL. Challenges within RUL assessment are indicated. A terminology study is deduced stating from lifetime, following useful life and residual useful life. The definition and presentation of RUL are based on two main aspects, engineering perspective and statistical perspective. Chapter 2 also gives an introduction on technical condition indicators (TCI). Relevant academic work within TCI research is reviewed. A state-of-the-art review on RUL assessment methodology is included. Chapter 3 compares RUL definitions survived in existing literatures and proposes a new approach to interpret the term.

Part two, chapter 4, identifies critical equipment and revives literature view on relative deterministic, probabilistic and combined models linking degradation measures to RUL assessment. RE is the targeted system. A depth methodological review with RE focused is presented in view of previous literatures in chapter 2. Recent academic contributions within RUL assessment of rotating equipment are investigated and summarized.

The third part performs case studies. Chapter 5 carries out statistical analysis and applies real condition data in the ageing and life extension management. The SAP (Statoil Computer-aided Maintenance Management System) data of AC generators and gas turbines are processed and analyzed, in order to catch their failure tendencies. Chapter 6 proposes the case study on maintenance optimization. Degradation models suitable for a piece of presumed mechanical equipment are constructed where concentrates on deterioration state modelling. Cost models are established based on two distinct maintenance policies.

Chapter 7 gives the summary and conclusion of this thesis. Recommendations for further work are presented in the end.

The preliminary study report and progress report of this thesis are not included in keeping with requirements of the responsible supervisor, Professor Jørn Vatn.

Chapter2 Literature Review

To acknowledge the full scope of RUL assessment, it is required to give a clear definition of the term residual useful life. Chapter 2 reviews the literature with respect to various use of the term RUL and gives a distinct definition of RUL used in the thesis. It first starts with an overview of industrial practice on RUL assessment, addressing its practical significance, its role in this thesis and a number of challenges within such field. At the end of this chapter, several explanations used to describe RUL are examined and compared, aiming to rationalize the term residual useful life. The end of this chapter gives an introduction on technical condition indicator.

2.1 Overview of Applications on RUL Assessment

RUL assessment or estimation has received the industry's great interests recently with environmental, economic and operational purposes. It is regarded as a useful tool in decision-making, specifying current state of the installation and predicting the future remaining life, to decide whether the remaining life of equipment is sufficient for a second life. Great efforts on RUL assessment have been performed in a variety of fields.

As far as I know, the earliest research within RUL assessment is carried out by Watson and Wells (1961), where the work uses mean residual life to study burn-in. In modern industry, RUL assessments are becoming mandatory for economic consideration and assurance of RAMS (Reliability, Availability, Maintainability and Safety) requirements. The aerospace industry predicts the RUL of aircraft critical systems in advance so that effective corrective maintenance can be implemented in time and thereby assures flight safety (Chen et al., 2011). The motivation for RUL assessment in nuclear industry derives from the demand to avoid loss of revenue on condition that unexpected equipment failures will hamper power production of the plant (Shumaker, 2011). In railway domain, RUL assessment is primarily performed as fatigue life evaluation which is addressed in aging management as well as safe transport (Yasniy et al., 2013). The other applications of RUL prediction lie in finance, medicine and weather forecast etc. (Son et al., 2013).

RUL assessment additionally plays a significant role in managing product reuse and recycle. The industries, especially manufacturing and energy domains, are facing a great deal of pressures both from authorities and the public to reduce their industrial wastes. An effective and widely-used strategy is to avoid discarding products and facilities prematurely, which reduces the energy consumption to process raw materials and components. The associated concern will be how to ensure the reliability of used parts without compromising their desired performance. RUL assessment is able to deal with such challenges through estimating the reuse potential of used parts and facilities (Mazhar et al., 2007; Si et al., 2010).

As various areas, the oil and gas industry also requires RUL assessment to be performed on parts, components and systems in order to ensure production regularity, achieve lifetime optimized operation and hereby gain considerable profits.

Particularly for offshore industry in the North Sea Norway, the easy oil and gas has been recovered by the large, nevertheless, continuing production is anticipated owing to improved extraction technologies and respectable energy prices. This requires extending the lifetime of production and process facilities since most of them are approaching their design life (Hudson, 2010). Relating to the safety concern in offshore O&G industry, catastrophic failures should be avoided during both normal production and extend-lifetime phase, knowing the RUL facilitate system operators to implement timely maintenance actions for this case.

In this thesis work, the role of RUL assessment is highlighted as a tool to plan necessary maintenance optimally and further eliminate unnecessary maintenance work in aging and life extension management. The practice of RUL assessment is expected to bring benefits to the O&G industry comprising reduced downtime and maintenance cost, optimal management of spare parts together with improved equipment availability.

2.2 Challenges of RUL Assessment

Although extensive work have been done in RUL assessment, it is still difficult to accurately predict the residual useful life under complex operating environments and dynamic loads, particularly with multiple failure modes considered. Operating RUL is dependent on the real conditions of use. The stochasticity, as one of the main characteristics in the system operation, leads to many difficulties and uncertainties in assessing the RUL of equipment, both for deterministic approaches based on failure mechanisms and probabilistic approaches utilizing statistical techniques. As Jin et al. (2013) indicated, uncertainty management is the most challenging aspect of residual life performance prediction.

For complex or large-scale engineering systems, it is typically either cost-expensive or time-consuming to obtain the physical failure mechanisms ahead to capture the physics of failure. The specific failure mechanism knowledge is often hard to gather without interrupting operation. Each engineered system may require creating an entirely new algorithm and model to assess the RUL. The RUL assessment based on failure mechanisms hence has limited ability to transfer from one component to other types of components. Practically deterministic approaches have been realized their inadequacies in tackling the stochastic nature of deterioration process in RUL assessment. On the other hand, the probabilistic approach to assess RUL needs a large quantity of data as well as specialized analysis techniques to process such data. The accuracy is dependent on the quantity and quality of the data and statistical learning techniques. The uncertainties within such approach require rather complex probabilistic tools to handle, particularly taking into account the real operational mode (Si et al., 2013; Maio et al., 2012). To sum up, the recent research in RUL assessment mainly intends to find out solutions for the following questions, which also denote the challenges within RUL assessment:

1. How to develop practical models to describe the residual useful life on various types of equipment concerning the integration of real world dynamical situations?

2. For two main approaches to assess RUL of a piece of specific equipment, utilization of deterministic models based on failure mechanism and probabilistic models dependent on distribution of failure records. Which one is promising?
3. Refer to deterministic models, what kind of knowledge is required to adopt such models to assess RUL and correspondingly how to validate their usefulness?
4. Refer to probabilistic models, what kind of data is required to feed these models and how to evaluate the credibility of such models?
5. For industrial application, it may be interested in: How to integrate results of such assessment to the decision-making process? Further, one is perhaps interested in knowing how to standardize or simplify the procedure for RUL assessment?

2.3 Terminology

The result of terminology study on RUL and TCI is shown in this section. A deep and comprehensive understanding of RUL cannot be achieved without a clear cognition of the term lifetime and useful life. The procedure to explain RUL in this section is conducted sequentially starting from the term “lifetime”, followed by “useful life” and ending up with “residual useful life”.

2.3.1 Lifetime

The research of lifetime is extremely widespread through studying length of life of organisms, electronics, structures, materials and devices etc. Normally, it is measured in hours, cycles or in other unit (Finkelstein, 2008). The lifetime in the thesis refers to the time period from the activation time of an item till its end point of service. The lifetime is generally treated as a positive random variable T, characterizing by its distribution function $F(t)$. Researchers are interested in knowing the mean life T_M in practice, which is obtained by analyzing time-to-failure data of the same type of components under same conditions. For example, the mean life $T_M = \eta\Gamma[(\beta+1)/\beta]$ is obtained with using Weibull distribution to model the failure event data of an item (Mazhar et al., 2007). The RUL assessment essentially needs to describe the lifetime in the whole remaining interval of time.

Chakravorti et al. (2013) conceptualized the lifetime of equipment in three ways: physical lifetime, technical lifetime and economic lifetime. *Physical Lifetime* links to the state where the equipment cannot be used any more in its normal operating state. *Technical Lifetime* corresponds to the state where the equipment has to be replaced owing to technical reasons even if it can perform its functions physically. *Economic Lifetime* refers to the situation where the capital value of a piece of equipment depreciates annually.

The technical lifetime links to the case that maintenance of the equipment is exceedingly difficult due to unavailability of spare parts. The economic lifetime relates to the case that operating and maintenance costs may increase over time because of aging and are even beyond the depreciated value of the equipment, indicating the replacement of the equipment is cost-effective (Chakravorti et al., 2013). For a piece of equipment, its technical life or economic life can go to the end even though its physical life left is sufficient to perform the desired performance. The term of life in RUL assessment in this thesis therefore varies to different conditions of the equipment and technical or economic factors that affects the residual useful life of the equipment.

2.3.2 Useful Life

There are a number of definitions with respect to the term useful life. "InvestorWords.com" defines the useful life as "the length of time that a depreciable asset is expected to be usable", while "Accounting Coach" demonstrates the useful life as "the period of time that will be economically feasible to use an asset." In "Businessdictionary.com", the useful life is defined as "the period during which an asset or property is expected to be usable for the purpose it was acquired". For an industrial system, its useful life is the operating time in which it can perform required functions within the specified performance limits. The useful life perhaps terminates upon a failure or by a determination that the system is no more useful. Figure 2 shows the timeline of the useful life of a system concerning its potential for life extension. At time t_0, the decision regarding life extension has to be taken. The system's predicted useful life is t_2.To ensure that the system will not terminate before t_2, either opportunistic repairs/replacements are required to be planned till t_2 or all the crucial replacements are required to be done at t_0 (Vaidya and Rausand, 2009).

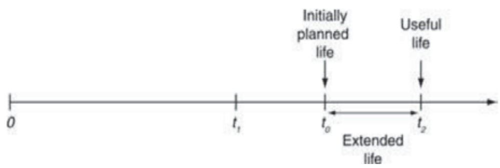


Figure 2 Timeline of the useful life of a system (Vaidya and Rausand, 2009)

With various definitions, it is evident to see that the key word in the term is "useful" and is difficult to get its uniform definition. Various criterion may be taken to assess whether an asset or equipment is useful or not, for example, depreciation, economic returns and physical condition. To acquire useful life criterion for industrial systems, Vaidya and Rausand (2009) give suggestions to combine expertise from the field of design, manufacturing, safety and system, material degradation, structural integrity, finance and human factors. The research work specifically addresses several criteria to answer if a subsea system will be "useful": (1) predefined functional requirements, (2) availability, (3) safety and regulatory requirements, (4) environmental requirements, (5) maintenance cost and (6) overall profit margins (Vaidya and Rausand, 2011).

In the bath-tub curve, the useful life is a period of time where an item performs its required functions stably in the normal operating state, typically referring to the normal life period. However, a specific facility perhaps discards even though it is in its normal life period, which is due to undesirable uptime or unavailability of spare parts support. It is more necessary and realistic to consider the value of profits to define the useful life in reality. The useful life in this thesis consequently signifies the period in which a piece of equipment performs its required functions stably meanwhile brings desirable benefits to the owner.

2.3.3 Residual Useful Life

The term of residual useful life is widely-used both theoretically and practicably in operational research, statistics literature, reliability assessment, maintenance optimization and various engineering fields, sometimes named remaining useful life and the acronym RUL is used. Engineers and statisticians give different explanations on this term. From the engineering point of view, RUL is closely associated with physics of an item and failure modes of the equipment. With statistical thinking, the analysis of RUL is established upon probabilistic models and further work in adopting this sort of model to describe residual useful life. In this thesis, the former view corresponds to deterministic models for RUL assessment while the latter view is denoted as probabilistic models. It is expected that the determination of RUL will not be particularly restricted to a specific date and time.

2.3.3.1 Define RUL from engineering perspective

There is no uniform concept survived in the literature review to define RUL in engineering area. The meaning of RUL depends on various context and conditions used in research and study. For instance, Chakravorti et al. (2013) indicated that RUL of transformers is expressed as the service years left to lose the mechanical strength of solid insulation under operational conditions. Yet for carbon filters, its RUL is described as breakthrough times affected by adsorption rate, carbon properties, airflow rate etc. (Mason et al., 2014). Hudson (2010) demonstrates the remnant life of an asset during its life-extended phase, as shown in figure 3. Therein a remnant life assessment is regarded as an estimation of the remaining life by calculating or quantifying the effect of the deterioration mechanisms in comparison with the original design. Failure modes play a significant role in understanding RUL for engineers. It is common to link residual useful life in materials engineering to fatigue life, crack propagation rate and corrosion rate, etc. In mechanical engineering, RUL refers to wear rate. Apart from calendar time, the number of cycles/revolutions is also used in expressing RUL, especially for rotating machinery (Ahmadzadeh & Lundberg, 2013a).

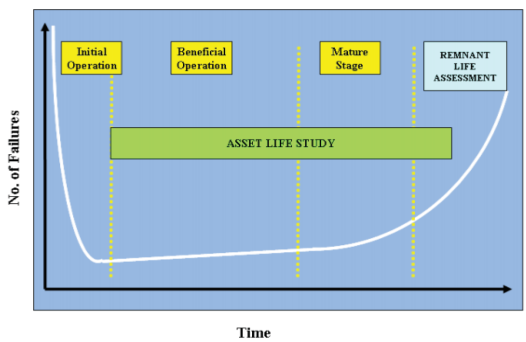


Figure 3 The asset life cycle (Hudson, 2010)

Industrial and maintenance engineers are constantly making efforts to anticipate the failure manifestation and act proactively in order to maximize the equipment's performance and profits. Recently the modern industry has put considerable attention on implementation of condition based maintenance (CBM), which effectively utilizes knowledge of failure modes to predict RUL of the equipment. CBM is a decision-making strategy to diagnose impending failures, reduce the uncertainty of maintenance activities and foretell the remaining operational life (Peng et al., 2010). It is defined as "predictive maintenance performed as governed by condition monitoring programs" (ISO 13372:2012). Practically condition monitoring data, such as vibration data and oil analysis data, are collected and processed to decide future equipment health condition and further to predict its RUL (Tian et al., 2011). The reliability and maintenance cost are main criterion frequently adopted by maintenance engineers to schedule maintenance work in reality. Figure 4 shows the relationship between RUL and such two criterions. RUL denotes as time to failure. When it reaches zero, the system will break down, correspondingly, the maintenance cost increases significantly and the reliability of the system decreases. It needs to be emphasized that knowledge on the failure propagation process and failure mechanisms are important in an effective CBM program (Peng et al., 2010). In the view of maintenance engineering, the understanding of RUL is closely related with diagnostics and prognostics which are two significant aspects of CBM.

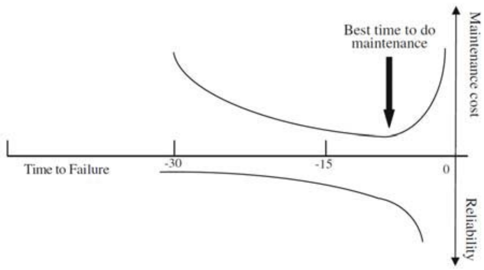


Figure 4 Relationship between RUL and maintenance cost & reliability (Peng et al., 2010)

Diagnostics is defined as "examination of symptoms and syndromes to determine the nature of faults or failures (kind, situation, extent)" by ISO 13372:2012. Its main task is to detect, isolate and identify faults when abnormity occurs. It shows whether the monitored system indicates something wrong, locates the faulty item and determines the nature of the fault. Although diagnostics do not address direct information on RUL assessment, it provides the operator reports on whether a specific failure is present or not, particularly when failure prediction of prognostics fails and a failure occurs RUL estimation is more likely a prior event analysis in analogy to prognostics but not a posterior event analysis as diagnostics (Jardine et al., 2006)..

In comparison with diagnostics, the term prognostic is used more frequently in relation with RUL. RUL estimation is regarded as one of the most critical components in prognostics and health management (PHM) (Si et al., 2013). The objective of prognostics is to predict the RUL (Ahmadzadeh and Lundberg, 2013a). ISO 13372:2012 defines prognostics as "analysis of the symptoms of faults to predict future condition and residual life within design parameters". Similarly, ISO 13381-1:2004 defines prognosis as a "technical process resulting in determination of remaining useful life". IEEE Reliability Society gives a relative definition combining

PHM as "a system engineering discipline focusing on detection, prediction and management of the health and status of complex engineered systems" (Ma, 2009). Farrar and Lieven (2006) describe damage prognosis as "the estimate of an engineered system's remaining useful life".

Prognostics are usually effective for faults and failure modes with known, age-related, or progressive deterioration characteristics (ISO 13381-1:2004). It uses automated methods to detect, diagnose, and analyze the degradation of physical system performance, calculating the acceptable remaining life before the occurrence of unacceptable degraded performance (Peng et al., 2010). Predicting the residual useful life of an item is a main concern of prognostics, as Jardine et al. (2006) pointed out, the most widely used prognosis is to predict the time left before the occurrence of a failure given the current machine condition and past operation profile. Therein the time left before failure observation usually refers as RUL.

The end of this section reviews how an engineer gives response when he is asked about RUL. In the engineer's opinion, RUL is the operating time left on equipment before it is down for required major maintenance. Some RUL is dependent on Vendor recommendations, some are based on experience, and the others are counted on deterministic analyses. The majority of them are dependent on experience. In the operation, remaining life and risk of failure are both useful to be predicted. A number of maintenance actions are based on RUL while others are relied on current condition. The engineer stressed that RUL turns out to be critical when failure modes are known or predictable within scheduling maintenance. In the event of unpredictable failures and randomly changing conditions, the RUL becomes meaningless in planning maintenance (Banjevic, 2009).

2.3.3.2 Define RUL from statistical perspective:

Compared to engineers, researchers in the field of statistics, operation and reliability analysis generally talk about life models, economic models and replacement policies (Ahmadzadeh & Lundberg, 2013a). The residual useful life of a component or system is typically demonstrated as the length from the current time to the end of its useful life, expressed as a nonnegative random variable T_u. A simple and concise way to acquire T_u is through achieving the period between the static mean life T_M and the dynamic actual used life T_A (Mazhar et al., 2007). According to Rausand & Høyland (2004), Finkelstein (2008), Nystad (2008), Banjevic (2009) and Ahmadzadeh & Lundberg (2013a), the following part of this section is deduced to define residual useful life for non-repairable and repairable items separately in the perspective of a reliability analyst or a statistician. This part is carried out in a general way and not refers to a specified industrial system. The end of this section further gives an application case, which demonstrates RUL of an industrial system from statistical perspective, namely RUL in a subsea context.

<u>RUL for non-repairable items</u>

Non-repairable items are generally discarded by the first failure. For an item of age t, consider the nonnegative lifetime random variable T, representing random time to failure of this unit. Let $R(t) = \Pr(T > t), t \ge 0$, be its reliability function. T is assumed to be absolutely continuous for simplicity. Its existing probability density function (Pdf) is denoted as $f(t)$ and its cumulative distribution function (Cdf) as $F(t)$:

$$F(t) = \begin{cases} \Pr(T \le t) = 1 - \Pr(T > t) = 1 - R(t) = \int_0^t f(u)du, t \ge 0, \\ 0, \qquad t > 0. \end{cases}$$

$$f(t) = \frac{d}{dt}F(t) = \lim_{\Delta t \to 0} \frac{F(t+\Delta t) - F(t)}{\Delta t} = \lim_{\Delta t \to 0} \frac{\Pr(t < T \le t + \Delta t)}{\Delta t}$$

$F(t)$ denotes the probability that the item fails within the time interval $(0, t]$ and a maintenance action is required to be performed. The failure rate function $z(t)$ of the item is obtained:

$$z(t) = \lim_{\Delta t \to 0} \frac{\Pr(t < T \le t + \Delta t | T > t)}{\Delta t} = \lim_{\Delta t \to 0} \frac{F(t+\Delta t) - F(t)}{\Delta t} \frac{1}{R(t)} = \frac{f(t)}{R(t)}$$

Extending from the statement above, the residual useful life $RUL(t) = T_u = T - t$ (when $T > t$), is used to describe the remaining time to failure beyond the age t, see figure 5. Let $R_u(x) = P_u(T_u > x) = P(T - t > x | T > t), \quad x \ge 0$ be its reliability function, $\lambda(x) = \frac{f_u(x)}{R_u(x)} = z(t + x)$ be RUL failure rate function,

$f_u(x) = \frac{f(t+x)}{R(t)} = z(t+x)R_u(x)$ be RUL probability density function and

$F_u(x) = 1 - R_u(x) = 1 - P_u(T_u > x) = 1 - P(T - t > x | T > t)$ be RUL cumulative distribution function. Further, mean residual useful life (MRUL) is defined as

$\mu(t) = E(T - t | T \ge t) = \int_0^\infty R_u(x)dx = \int_0^t R\ (x|t)dx = \frac{\int_t^\infty R(x)dx}{R(t)}$, where $R(x|t)$ is the conditional survival function of an item that has survived till the age t.

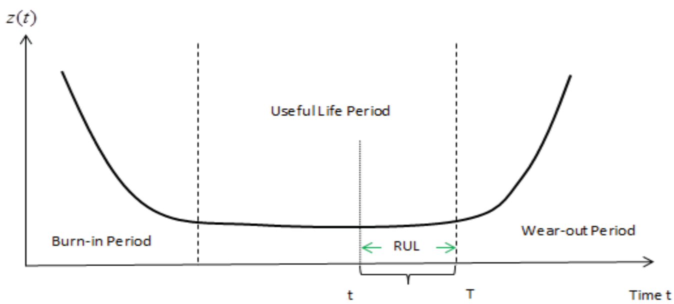


Figure 5 RUL for non-repairable items

RUL for repairable items

Repairable items are able to perform the desired functions after the implementation of proper maintenance actions. They are typically not discarded by the first failure. The end service time for them may be determined by high maintenance cost or unavailability of maintenance support.

Consider a repairable item that is put into operation at time $t = 0$. S_1 denotes the time of first required maintenance action. It is assumed that the repair action is perfect which is able to bring the failed item back to the functioning state. It is further assumed that the repair time is neglected. A sequence of required maintenance action times $S_1, S_2...$ will be obtained. Let T_i be the interoccurrence time for $i = 1, 2...$ and $N(t)$ be the integer number of maintenance actions in the time interval (0, t]. S_i refers to the global time while T_i indicates the local time, hence $S_i = T_1 + T_2 + ... + T_i$. $\{N(t), t \geq 0\}$ is called a counting process. It can be represented by the sequence of maintenance action times $S_1, S_2...$ or by the sequence of interoccorrence times $T_1, T_2...$. The most popular stochastic point processes used to model repairable systems are homogeneous Poisson process (HPP), renewal process (RP), and nonhomogeneous Poisson process (NHPP). The RUL corresponds to the period between an arbitrary point in time t (a specific point in time irrespective of global time and local time) and the time to next required maintenance action. For instance, if we stand at time t' and intend to know the RUL of the item, its RUL can be described as $S_3 - t'$, see figure 6.

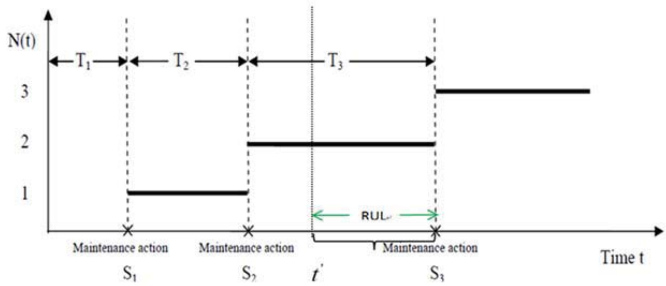


Figure 6 RUL for repairable items (adapted from Nystad, 2008)

RUL in a subsea context

The research work to define RUL within a subsea context is performed by Vaidya and Rausand (2009; 2011) from a statistical view. The technical health, future operating conditions and future environmental conditions are decided as main factors influencing RUL of a subsea system: (1) TH_1 denotes the technical health of the system at time t_1, see figure 7. It corresponds to the knowledge (K) about the equipment up to time t_1. The survivor function $R(t|t_1, TH(t_1), K)$ expresses the relation between the technical health and the reliability of the equipment. (2) $O(t_1)$ describes expected operational conditions and planned interventions that are predicted at time t_1, estimating the operating condition that would prevail from t_1 till the end life of the item. The estimation relies on the experience and expert judgment. (3) $E(t_1)$ expresses the expected environmental conditions that may prevail after time t_1. T_u is used to measure the time from t_1 until the system is no longer useful. The distribution of T_u relies on the technical health TH_1 at time t_1, the expected operational conditions $O(t)$ and the expected environmental conditions $E(t)$. The probability distribution function of T_u at t_1 is achieved to be $F_u(t|t_1) = \Pr[T_u \le t | TH_1, O(t_1), E(t_1)]$.

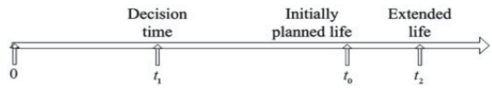


Figure 7 Timeline for remaining useful life (Vaidya and Rausand, 2011)

2.3.4 Technical Condition Indicator

Technical condition can be viewed as a static value. It affects the residual useful life of a component or system, particularly for cases when operators change the operating conditions of equipment (Thorstensen, 2007). A simple example could be: the residual useful life of an engine shaft may increase or decrease in case the external stresses are reducing or increasing. Through the literature review, the main contribution to use technical condition indicator for estimating RUL lies in Thorstensen (2007), Nystad (2008) and Vaiyad & Rausand (2009, 2011).

The technical condition of an item at time t in Vaiyad & Rausand (2009, 2011)'s research is defined as the status or perform ability of the item as measured by a set of indicators at, or immediately before time t. A number of indicators either continuously measurable or discrete are needed to tell the status of the item, such as vibration, oil level, speed etc. The technical condition of an item at time t is denoted as $x(t) = (x_1(t), x_2(t), \ldots x_k(t))$ with k different indicators measured. It is regarded as a measurement (sensor readings) and no assessment is contained.

In the Thorstensen (2007) and Nystad (2008)'s research, technical condition indicator refers to technical condition index. It is a measure developed in the EUREKA project "Ageing Management (1996-1999) (www.eureka.be)", as part of the Norwegian Research Council founded program PROSMAT 2000. The purpose of this project is to develop a new and reliable variable, technical condition index, which is only affected by the change of the system's technical integrity. The following definition is used:

The Technical Condition Index, denoted TCI, is defined as the degree of degradation relative to the design condition. It may take values between a maximum and a minimum value, where the maximum value describes the design condition and the minimum value describes the state of total degradation.

Early alerts will be available in case problems are developing by using TCIs and the organization can take necessary actions. Compared to traditional indicators, for instance, regularity, accident statistics and environmental emissions, TCI has a high sensitivity with respect to technical condition. The evaluation of technical condition is related to five principal contexts: safety, environment, availability, man-hours and costs (Nystad, 2008).

Thorstensen (2007) presents a model developed to examine and obtain optimal solutions when it is possible to classify the present technical condition of the items and predict the residual life. The thesis work uses a Markov model to describe the deterioration process, where the sequential decision problem is modelled as a discrete time Semi-Markov Decision Process. An offshore gas turbine is worked on as a cases study. Nystad (2008)'s research utilizes aggregated TCI paths to estimate the RUL of natural gas export compressors. The technical condition determination methods are derived from the TeCoMan software. TeCoMan possessed by Marintek is a program developed to calculate the TCI as well as other types of KPI's. It is supported with a range of different aggregation methods and functions to transfer measurement readings to a unified indicator (TeCoMan Wiki).

As reviewed from Nystad (2008)'s project work, the RUL assessment only uses reliability as the single criteria to evaluate the usefulness of the equipment, which may not be so appealing on condition that maintenance cost, spare parts availability etc. are considered in reality. Integrating information obtained from RUL estimation to decision-making in maintenance planning is the most important aspect which gives the assessment process meaningful. The lack of incorporating maintenance issues in RUL assessment may weaken the producing practical significance. Another limitation is related to the real condition data required to feed TeCoMan program and reliability models. The uncertainty management in the RUL assessment is not performed in the research, which reduces the accuracy of the estimation. The assumption of perfect inspection in Thorstensen (2007)'s thesis is quite limited in reality.

2.4 State-of-the-art Review on RUL Assessment Methodology

RUL assessment comprises two aspects. One is related to RUL estimation, namely systematic use of information to predict or calculate RUL, depending on specific contexts, either to achieve a numerical value or the probability of surviving a particular period of time, or simply a classification of degradation states. The other is to describe the process of judging the tolerability, the goodness etc. of the results from RUL estimation/analysis. The former finds the 'values' of RUL and the latter compare it with relevant requirements, such as RAMS requirements (Lecture note: TPK5170). RUL estimation is the core part of assessment procedure. The sequential comparison of estimation results with requirements generally appeals for an establishment of maintenance program for a piece of equipment in case its estimated RUL does not fulfill the expectation.

This section summarizes and compares current RUL estimation methods used both in the theoretical and practical work. The deterministic models based on physics of failure and probabilistic models relied on statistical techniques are two separate approaches to carry out RUL estimation, where the hybrid of such two methods also survive in the research. The review watches the probabilistic model closely in view of that no specific equipment is focused and no background information from the industry is provided.

Table B. 1 (page 54) summarizes the state-of-the-art review on various RUL estimation methodologies presented by different authors. The review is performed through using the database 'Engineering Village' and limited to the accessibility to full texts. Most relevant and recent papers are recorded while non-relevant and outdated papers are neglected. The literature investigation shows that prognostic models are widely-adopted to perform RUL estimation through using given condition and health monitoring information (Ahmadzadeh & Lundberg, 2013a; Son et al., 2013; Si et al., 2012). Figure 8 demonstrates the taxonomy of different approaches for RUL estimation. The techniques can be broadly classified as physics-based, experimental, data-driven and hybrid approaches, where experience based approach is not addressed. The comparison of these methods is presented in table B. 2 (page 59).

Physics based methodology typically builds theoretical models to demonstrate the physics of the system and relative failure modes, for instance, fatigue crack growth, corrosion and wear. Experimental based methodology uses experiments to collect essential raw data to achieve a better understanding of the life time of components. The studies include, for example, energy engineering, engineering materials and chemical processing. Even though scientists and researchers in such fields do not use the terminology RUL, actually the experiments are designed for this purpose. Differ from the two methods above, the data-driven methodology does not require specific knowledge about products, but depends on the utilization of condition monitoring data to estimate RUL, where generally expects a large quantity of data to be available. Hybrid methodology indicates using two or more prediction methods in conjunction to improve the accuracy of RUL estimation (Ahmadzadeh & Lundberg, 2013a; Son et al., 2013; Si et al., 2012).

In this thesis, physics based methodology refers to the utilization of deterministic models for RUL estimation. The data driven methodology corresponds to the adoption of probabilistic models for this purpose. The hybrid approach uses several different methods to estimate RUL. Experiment-based approach is not addressed since it closely relates to specific engineering domains and requires experiments.

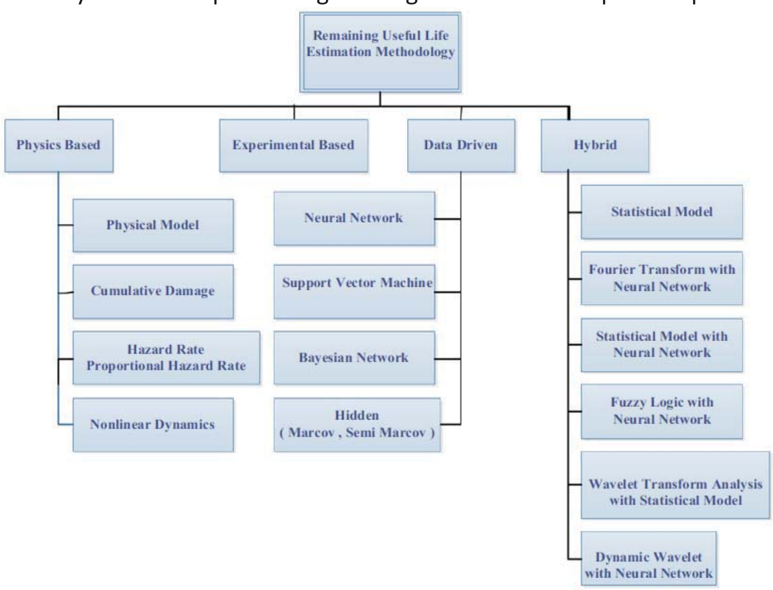


Figure 8 Taxonomy of approaches to estimate RUL (Ahmadzadeh & Lundberg, 2013a)

Chapter 3 A Novel Approach to Define RUL

Chapter 3 gives a novel approach to define RUL. The term has various definitions with different interpretation aspects based on review work. As a key measure of using RUL to realize maintenance optimization, the new way to define RUL considers maintenance issues as main target. Practically evaluating the usefulness of equipment may become complex and difficult. Many efforts are required and expected.

3.1 Comparison of Various RUL Definitions

The engineering perspective to define RUL is based on knowledge of engineering principles, physics of failure and underlying failure mechanisms. In this domain, engineers are required to possess professional knowledge on various deterioration mechanisms, for instance fatigue, corrosion, embrittlement, erosion and mechanical wear. The level of expert comprehension decides the accuracy of RUL estimation. Generally there is a number of failure mechanisms associated with one specified failure mode. The dominant failure mechanism takes the leading part in assessing RUL of equipment. It is therefore not necessary to analyze all failure mechanisms but competing ones to identify the dominant failure mechanism that limits the length of RUL (Vaidya and Rausand, 2011).

A useful tool to identify the different failure modes in a hierarchical structure is Failure Modes, Effects & Criticality Analysis (Rausand and Høyland, 2004). In industrial and maintenance engineering, RUL assessment needs to consider monitored condition monitoring information, operational, performance, environmental information and degradation signals. Bespoke condition monitoring equipment are required to be installed to provide such information, such as vibration, oil condition, temperature, humidity, pressure, speed, loading etc. (Si et al., 2011).

The statistical view to define RUL only considers a component or system's physical condition without counting on any physics or engineering principle. Its fundamental issue is to find the probability density function (PDF) of the RUL. Estimating the RUL is then realized by evaluating the conditional lifetime distribution given that a system has survived up to a specified time, for instance $T-t|T>t$, where T signifies the lifetime. The obtained RUL distributions generally depend on the life characteristics of a population of identical systems and available lifetime data (Si et al., 2013). The available statistical data determines the accuracy and authenticity of RUL assessment. This point of view to define RUL properly applies to the situation where the relative reliability function can be obtained, for example, in case the degradation life of an item is described as a Weibull distribution, then the corresponding Pdf and Cdf is known, further $MRUL(t)$ can be obtained.

Through the literature review, it is hard to arrive that whether the engineering thinking to define RUL is more accurate or the statistical perspective to describe RUL is more appropriate. Both of them have their own characteristics. The engineering view requires professional knowledge on material degradation, equipment operation etc. Generally speaking, knowing the dominant reason why the equipment fails obviously contributes to better understanding its RUL survival length (Vaidya and Rausand, 2011). The statistical view requires lifetime data to express the RUL. Si et al. (2013) pointed out that such data are in short supply in reality or even non-existent at all for systems that are costly or time-consuming to collect. An exact and closed-form of the RUL distribution is perhaps only available for some special cases. The real situation in defining RUL is normally restricted to the knowledge of equipment possessed by operators and available data that can be used to feed RUL estimation models. A hybrid approach to treat RUL assessment both dependent on engineering thinking and statistical techniques is expected to be more realistic and make up their own shortages.

The literature review indicates that the most fundamental challenge to define RUL in industry still lies in which criterion is used to answer whether one component or system is "useful" or not. The criterion differs to various duty holders and operating environments. A starting point to define RUL should demonstrate how the term "useful" means to the operator and what level of performance is anticipated on the equipment. In case various criteria exist, the optimal ones can be decided through utilizing multi-objective optimization methods.

3.2 A new idea to define RUL

Considering multiple criteria used to evaluate the usefulness of equipment

Differ from the conventional illustrations of RUL in the field of engineering and statistics, a new way to demonstrate the RUL refers to the remaining time period of a piece of equipment in where realize its anticipated performance and is able to bring desirable profits to the owner. The criteria used to evaluate whether the performance is desired or not, meanwhile to decide the threshold value shown in figure 9, may vary due to different operation surroundings and various duty holders.

Table 1 A generic list of criteria to evaluate the performance of equipment (Adriaan et al., 2010)

Criteria used to evaluate the performance of equipment	
Output quality	Output quantity
Reliability	Availability
Maintainability	Safety/Risk
Overall equipment effectiveness	Logistics
Inventory of spare parts	Personnel management
Environmental impact	Technical support
Deprecation cost	Operation cost
Maintenance costs(discounted)	Maintenance quality

Table 1 gives a generic list of criteria for this concern. The owner can define the required criterion to determine the point of time where the residual useful life ends, namely the time reaching the limit of threshold value. The RUL is then more likely an economical quantity, taking various criterions into account. Compared with traditional probabilistic approach to assess RUL through using reliability as unique criterion, the utilization of various criteria for RUL assessment will make it more widespread and practically appealing.

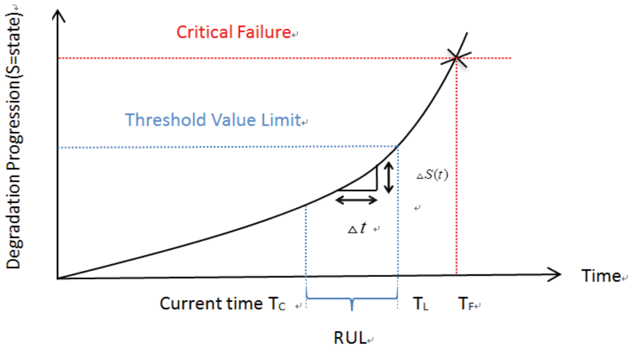


Figure 9 A new way to determine RUL

As shown in figure 9, the threshold value may be derived from one of the criterion listed in table 1, or a vector of several ones. A better practice of setting this value can be achieved by considering engineering experience, the analysis of past data and the recommended standards. The date T_L for the equipment to reach the threshold value is assumed to be prior to the time T_F where critical failure occurs, otherwise such thinking is meaningful less. RUL is then determined by the period between the current time T_C and the time in which the equipment reaches the limit value, namely RUL=$T_L - T_C$. Correspondingly, the residual useful life is equal to $T_F - T_C$.

The degradation progression curve is required to be established prior to determination of RUL. $S(t)$ denotes the degradation level or state. Degradation rate is then equal to $d(t) = \Delta S(t) / \Delta t$. The assessment of degradation rate requires degradation models as well as data of measured historical degradation rate and influencing factors.

The critical failure indicates a failure where brings huge damage to the equipment, or even personnel injury and disasters. A direct and convenient way to determine the critical failure time is through lifetime modeling. The second method to decide the critical failure could be through using deterministic models based on failure mechanisms. With proper treatment, the external triggering events, such as shock, are also able to be included in this illustration.

In case reliability is selected as the single criteria, the traditional statistical way to define RUL is sufficient for the assessment process. With this view, RUL assessment equals to residual lifetime assessment. On condition that other criterions are considered, for instance, safety and operation cost, it needs novel approaches, perhaps relevant economic models, to integrate such input parameters to the RUL assessment procedure.

Chapter 4 RUL Assessment on Rotating Equipment

Chapter 4 starts to perform RUL assessments for critical type of equipment. The determination of critical equipment follows the project “Kristin Regularity”. Kristin is located in the southwestern part of the Norwegian Sea, 16 km south west of the Åsgard field. It has been developed with twelve production wells in four subsea templates tied back to a semi-submersible platform. Kristin produces about 10 million cubic meters of gas per day. Production capacity is 125,000 barrels of condensate and more than 18 million cubic meters of rich gas (www.statoil.com).

The analysis of data derived from SAP indicates that the gas export system contributes the largest to production loss, and the maintenance cost of main power systems is the highest. Based on study and discussion with expertise in the project team, the rotating equipment is determined as the first type of critical equipment for RUL assessment. This chapter starts with the study of major failure causes of rotating equipment, following a state-of-the-art overview of most-relevant RUL assessment methods.

In view of supported background information and already acquired maintenance data from Statoil, RUL assessment will mainly takes reliability as criteria to evaluate the usefulness of concerned equipment, meaning that the length of RUL ends at the point of time when a critical failure occurs. In other words, the majority of RUL assessment work equals to prediction of residual lifetime for specific equipment. The novel definition of RUL given in chapter 3 requires various types of data for relevant assessment work, for instance operation cost and depreciation cost, consequently the innovative approach to estimate RUL is not able to be developed due to lack of required data.

4.1 Rotating Equipment and Major Failure Causes

Rotating equipment are equipment that moves liquids, solids or gases through a system of drivers, driven components, transmission devices and auxiliary equipment, which is used to add Kinetic energy to a process. It is mainly classified as four types on the basis of different functions (Forsthoffer, 2005), see table 2.

Table 2 Major types of rotating equipment (Forsthoffer, 2005)

Driven equipment	Drivers-prime movers	Transmission devices	Auxiliary equipment
•Compressors	•Steam turbines	•Gears	•Lube and seal systems
•Pumps	•Gas turbines	•Clutches	•Buffer gas systems
•Extruders	•Motors	•Couplings	•Cooling systems
•Mixers	•Engines		
•Fans			

Like other types of equipment, rotating equipment does not fail without a cause. A comprehensive understanding of major failure causes of rotating equipment contributes to better forecasting machinery failures as well as predicting the RUL. Certainly, there are a number of factors required to be considered in RUL assessment for rotating machinery, for instance, original design, manufacturing tolerance, assembly, working environment, load nature and maintenance work. Particularly taking the design philosophy into consideration, the interaction between applied forces on rotating equipment under normal condition will lead to a stable operation with minimum noise and vibration. The loss of equilibrium force as a result leads to further fault enhancement (Da Costa et al., 2010). Noise and vibration signals therefore provide distinct measurements on degradation status of rotating equipment.

As a specialist providing rotating machinery consulting service to the O&G industry over 40 years, Forsthoffer (2005) points out that the root cause of rotating machinery failure lies in the supporting auxiliary system. A persistent inspection of auxiliary equipment condition, such as temperature and lubrication oil level, is recommended even during component replacement. OREDA handbook (2009) gives a list on failure modes of gas turbines operating in the North Sea: abnormal instrument reading, breakdown, external leakage-fuel, external leakage-utility medium, erratic output, fail to start on demand, high output, internal leakage, low output, noise, overheating, parameter deviation, minor in-service problems, structural deficiency, fail to stop on demand, spurious stop and vibration. Therein noise and vibration is specially focused in the thesis, intending to relate such failure modes to RUL estimation. Other failure modes, for instance leakage and output issues, are not addressed due to inadequate techniques for relating them to RUL estimation.

4.2 State-of-the-art Methodological Review on RUL Assessment of Rotating Equipment

The existing methods to estimate RUL of rotating equipment can be grouped into three main categories: (1) Reliability approaches-event data based estimation; (2) Prognostics approaches-condition monitoring data based estimation; and (3) Hybrid approaches-estimation based on both event and condition monitoring data (Heng et al., 2009; Gebraeel et al., 2009; Sikorska et al., 2013). An overview of utilizing various methods to estimate the RUL of rotating machinery can draw on relevant articles listed in table B. 1 (page 54), article number: 4, 6, 10, 15, 17, 18, 22, 24, 30, 33, 35, 36, 43, 44, 45 and 47. The review shows that recent RUL assessment research is mainly rotating-machinery-concerned, taking bearings for instance. Provided sufficient information and data, both physics based and data-driven RUL estimation methods are able to achieve the desired assessment purpose.

Generally, reliability approaches to estimate RUL are dependent on the distribution of failure event records of a population of identical units. Machine reliability is modelled through using parametric failure models, for instance Exponential, Weibull and Lognormal, where a number of them are elaborated in most reliability-focused books, like Rausand and Høyland (2004). This type of estimation is greatly useful to manufacturers since high volumes of units are available to be taken as analysis sample, but is less valuable to end users, for instance, mean-time-to-failure of a whole population cannot attract interests of a maintenance engineer yet the ongoing reliability information of a specific component or system does (Heng et al., 2009; Gebraeel et al., 2009; Sikorska et al., 2013). This approach does not consider multiple types of failure modes as well as dynamics of operating conditions and environments, which limits its application in RUL assessment on rotating equipment working in Kristin field.

Compared to reliability methods, prognostics approach and hybrid approaches is much more promising in estimating RUL of rotating machinery (Heng et al., 2009; Gebraeel et al., 2009; Sikorska et al., 2013). The defects caused by imbalance, misalignment, bearing faults and lubrication faults all lead to variation of rotation of the equipment. Therein the vibration inspection is widely adopted as diagnosis methods to describe the deterioration process of rotating machinery (Goto et al., 2008). An example could be predicting the RUL of rotating machinery through sampling the acoustic signal over its lifetime. Scanlon et al. (2013) argues that the acoustic noise signal contains sufficient information to effectively predict the RUL of rotating equipment, illustrating by a case study where the used rotating machine has several moving parts, including two rotating element bearings.

The following section demonstrates how to link vibration, noise signal and lubrication oil condition to RUL estimation, with focus on vibration. The purpose is to demonstrate most recent research work in this area and establish a solid foundation for further determination of proper method utilized in case study considering real condition data.

4.2.1 Vibration Signal Analysis for RUL Assessment

There has been an increasing strong interest to indicate the health of rotating equipment through the analysis of vibration signature, normally frequencies and magnitudes (Atoui et al., 2013). The vibration signal is not a direct source of information and its effectiveness in RUL assessment depends on available signal processing techniques.

<u>Fourier Transform</u>

The Fourier Transform is a traditional approach for vibration signal analysis, particularly with the consideration of stationary signals. It exposes the frequency feature of a time series $x(t)$ through transforming it from the time domain into the frequency domain, hence generating the spectrum $X(f)$ that includes the entire signal's fundamental and its harmonics (Al-Badour et al., 2011). One of its definition is given by Gao and Yan (2011): $X(f)=\int_{-\infty}^{\infty} x(t)e^{-i2\pi ft}dt$, where $x(t)$ is the time-series signal and f denotes the frequency composition. Afterwards, the Fourier Transform is extended to the fast Fourier transform (FFT)-based order analysis (OA) technique, discrete Fourier Transform (DFT) and short time Fourier Transform (STFT) in the particular field of vibrations and machinery health monitoring, allowing for an effective tracking of speed-driven harmonics of rotating equipment. Although FFT is widely used in signal processing, whereas it has no ability to demonstrate the time dependency of the spectrum of analyzed signal, which limits its application in dealing with non-stationary signals. It is recommended to employ FFT to process stationary signals (Al-Badour et al., 2011).

<u>Wavelet Transform</u>

Wavelet transform (WT) is an effective tool to process non-stationary signals and extract the signal's time domain (Loutas et al., 2013). Al-Badour et al. (2011) point out that the utilization of wavelet transform is able to present a local signal analysis or zoom on concerned time intervals whereas keep the spectral information intact. This tool is particularly significant for applications on damage (crack) or fault detections.

Mathematically, a wavelet is a square integral function $\psi(t)$ which satisfies $\int_{-\infty}^{\infty} \frac{|\Psi(f)|^2}{(f)} df < \infty$, where $\Psi(f)$ is the Fourier transform (i.e. frequency domain) of the wavelet function $\psi(t)$ (time domain). Its continuous version, the continuous wavelet transform (CWT), is defined as $wt(\upsilon,\omega) = \frac{1}{\sqrt{\upsilon}} \int_{-\infty}^{\infty} x(t)\psi^*(\frac{t-\omega}{\upsilon})dt$, where $\psi^*(\cdot)$ is the complex conjugate of the scaled (parameter υ) and translated (parameter ω) wavelet function $\psi(\cdot)$. The practical signal processing normally employs the discrete wavelet transform (DWF), since performing the CWT will lead to the problem of redundant information. The DWF can be achieved by discretizing the scale parameter υ and translation parameter ω, until get the satisfied signal mapping. Another major wavelet transform is wavelet packet transform (WPT). It is an attractive tool to detect and differentiate transient elements with high-frequency features. The wavelet packet is defined as $\begin{cases} u_{2n}^{(j)}(t) = \sqrt{2}\sum_k h(k)u_n^{(j)}(2t-k) \\ u_{2n+1}^{(j)}(t) = \sqrt{2}\sum_k g(k)u_n^{(j)}(2t-k). \end{cases}$ with $n = 0,1,2,...$ and $k = 0,1,...,m$, where $u_0^{(0)}(t)$ is the scaling function $\phi(t)$ and $u_1^{(0)}(t)$ is the base wavelet function $\psi(t)$. The superscript (j) signifies the jth level wavelet packet basis. There will be 2^j wavelet packet bases at the jth level (Al-Badour et al., 2011; Gao and Yan, 2011).

Loutas et al. (2013) perform the latest RUL assessment work through using wavelet transform technique combined with data-driven probabilistic ε-Support Vectors Regression (SVR) (Article No. 46 in table B.1, page 54). The gradual degradation of rolling bearings is considered and their features are extracted from the acceleration waveforms. Several run-to-failure experiments in bearings under various loading conditions are carried out with two vibration sensors mounted on the bearings for the monitoring of degradation phenomena. The threshold value is decided as a failure criterion in the test, namely an indicator of critical fault, and the RUL therefore ends in case the critical fault occurs. The tests are stopped when the vibration root mean square (RMS) acceleration hit the threshold. Both FFT and WPT are employed to acquire the most monotonic behavior during the test, which is chosen as inputs to the SVR model (Appendix A Technical Background). The established probabilistic SVR model is used to predict the RUL of rolling element bearings.

Goto et al. (2012) execute another RUL assessment work based on vibration signal analysis (Article No. 37 in table B. 1, page 54Table B. 1). The RUL evaluation is verified by actual data collected from rotating equipment in thermal power plants. The velocity and acceleration of vibration are state variables to indicate the deterioration of rotating equipment, refers to as the deterioration management values, meaning that if the deterioration management value is beyond a threshold value, a repair or replacement is required. RUL in this research therefore ends when the deterioration management value reaches the threshold value. Special acceleration sensors are used to map the amplitude of vibration acceleration and velocity for rotating equipment. Figure 10 shows the conceptual diagram of RUL estimation based on the prediction of the deterioration management value. The deterioration management value for velocity is $y_v(t_n) = c_{v1}t_n + c_{v2}$ and for acceleration is $y_a(t_n) = c_{a2}\exp(c_{a1}t_n)$, where t_n is the n th measurement of time and c_{v1}, c_{v2}, c_{a1} and c_{a2} are parameters of the model. The model parameters are estimated through using the exponentially weighted recursive least squares approach. $y(t_{n+m}), m = 1,...,l$ denotes the predicted deterioration management value, where t_n is the current time. $y(t_{n+m})$ is calculated by $y_v(t_{n+m}) = d_v(t_n) + c_{v1}(t_n)t_{n+m} - y_v(t_n), m = 1,...,l$ for velocity and $y_a(t_{n+m}) = d_a(t_n) + c_{a2}(t_n)\exp(c_{a1}(t_n)t_{n+m}) - y_a(t_n) m = 1,...,l$ for acceleration.

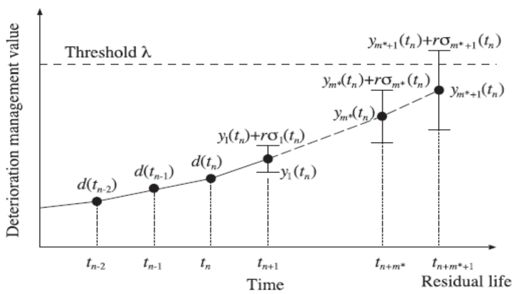


Figure 10 Concept diagram of residual useful life prediction (Goto and Kenta, 2012)

The predicted deterioration management value $y_i(t_{n+m})$ at time t_{n+m} is calculated by using the deterioration model. The standard deviation of the prediction errors $e_i(t_{n+m}) = y_i(t_{n+m}) - d_i(t_{n+m})$ of the deterioration management values are used to evaluate the confidence interval of the predicted value, where $d_i(t_{n+m})$ is the actual deterioration management value at time t_{n+m}. $e(t_{n+m})$ are assumed to be independently and identically distributed as $N(0, \sigma_i^2(t_{n+m}))$ where $\sigma_i(t_{n+m}) = \sqrt{\frac{1-\rho}{1-\rho^n}\sum_{k=1}^{n}\rho^{n-k}\{y_i(t_{k+m}) - d_i(t_{k+m})\}^2}, i = v, a, \quad m = 1,...,l$. Then the residual useful life m^* of the rotating equipment is evaluated by $m^* = \arg\{\min_{m(=1,2,\ldots,l}\{y_i(t_{n+m}) + r\sigma_i(t_{n+m}) > \lambda_i, i = v, a\}\}$. In case the upper value of the confidence interval $y_i(t_{n+m}) + r\sigma_i(t_{n+m}), i = v, a$ is beyond a threshold value λ_i, it appeals for maintenance intervention, where λ_i can be prior determined by expert judgment.

4.2.2 Lubrication oil analysis for RUL Assessment

Lubrication oil analysis plays a critical role in detecting gas turbine failures as well as in condition-based maintenance. The availability of a functioning turbine is mainly dependent on the protective performance of the lubrication oil for its transmission parts (Zhu et al, 2013). Poley (2012) claims that condition monitoring of lubrication oil delivers roughly 10 times earlier warnings for machine failures compared to vibration based monitoring techniques. Zhu et al. (2013) carry out the recent research work within this domain (Article No. 6 in table B. 1, page 54). Particle filter technique is utilized to estimate the RUL of the lubrication oil depending on the viscosity or dielectric constant sensor observations. An l-step ahead estimator is established to give a long term prediction of the state pdf $p(x_{k+l}|Z_k)$ of oil condition, for $l = 1,\ldots,T-k$, where T is time of failure. An unbiased l-step ahead estimator is $p(x_{k+l}|Z_k) = \int\ldots\int \prod_{j=k+1}^{k+l} p(x_j|x_{j-1})p(x_k|Z_k)\prod_{j=k}^{k+l-1} dx_j$, where the state $x_{t=k}$ denotes the particle contamination level at current time k. RUL is the object's remaining usable time before it needs maintenance or fails. For instance, let $\lambda_{thr.}$ represents a pre-specified threshold value for the state of oil condition, the object's RUL at time k is computed as $RUL_k = (k+l) - k = l$ given $x_{t=k+l}$ is beyond $\lambda_{thr.}$. With the determination of $\lambda_{thr.}$, the estimation of RUL$\le l$ is equal to the estimation of $x_{k+l} \ge \lambda_{thr.}$, which is $\Pr(RUL \le l|Z_k) = \Pr(X_{k+l} \ge \lambda_{thr.}|Z_k)$ (Zhu et al., 2013).

The implementation of particle filter technique for RUL assessment requires a physical model that relates the water contamination level and temperature to the dielectric constant and kinematic viscosity.

4.2.3 Nosie Signal Analysis for RUL Assessment

Noise signal from rotating machinery contains essential information about the internal process and is capable of providing valuable information for RUL assessment. Kavanagh et al. (2008) argues that sound intensity and sound pressure that explains the mechanism of noise generation contributes to distinguish the good from the bad bearings with spectral analysis and statistical analysis. Scanlon & Bergin (2007) and Kavanagh et al. (2008) employ the analysis of acoustic noise signal to predict the RUL of rotating machines.

Scanlon et al. (2013) present the latest RUL prediction work using noise signal analysis based on the prior research work within this domain. An advantage of using noise signal for RUL prediction is its allowing for remote and non-contact monitoring of the machine in contrast with vibration analysis that requires a direct contact with the equipment. The research proposed a novel approach which utilizes an information theoretic method to feature subset selection of modulation spectra features, namely a hybrid method combined MS (modulation spectral) plus MS-MI(mutual information)-PCA(principal component analysis). Life tests of four different rotating machines with the same type are conducted in the experiment to record the acoustic data over the machine's lifetime. The K-means clustering algorithm is employed to determine the state of machine degradation. Its RUL assessment result is a classification of degraded machines.

4.3 Summary and Discussion

In summary, RUL assessment based on vibration signal analysis, lubrication oil analysis and noise signal analysis generally has two phases. The first stage, off-line learning, is to learn and develop a behavior model from the condition monitoring data. The second stage, on-line prognostic, will utilize the established model to get a clear picture of the current condition of the equipment and to predict its future health state, see figure 11. Most research work (e.g. Loutas et al, 2013; Wang and Wang, 2012 and Tobon-Mejia et al., 2011) perform necessary experiments to derive sufficient raw data to construct the proper degradation model given different types of equipment and operating environments.

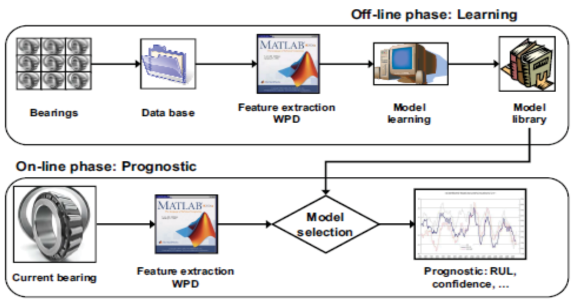


Figure 11 General diagnostics and prognostics step (Tobon-Mejia et al., 2011)

The principle of signal processing during the first phase is virtually the same; either FFT or WT is employed. FFT is sufficient for treatment of stationary signals where WT is preferred in processing non-stationary signals. Behavior models developed during the second stage have many branches, for instance, ε -Support Vectors Regression model (Loutas et al, 2013), continuous hidden Markov model (Wang and Wang, 2012) and mixture of Gaussians hidden Markov models (Tobon-Mejia et al., 2011). The selection or construction of degradation models vary to several factors apart from the type of equipment, such as the knowledge in understanding degradation process, the level of comprehension in mathematical models, the availability of acquired monitoring data and the experiment techniques. Model transfer in industry should be paid with special caution since operating surroundings and system boundaries make a big effect on degradation behavior. Maintenance actions based on improper degradation models are costly. For industrial application, it is therefore highly recommended to develop appropriate models in view of principles lied in research work.

Chapter 5 Case Study - Statistical Analysis

Chapter 5 performs the case study and applies methods and real condition data in ageing and life extension management of critical equipment. In agreement with the supervisor and project team 'Kristin Regularity', AC generators and gas turbines are determined for further analysis. It is proposed to carry out RUL assessment based on collected real condition data from Kristin field.

Kristin production field operates two AC generators and gas turbines. The SAP records the notification of their health conditions, classified as 'unwell', 'sick' and 'dead'. The PI system collects condition monitoring (vibration) data of gas turbines. The desired data, for instance noise signals and lubrication oil condition, is not obtained because of project constraints. No experiments are performed to train and develop proper assessment model. Only a sampled monitoring data of gas turbine is available. These objective conditions limit the realization of RUL assessment through employing various techniques, for instance FFT and WT.

Being subjected to acquired event data, the feasible approaches to process existing data lie in statistical techniques, and the procedure is implemented and demonstrated in Minitab, a statistics package developed at the Pennsylvania State University. We use alpha level 0.05, as common.

In the following, failure impact refers as failure state, digit 1 denotes an unwell event (blue color), digit 2 means a sick event (orange color) and digit 3 indicates a dead event (red color).

5.1 Statistical Techniques

Statistical techniques are frequently employed in processing event data, to identify the tendency of failures, for instance an increasing ROCOF. This section introduces a fraction of them that are utilized in the case analysis from an application perspective.

5.1.1 Counting Process

Conventional types of counting process include HPP, Renewal Processes, NHPP and imperfect repair processes. The following definitions are derived from Marvin and Høyland (2004).

5.1.1.1 Homogeneous Poisson Process

The counting process $\{N(t), t \geq 0\}$ is said to be an HPP characterizing a rate parameter λ, for $\lambda > 0$, if $N(t) = 0$, and the intercurrence times $T_1, T_2 \ldots$ are independent and exponentially distributed with parameter λ. The ROCOF (rate of occurrence of failures) of the HPP is $\omega(t) = \lambda$ for all $t \geq 0$. The number of failures in the interval $(t, t+v]$ is Poisson distributed with mean λv,

$\Pr(N(t+v)-N(t)=n)=\frac{(\lambda v)^n}{n!}e^{-\lambda v}$ for all $t \geq 0, v > 0$. The mean number of failures within the time interval $(t, t+v]$ is $W(t+v)-W(t)=E(N(t+v)-N(t))=\lambda v$.

5.1.1.2 Renewal Process

A renewal process is a counting process $\{N(t), t \geq 0\}$ with intercurrence times $T_1, T_2 \ldots$ which are independent and identically distributed with distribution function $F_T(t)=\Pr(T_i \leq t)$ for $t \geq 0$, $i = 1, 2, \ldots$. The renewal function $W(t)$ is the mean number of renewals in the time interval $(0, t]$, $W(t)=E(N(t))$. The mean number of renewals within the time interval $(t_1, t_2]$ is $W(t_2)-W(t_1)=\int_{t_1}^{t_2}\omega(t)dt$.

5.1.1.3 Nonhomogeneous Poisson Process

A nonhomogeneous Poisson Process is a Poisson process with rate parameter $\omega(t)$. The cumulative rate of the process is $W(t)=\int_0^t \omega(u)du$. The number of failures in the interval $(0, t]$ is Poisson distributed $\Pr(N(t)=n)=\frac{[W(t)]^n}{n!}e^{-W(t)}$ for $n = 0, 1, 2, \ldots$.

Minitab presents the parametric analysis of repairable systems through using the Power Law Process, one type of parametric NHPP models. In the power law model the ROCOF of the NHPP is defined as $\omega(t)=\lambda\beta t^{\beta-1}$ for $\lambda > 0, \beta > 0$ and $t \geq 0$. A repairable system modeled by Power-Law Process model is seen to be happy (improving) if $0 < \beta < 1$, and sad (deteriorating) if $\beta > 1$. The model reduces to an HPP if $\beta = 1$.

5.1.1.4 Imperfect Repair Processes

When using a renewal process, the system is assumed to be 'as good as new' after the repair action. The use of NHPP assumes that the system is 'as bad as old' after the repair action. For those repairs between these two extremes, imperfect repair models are required.

A large amount of models have been developed for modeling imperfect repair processes. These models are mainly used to model repair actions that reduce ROCOF and that reduce the age of the system. A large amount of models have been developed for modeling imperfect repair processes. These models are mainly used to model repair actions that reduce ROCOF and that reduce the age of the system. Typical models are Brown and Proschan's model, Failure rate reduction models, age reduction models and trend renewal process.

5.1.2 Prediction Method-Regression Analysis

Regression analysis is a statistical tool for investigating relationships between variables. This technique is used to ascertain the causal effect of one factor upon another, for instance, the effect of failure impact upon the notification date. Minitab provides both linear and nonlinear regression analysis. A p-value less than 0.05 indicates the strong relationship between variables.

Linear Regression

In linear regression, let i index the observations on the data (x, y). The simple linear model is $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$, $i = 1, \ldots, n$. y_i is a linear combination of the parameters. x_i is the independent variable. β_0 and β_1 are two model parameters (Wikipedia).

Nonlinear Regression

Minitab has various models for nonlinear regression analysis, for instance exponential and Weibull. An example of exponential regression model is $y_i = \beta_1 e^{\beta_2 \cdot x_i}$. Minitab also provides the growth curve for each tested function (Wikipedia).

5.1.3 Trend Test

5.1.3.1 Graphical Technique: Nelson-Aalen Plot

For a repairable system, given a number of failures and their failure times S_i for $i = 1, 2, \ldots$. Let $N(t)$ denotes the number of failures and by definition jumps (1 unit) at the failure time S_i. Draw a plot to map the jumping points $(S_i, N(S_i))$ for $i = 1, 2, \ldots$. The plot is called a Nelson-Aalen plot. For a sad system, the Nelson-Aalen plot will be convex, as shown in figure 12. Correspondingly, the plot will tend to be concave for a happy system. The system is steady if the Nelson-Aalen plot is approximately linear (Marvin and Høyland, 2004).

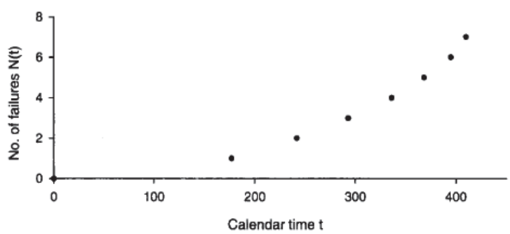


Figure 12 Nelson-Aalen plot for a sad system (Marvin and Høyland, 2004)

5.1.3.2 Statistical tests: Laplace Test, Military Handbook Test and Anderson-Darling Test

The Nelson-Aalen plot is intuitive to examine the ROCOF of a system. Nevertheless based on graphical methods, we still do not know whether or not the observed trend is statistically significant. Minitab gives three tests concerning this issue: Laplace test, MIL-Hdbk-189 test and Anderson-Darling (AD) test. The hypotheses for the trend tests are same.

- H_0: No trend in data (homogeneous Poisson process)

- H_1: Trend in data (nonhomogeneous Poisson process)
- Reject Criteria: Reject H_0 with p value larger than 0.05 with alpha level = 0.05.

We can arrive that there is some trend in the data if the null hypothesis is rejected. The data should be modelled with a nonhomogeneous Poisson process, such as Power-Law process. For the case that fails to reject the null hypothesis, the conclusion is that there is no sufficient evidence to reject the homogeneous Poisson process model. Even though the Power-Law model is appropriate, the homogeneous Poisson process is a preferable choice (Minitab 17 Support).

Laplace Test

The test statistic for the situation where the system is observed until n failures have occurred is $U = \dfrac{\frac{1}{n-1}\sum_{j=1}^{n-1} S_j - (S_n/2)}{S_n/\sqrt{12(n-1)}}$ where $S_1, S_2, \ldots$ denote the failure times. The value of U is an indicator of increasing or decreasing ROCOF, with $U > 0$ for a sad system and $U < 0$ for a happy system (Marvin and Høyland, 2004).

Military Handbook Test

The test statistic of MIL-Hdbk-189 (Military Handbook Test) for the system with n observed failures is $Z = 2\sum_{i=1}^{n-1} \ln \dfrac{S_n}{S_i}$. Low values of Z indicates a sad system. Large values of Z corresponds to a happy system (Marvin and Høyland, 2004).

Anderson-Darling Test

The test statistic of Anderson-Darling is $A^2 = -n - S$ for n observed failure events, where $S = \sum_{i=1}^{n} \dfrac{2i-1}{n}[\ln(F(Y_i)) + \ln(1 - F(Y_{n+1-i}))]$. $Y_1, \ldots Y_n$ are ordered failure data. F is the cumulative distribution function of the specified distribution. AD-statistic cannot reveal a sad or happy system but is employed to verify whether these data follows HPP or not. The decision to reject or accept the null hypothesis is dependent on comparing the p-value for the hypothesis test with the specified significance level (Wikipedia).

5.2 Statistical Analysis on AC Generators

Assumptions: AC generator A and B are independent and identical. AC generators and their spare parts are in same type and their operation surroundings are comparable. The SAP data set is homogeneous.
5.2.1 AC Generator A

Table 3 shows the notification data of AC generator A. The data in year 2008 is not available and for statistical analysis, we use the dataset recorded from date 2009/11/24 as time $t = 0$ until 2013/11/24 in which the 12th notification is recorded during a total time of 1461 days. S_j denotes calendar time and T_j denotes interoccurrence time for $j = 1, 2, \ldots$.

Table 3 SAP data AC generator A

Generator A	Notif Crea	Failure Impact	Failure State	NO. of notificaitons	Calendar time(Sj)	Interoccurence time(Tj)
	2009/11/24	U	1	0	0	0
Year 2009	2009/12/2	U	1	1	8	8
	2010/1/12	U	1	2	49	41
	2010/4/19	D	3	3	146	97
Year 2010	2010/9/9	U	1	4	289	143
	2011/6/29	U	1	5	582	293
	2011/9/12	S	2	6	657	75
Year 2011	2011/10/19	D	3	7	694	37
	2012/1/12	D	3	8	779	85
	2012/4/21	D	3	9	879	100
Year 2012	2012/10/20	D	3	10	1061	182
	2013/1/2	U	1	11	1135	74
Year 2013	2013/11/24	D	3	12	1461	326

5.2.1.1 Failure Trend Investigation

a) Regard all notifications as failures

In section (a), it is assumed that maintenance intervention is available for each notification event. The repair action will restore the system to a functioning state. We do not make further assumptions concerning whether this state is ‘as good as new’ or ‘as bad as old’. Figure 13 indicates that generator A may enter into the dead state following either an unwell state or a sick condition.

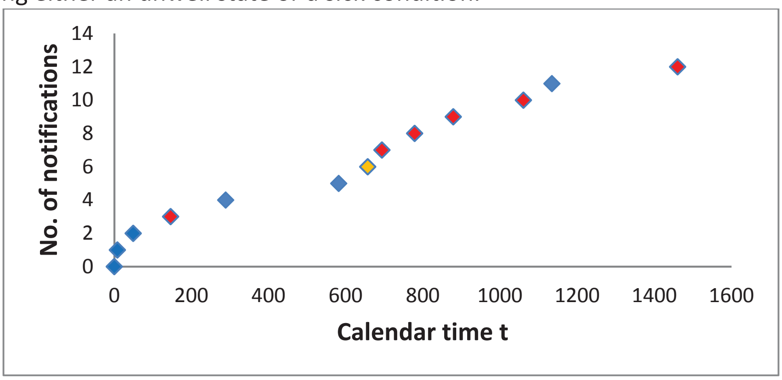


Figure 13 Nelson-Aalen plot for AC generator A

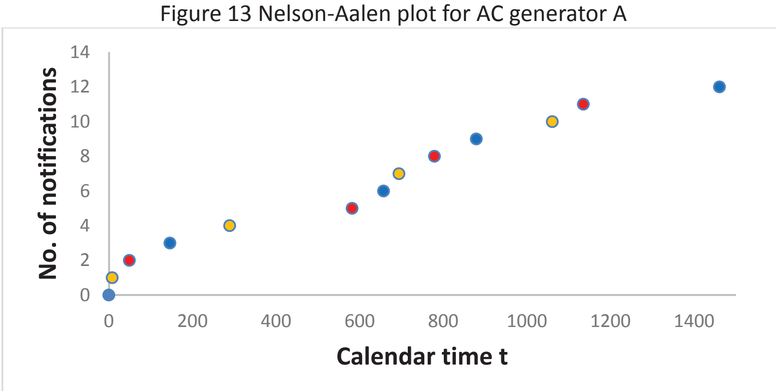


Figure 14 The sequence of failure impacts under ideal condition

Ideally, the notification records an unwell event at first, then the sick state and ends in the dead condition, see figure 14, if only considering the sequence of failure impact. Due to the limited number of notifications, this ideal trend cannot be verified. The Nelson-Aalen plot tends to be concave, which indicates a *happy* system with a decreasing ROCOF. A deep analysis is performed in the following.

Statistical trend tests are employed. H_0: there is no trend in data, homogeneous Poisson process; H_1: trend in data, non-homogeneous Poisson process. Rejection criteria: Reject H_0 with p-value less than 0.05.

Parametric Growth Curve: Calendar time

Model: Power-Law Process
Estimation Method: Maximum Likelihood

Parameter Estimates

Parameter	Estimate	Standard Error	95% Normal CI Lower	95% Normal CI Upper
Shape	0.718581	0.200	0.416895	1.23858
Scale	46.0075	48.579	5.80840	364.419

Trend Tests

	MIL-Hdbk-189	Laplace's	Anderson-Darling
Test Statistic	33.40	-1.26	1.24
P-Value	0.113	0.209	0.254
DF	22		

Parametric Growth Curve: Calendar time

Model: Poisson Process
Estimation Method: Maximum Likelihood

Parameter Estimate

Parameter	Estimate	Standard Error	95% Normal CI Lower	95% Normal CI Upper
MTBF	121.75	35.146	69.1430	214.383

Trend Tests

	MIL-Hdbk-189	Laplace's	Anderson-Darling
Test Statistic	33.40	-1.26	1.24
P-Value	0.113	0.209	0.254
DF	22		

Figure 15 Statistical tests on notification trend, AC generator A

As shown in figure 15, the p-value of Military Handbook Test (MIL-Hdbk-189), Laplace test and AD test is all larger than 0.05 and we do not have strong evidence to reject H_0. The following arguments are provided:

(1) The decreasing ROCOF is not statistically significant and perhaps accidental.
(2) The assumption of identical systems or homogeneous data may not be realistic and that produces a non-statistical-significant result for trend tests.
(3) On condition that we reject H_0 and accept H_1 with weak statistical significance, the Power Law model proposed by Minitab indicates a happy system and presents a decreasing ROCOF. This trend will only be realistic given that the repair team improves the system with each maintenance action, not just brings the system to a functioning state, and even better than 'as good as new'.
(4) On condition that we accept H_0 following statistical tests, no notification trend is verified. The interoccurrence times are independent and identically exponentially distributed with $\lambda = 0.0082$.

Two different situations are given regarding further analysis:

Situation A.a.1-Decreasing failure trend with weak statistical significance

In situation A.a.1, there is trend in notifications of failures, although with a weak statistical significance. Either a NHPP or imperfect repair models could be utilized to further analyze the data. The selection of models must be decided by a qualitative analysis of the repair actions. Statoil SAP actually records details of each maintenance action, for instance, type of replaced component and equipment adjustment, and that is available for qualitative analysis of repair performance, whereas not feasible in the thesis without permits to the SAP details. Based on the available information and analyzable results, the negative Laplace test statistic -1.26 (figure 15) and shape parameter of Power-Law Process $0 < \beta = 0.718581 < 1$ indicate that AC generator A is a happy system under situation A.a.1.

Situation A.a.2-No trend in notification of failures, HPP

In situation A.a.2, the failures follow a homogeneous Poission process with statistical significance. Minitab gives a estimate value of MTBF as 121.75 days. We can get that the ROCOF of the system is $w(t)=0.0082$ for all $t\geq 0$. The number of failures in the interval $(t,t+v]$ is Poisson distributed with mean $0.0082v$, $\Pr(N(t+v)-N(t)=n)=\dfrac{(0.0082v)^n}{n!}e^{-0.0082v}$ for all $t\geq 0, v>0$. The mean number of failures in the time interval $(t,t+v]$ is $W(t+v)-W(t)=E(N(t+v)-N(t))=0.0082v$, particularly $E(N(t))=0.0082t$. The time of the nth failure S_n has a gamma distribution with parameters $(n,0.0082)$ and its probability density function is $f_{S_n}(t)=\dfrac{0.0082}{(n-1)!}(0.0082t)^{n-1}e^{-0.0082t}$ for $t\geq 0$.

b) Regard dead events as failures

In situation (b), it is assumed that that maintenance intervention is not available for unwell and sick events. The repair action is only performed in case the system is in a dead condition and will bring it back to a functioning state. Figure 16, the Nelson-Aaelon plot still indicates that the system has a decreasing ROCOF. The p -values presented in figure 17 are all larger than 0.05 and closely to 1.0, which means that this decreasing ROCOF is quite occasional. Corresponding to A.a.1 and A.a.2, situation A.b.1 and A.b.2 can be obtained. They will not be repeated since the result is not statistically significant.

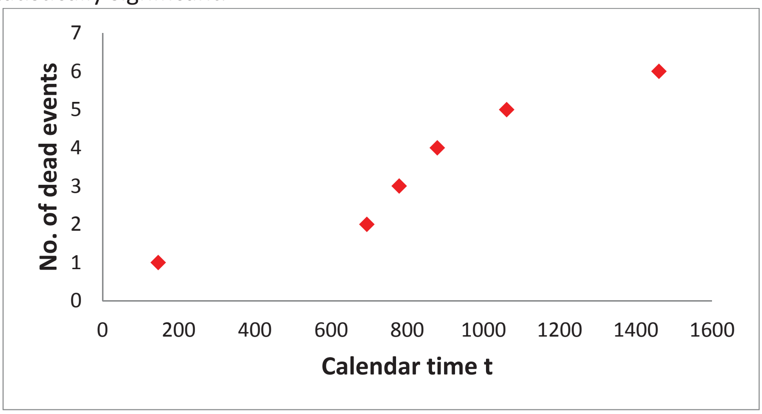


Figure 16 Nelson-Aalen plot for dead events, AC generator A

Parametric Growth Curve: C1

```
Model: Power-Law Process
Estimation Method: Maximum Likelihood

Parameter Estimates

                      Standard    95% Normal CI
Parameter  Estimate      Error     Lower    Upper
Shape       1.33199      0.506  0.632342  2.80575
Scale       380.582    234.470   113.772  1273.09

Trend Tests

                 MIL-Hdbk-189  Laplace's  Anderson-Darling
Test Statistic           9.01      -0.10              0.49
P-Value                 0.938      0.921             0.759
DF                         10
```

Parametric Growth Curve: C1

```
Model: Poisson Process
Estimation Method: Maximum Likelihood

Parameter Estimate

                      Standard   95% Normal CI
Parameter  Estimate      Error    Lower    Upper
MTBF          243.5     99.408  109.395  542.002

Trend Tests

                 MIL-Hdbk-189  Laplace's  Anderson-Darling
Test Statistic           9.01      -0.10              0.49
P-Value                 0.938      0.921             0.759
DF                         10
```

Figure 17 Trend tests on dead events, AC generator A

5.2.1.2 Relationship between notification date and failure impact

This section investigates whether there is a relationship between notification date (calendar time in days) and failure impact (failure state). Regression analysis is performed in Minitab, shown in figure 18.

In the summary report of linear regression analysis, a linear model is proposed as $Y = 1.434 + 0.001007X$ to describe the relationship between Y and X, where Y denotes the failure state and X denotes notification date (calendar time). A p value larger than 0.05, 0.131, means that changes in Y are not associated with changes in X. Conversely, a small p-value, less than 0.05, will indicate strong relationship between the predictor X and the response Y.

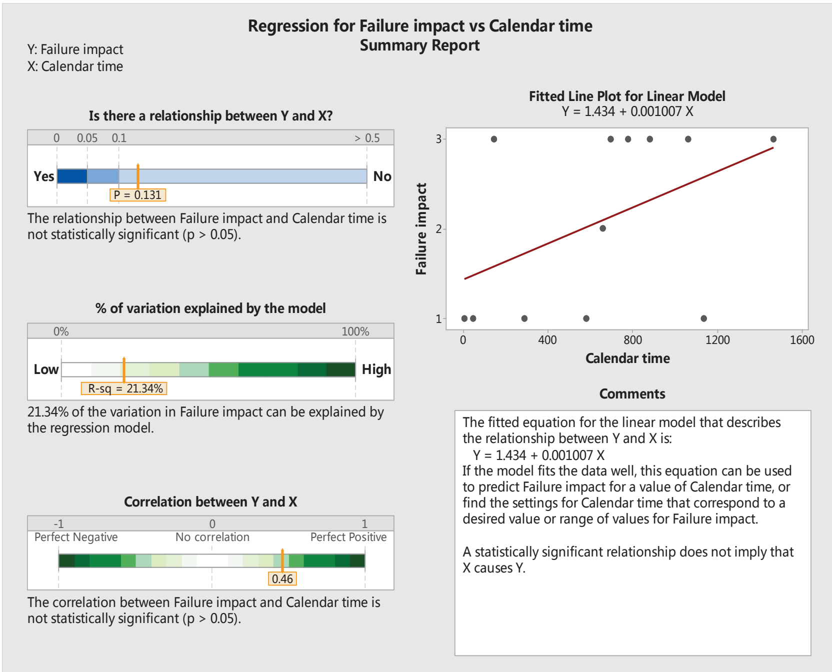


Figure 18 Linear regression analysis summary report, AC generator A

Further, the nonlinear regression analysis is performed with various examined expectation function, such as exponential, power and logistic. Due to few data items, lack of fit test cannot be carried out in Minitab. The test is used to verify whether the examined model fits the data. With unavailability of giving such a test, results from nonlinear regression analysis are not reliable. The test details are not copied here due to page limitation.

5.2.2 AC Generator B

The same analysis procedure is used to investigate SAP data of AC generator B.

5.2.2.1 Failure Trend Investigation

Table 4 SAP data, AC generator B

Generator B	Notif Crea	Failure Impact	Failure State	No. of notifications	Calendar time(Sj)	Interoccurence time(Tj)
	2009/3/22	S	2	0	0	0
	2009/12/13	U	1	1	266	266
Year 2009	2009/12/19	D	3	2	272	6
Year 2010	2010/11/29	S	2	3	617	345
	2011/3/23	D	3	4	731	114
Year 2011	2011/9/9	S	2	5	901	170
Year 2012	2012/1/15	S	2	6	1029	128
	2013/2/12	D	3	7	1423	394
	2013/3/29	S	2	8	1468	45
	2013/7/23	D	3	9	1584	116
Year 2013	2013/8/24	S	2	10	1616	32

a) Regard notifications as failures

Presented by figure 19, it is still difficult to conclude that the system enters into an unwell, sick and dead state in a sequence. The Nelson-Aalen plot tends to be convex but not in a consecutive way. AC generator B tends to be a *sad* system. A deep analysis is given in the following.

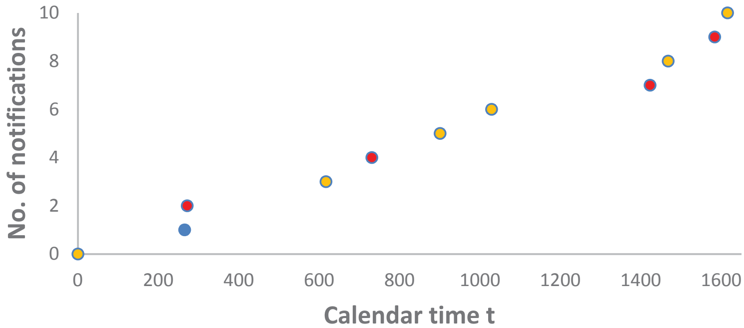


Figure 19 Nelson-Aalen plot for notifications AC generator B

Parametric Growth Curve: Calendar Time

```
Model: Power-Law Process
Estimation Method: Maximum Likelihood

Parameter Estimates

                      Standard     95% Normal CI
Parameter  Estimate    Error      Lower     Upper
Shape       1.51033    0.456    0.835332  2.73077
Scale       351.831   181.195   128.222   965.399

Trend Tests

                  MIL-Hdbk-189  Laplace's  Anderson-Darling
Test Statistic        13.24        0.73          0.56
P-Value               0.446        0.467         0.689
DF                       18
```

Parametric Growth Curve: Calendar Time

```
Model: Poisson Process
Estimation Method: Maximum Likelihood

Parameter Estimate

                      Standard     95% Normal CI
Parameter  Estimate    Error      Lower     Upper
MTBF         161.6    51.102   86.9496   300.341

Trend Tests

                  MIL-Hdbk-189  Laplace's  Anderson-Darling
Test Statistic        13.24        0.73          0.56
P-Value               0.446        0.467         0.689
DF                       18
```

Figure 20 Statistical tests on notification trend

Statistical tests are performed. H_0: there is no trend in data, homogeneous Poisson process; H_1: trend in data, non-homogeneous Poisson process. Rejection criteria: Reject H_0 with p-value less than 0.05. As seen in figure 20, the p-value of Military Handbook Test (MIL-Hdbk-189), Laplace test and AD test is all larger than 0.05 and we do not have strong evidence to reject H_0. The following arguments are provided:

(1) The increasing ROCOF is not statistically significant but accidental.

(2) The assumption of identical systems or homogeneous data may not be realistic and that produces a non-statistical-significant result for trend tests.

(3) *On condition that we reject H_0 and accept H_1 with weak statistical significance, the Power Law model proposed by Minitab indicates a sad system and presents an increasing ROCOF. This shows that the repair team takes the opposite maintenance strategy on AC generator B compared to system A.*
(4) *On condition that we accept H_0 following statistical tests, no notification trend is verified. The interoccurrence times are independent and identically exponentially distributed with* $\lambda = 0.0062$.

We have two different situations regarding further analysis:

Situation B.a.1-Increasing failure trend with weak statistical insignificance

In situation B.a.1, there is trend in notifications of failures, although with a weak statistical significance. Based on the available information and analyzable results, the positive Laplace test statistic 0.73 (figure 20) and shape parameter of Power-Law Process $\beta = 1.51033 > 1$ indicate that AC generator A is a sad system under situation B.a.1. The ROCOF of the NHPP is $w(t) = 352 \times 1.51 t^{1.51-1} = 532 t^{0.51}$.

Situation B.a.2-No trend in notification of failures, HPP

In situation B.a.2, the failures follow a homogeneous Poission process with statistical significance. Minitab gives an estimate value of MTBF as 161.6 days. We can get that the ROCOF of the system is $w(t) = 0.0062$ for all $t \geq 0$. The number of failures in the interval $(t, t+v]$ is Poisson distributed with mean $0.0062v$, $\Pr(N(t+v) - N(t) = n) = \frac{(0.0062v)^n}{n!} e^{-0.0062v}$ for all $t \geq 0, v > 0$. The mean number of failures in the time interval $(t, t+v]$ is $W(t+v) - W(t) = E(N(t+v) - N(t)) = 0.0062v$, particularly $E(N(t)) = 0.0062t$. The time of the nth failure S_n has a gamma distribution with parameters $(n, 0.0062)$ and its probability density function is $f_{S_n}(t) = \frac{0.0062}{(n-1)!}(0.0062t)^{n-1} e^{-0.0062t}$ for $t \geq 0$.

b) Regard dead events as failures

Figure 21, the Nelson-Aalen plot still indicates that the system has an increasing ROCOF (concave plot). The p-values presented in figure 22 are all larger than 0.05 and closely to 1.0, which means that this increasing ROCOF is quite occasional. Corresponding to B.a.1 and B.a.2, situation B.b.1 and B.b.2 can be obtained. They will not be repeated since the result is not statistically significant.

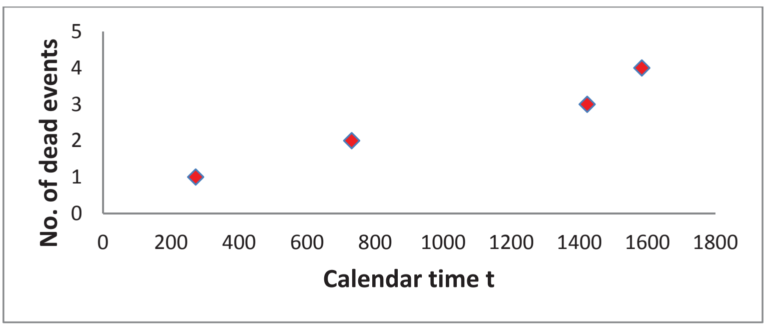


Figure 21 Nelson-Aalen plot for dead events, AC generator B

Parametric Growth Curve: C1

```
Model: Power-Law Process
Estimation Method: Maximum Likelihood

Parameter Estimates

                      Standard     95% Normal CI
Parameter  Estimate      Error     Lower     Upper
Shape       1.51378      0.685  0.623665   3.67431
Scale       633.923    353.934   212.222   1893.57

Trend Tests

                MIL-Hdbk-189  Laplace's  Anderson-Darling
Test Statistic          5.28       0.06              0.23
P-Value                0.984      0.950             0.978
DF                         6
```

Parametric Growth Curve: C1

```
Model: Poisson Process
Estimation Method: Maximum Likelihood

Parameter Estimate

                     Standard    95% Normal CI
Parameter  Estimate     Error    Lower     Upper
MTBF            396   198.000  148.626   1055.11

Trend Tests

                MIL-Hdbk-189  Laplace's  Anderson-Darling
Test Statistic          5.28       0.06              0.23
P-Value                0.984      0.950             0.978
DF                         6
```

Figure 22 Trend tests on dead events, AC generator B

5.2.2.2 Relationship between notification date and failure impact

This section investigates whether there is a relationship between notification time (calendar time in days) and failure impact (failure state) for AC generator B. Regression analysis is performed in Minitab, shown in figure 23.

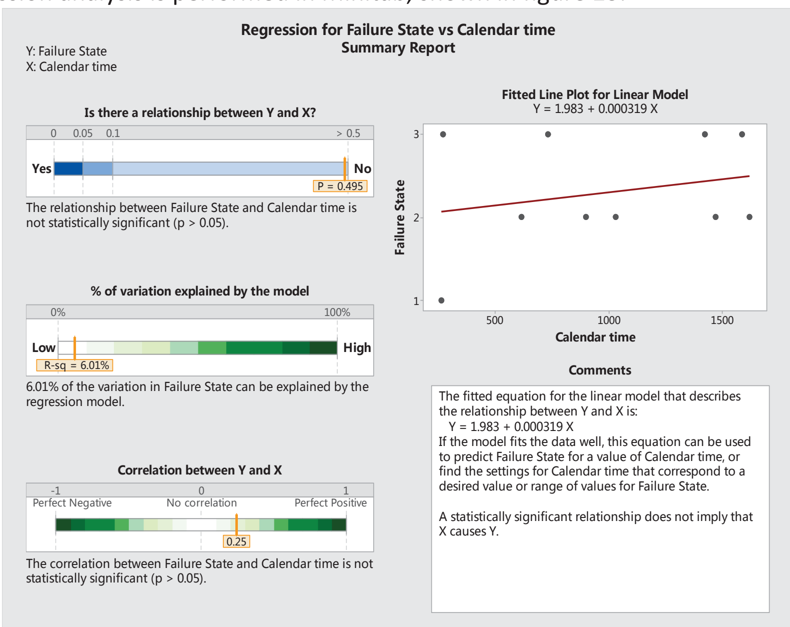


Figure 23 Linear regression analysis summary report, AC generator B

Figure 23 presents the summary report of linear regression analysis. A linear model is proposed as $Y = 1.983 + 0.000319X$ to describe the relationship between Y and X, where Y denotes the failure state and X denotes notification date (calendar time). A large p-value, 0.495, means that changes in Y are not associated with changes in X. Conversely, a small p-value, less than 0.05, will indicate strong relationship between the predictor X and the response Y.

Further, the nonlinear regression analysis is performed with various examined expectation function, for instance exponential, power and logistic. Due to few data items, lack of fit test cannot be carried out in Minitab. The test is used to verify whether the examined model fits the data. With unavailability of giving such a test, the results from nonlinear regression analysis are not reliable. The test result is not copied here due to page limitation.

5.2.3 Discussions on Analyzed Results

Table 5 Results of statistical analysis on AC generators

	Consider statistical significance	AC Generator A	AC Generator B
Regard all notifications as failures	Yes	HPP	HPP
	No	Decreasing ROCOF	Increasing ROCOF
Regard dead events as failures	Yes	HPP	HPP
	No	Increasing ROCOF	Increasing ROCOF
Relationship between notification date and failure impact	Yes	No relationship	No relationship

From statistical analysis of SAP data on AC generator A and B, we catch distinct results, see table 5. The notifications do not reveal a systematic pattern. Leaving out statistical significance, it arrives that AC generator A has a decreasing ROCOF while B has an increasing one in case all notification events are treated as failures. This supposes that Statoil operates two different types of generators nevertheless they are same in reality. Another possibility is that the repair team takes the opposite maintenance strategy for two generators. If we only treat dead events as failures, both systems show the increasing ROCOF as with most machinery. We can treat this finding as tendency estimate and it is infeasible to affirm its validity with a highly weak statistical significance.

5.3 Vibration Trend Analysis on Gas Turbine

For gas turbines, same assumptions as for AC generators are employed. Several sensors are installed on the gas turbines for monitoring their operation condition, such as pressure, compression and vibration. Vibration signals of gas turbine B are treated in the following analysis. SAP is used to track the date where an unsatisfied condition occurs. Subsequently, time series plots are employed to look into whether or not the unsatisfied day's monitoring data has a monotonic trend, where can be used as input for RUL assessment (section 4.2.1, page 21).

5.3.1 Gas turbine B

Table 6 shows the SAP data of gas turbine B. The regularity on the sequence of failure impact from this table cannot be found. The analysis of gas turbine B then concentrates on its vibration data. The sensor KRI.80VT6418A/Y/PRIM that monitors displacement of this turbine is utilized for the following analysis.

Table 6 SAP data, gas turbine B

Gas Turbine B	Notif Crea	Failure Impact	Failure State	No. of notificaitons	Calendar time (Sj)	Interoccurrence time (Tj)
	2009/6/3	U	1	0	0	0
	2009/6/9	U	1	1	6	6
	2009/6/11	S	2	2	8	2
	2009/11/4	U	1	3	154	146
Year 2009	2009/12/30	D	3	4	210	56
	2010/4/14	U	1	5	315	105
	2010/6/27	S	2	6	389	74
	2010/6/29	U	1	7	391	2
Year 2010	2010/10/28	U	1	8	512	121
	2011/3/28	S	2	9	663	151
	2011/9/8	U	1	10	827	164
	2011/10/1	U	1	11	850	23
Year 2011	2011/12/14	U	1	12	924	74
	2012/3/1	U	1	13	1002	78
	2012/4/25	U	1	14	1057	55
	2012/7/6	U	1	15	1129	72
	2012/10/2	U	1	16	1217	88
	2012/12/6	U	1	17	1282	65
Year 2012	2012/12/20	S	2	18	1296	14
	2013/2/28	S	2	19	1366	70
	2013/4/2	U	1	20	1399	33
	2013/5/23	S	2	21	1450	51
	2013/7/11	U	1	22	1499	49
Year 2013	2013/7/13	D	3	23	1501	2

First, vibration signals on unsatisfied days are analyzed. Figure 24, 25, 26 and 27 present relative signal trends in year 2010, 2011, 2012 and 2013 separately. The lateral axis is the time horizon from 0:00 to 23:00 within an unsatisfied day. The vertical axis denotes the monitoring displacement of gas turbine B. The situations where gas turbine stops running the whole day are removed for the sake of investigating signal trends. From these figures, we see that the highest displacement is close to 40(25/04/12) while the lowest value is 0(28/03/11). Table 7 summarizes the signal trend. It arrives that no uniform monotonic tendency is detected.

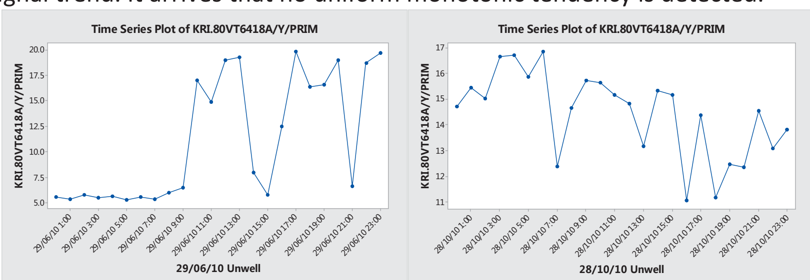
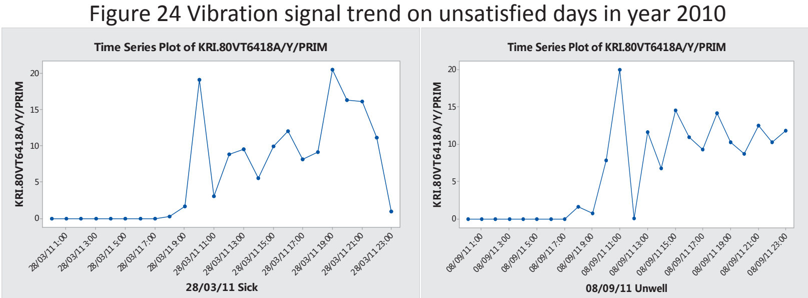


Figure 24 Vibration signal trend on unsatisfied days in year 2010



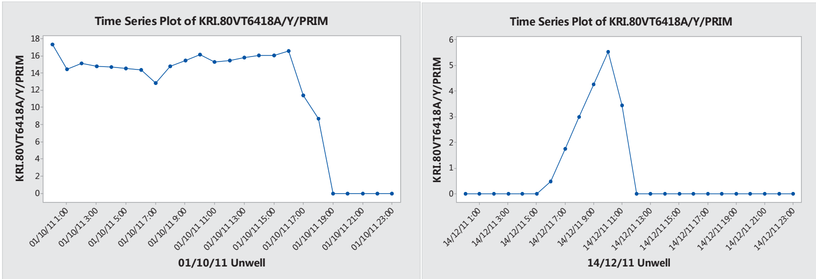


Figure 25 Vibration signal trend on unsatisfied days in year 2011

Figure 26 Vibration signal trend on unsatisfied days in year 2012

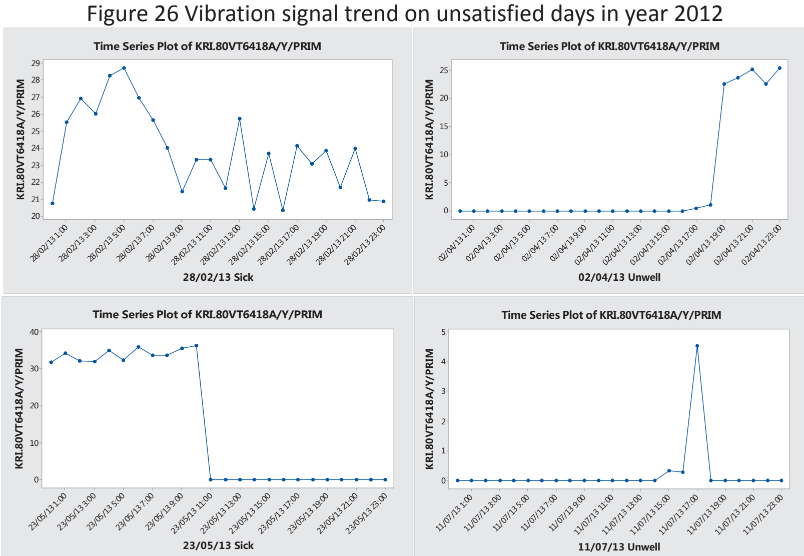


Figure 27 Vibration signal trend on unsatisfied days in year 2013

Table 7 Summary of vibration signal trend

Date of notification	Failure Impact	Signal trend
09/06/10	Unwell	Increasing
28/10/10	Unwell	Increasing→Decreasing
28/03/11	Sick	Increasing→Decreasing→Increasing→Decreasing
08/09/11	Unwell	Increasing→Decreasing
01/10/11	Unwell	Decreasing
14/12/11	Unwell	Increasing→Decreasing
25/04/12	Unwell	Decreasing→Increasing
02/10/12	Unwell	Decreasing→Increasing
06/12/12	Unwell	Increasing→Decreasing
20/12/12	Unwell	Increasing→Decreasing
28/02/13	Sick	Increasing→Decreasing
02/04/13	Unwell	Increasing
23/05/13	Sick	Decreasing
11/07/13	Unwell	Increasing→Decreasing

Following the first investigation, this part reviews how the signal changes over time, and for clear rendering of images, we use a period of two weeks (blue color) prior to an ‘unsatisfied’ days (red color). To improve analysis efficiency, graphs with unclear signal trends are not presented. Figure 28 records the ones where explicitly reveals vibration signal tendency.

The plot 2009/12/30 indicates that the monitored displacement increases on the notification date compared to prior two weeks. This value shown in 2013/5/23 and 2013/7/13 goes down to zero on the notification day. 2011/3/28 and 2012/12/20 present a sudden increasing of displacement and a decreasing in a rapid sequence. The displacement on the notification day 2013/2/28 remains a similar level compared to the control period.

Since vibration signals do not illustrate monotonic tendency on unsatisfied days, it is unfeasible to correlate condition monitoring data to the time of failure. All known for sure is that a great contrast between peak values and valley values normally indicates an unsatisfied operating condition. A rapid decrease or increase of monitoring displacement could cause severe damage to gas turbines and that should be handled within manageable proportions. At which level the displacement shows a failure requires special knowledge on vibration of gas turbines, and equipment supplier may provide the threshold value.

Statoil practically operates a control room where monitors various parameters on technical condition of specific types of equipment. Equipment specialists set limits for these indicators, including displacement of gas turbines. Two alerts are kept for operation control. The higher limit value, second alarm, indicates a failure event where needs immediate maintenance intervention.

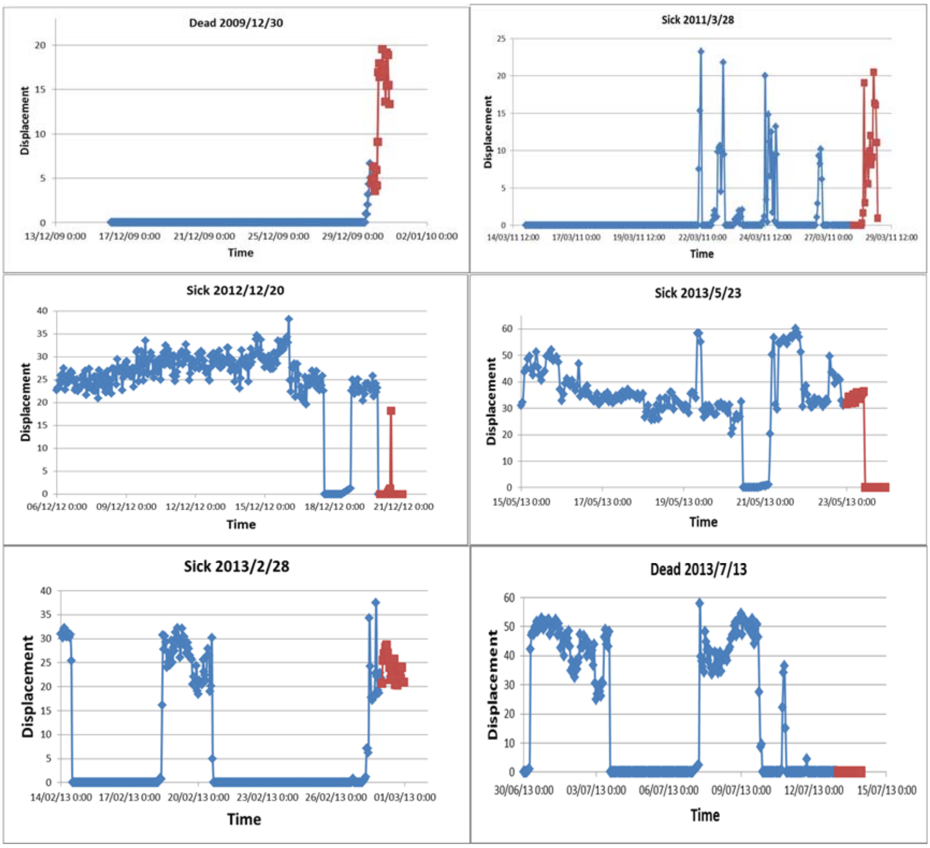


Figure 28 Vibration signals variation tendency

5.3.2 Use of Overall Vibration Data for RUL Assessment

Vibration monitoring is a fundamental element in diagnostics of rotating machinery within CBM. The thesis barely gets a sampled vibration data of gas turbines. Monotonic signal trend cannot be achieved. The analysis of sampled vibration data contributes to comprehensive understanding of turbine failures. It is appropriate for tracking the signal tendency in the notification day or during a specific period but cannot be of service to precise RUL assessment.

As discussed in section 4.3 (page 25) the establishment of degradation model requires large amount of raw data therein run-to-failure tests are desirable but is not realistic for the production-critical equipment. Experiments are performed to extract and capture monotonic behavior of vibration signals. Model training solely relying on imperfect data cannot gather our reliance.

5.4 Recommendations for Statoil on RUL Assessment

Based on discussions in section 5.2.3 (page37) and 5.3.2 (page41), it comes to the conclusion that the quality of data derived from SAP and PI is not sufficient to generate uniform and strong conclusions concerning ROCOF and monotonic signal tendency. Failures of AC generators and gas turbines are randomly changing and unpredictable with feasible techniques. In addition, no strong relationships between notification date and failure impact are revealed.

To some extent, improving the quality of notification records is not more challenging than analyzing the data. A number of factors may have negative effects on the quality of SAP, for instance delayed reports, editing errors and missing data caused by technical problems. Table 8 illustrates current situations, challenges and corresponding suggestions to better achieve RUL assessment for Statoil. Green ones are assumed to be easy for implementation. Orange ones perhaps have some difficulties to be realized. Red ones are the most difficult issues to be handled.

Table 8 Challenges for Statoil on RUL assessment and relative recommendations

Current Situation and Challenge	Recommendation
Specific issues	
Unwell, sick and dead event occurs randomly. Cannot get its reasonable sequence.	Improve the quality of SAP reports. Improve notification quality. Reexamine the nature of failure classification; maybe utilize more classification states. Build a classification system with different criteria, for instance reliability and maintenance cost.
Two comparable generators have opposite ROCOF. Cannot get a uniform failure tendency.	Check the difference in operating conditions for the two generators, such as stress and temperature. Investigate whether their spare parts are same or different.
Health condition of the equipment is unclear after each repair.	Evaluate the system's health condition for each completed maintenance intervention, for instance as good as new and as bad as old.
Vibration signals of gas turbine do not indicate any strong monotonic trend. Cannot use it as input for RUL estimation models.	Link PI to SAP. Collect and analyze vibration data for every time the monitoring value hits the first alarm and second alarm separately and give each of these situations a failure classification. Carry out specific run-to-failure tests to collect sufficient raw data where tracks the most monotonic trend for RUL assessment.
Cannot acquire data on lubrication oil condition and acoustic noise signals. Relevant estimation models are inapplicable.	Install bespoke monitoring equipment to collect such data. *Lubrication oil condition monitoring is highly recommended (see section 4.2.2, page 24)*
General issues	
Little condition monitoring data with limited types of monitoring parameters.	Equipment experts are necessary to set valuable monitoring parameters for concerned systems. Use effective and reliable sensors to collect required large amounts of monitor data.
Matching theoretical RUL assessment models with various types of equipment.	Test research models for concerned system. Adjust model parameters. Perform necessary experiments.

Chapter 6 Case Study - Maintenance Optimization

This chapter performs case study on maintenance optimization. The objective of this chapter is to link case studies to imagined current maintenance practice and future improved maintenance strategies. It is proposed to demonstrate potential savings through adopting more advanced methods using existing data in a better manner.

6.1 Introduction

As investigated in chapter 5, the thesis does not have sufficient data to develop degradation models for both AC generators and gas turbines. Statistical analysis on AC generators does not demonstrate any tendency on ROCOF. Deterioration models have difficulties to describe random failures without any regularity. It is unfeasible to correlate condition monitoring data of gas turbines to the time of failure. Traditional condition monitoring methods, for example, WT and FFT, cannot be demonstrated. The data analysis hence cannot give satisfactory results for further work on maintenance optimization. In this context, the case study conducted in this chapter is of principle where real condition data is not applied.

6.2 Degradation Models

The classification regime as previously shown in section 5.2.1.1 (page 30) is utilized. Figure 29 shows the assumed degradation process with ideal sequence of unsatisfied states. In this figure, $Y(t)$ is a performance variable to measure degradation processes. It describes the state of the system at time t. The first decision variable in the maintenance strategy based on this process is the inspection interval. The second one is the maintenance limit $Y(s)$, which is decided by time to a sick event T_s. Without any maintenance intervention, the system deteriorates into the dead state characterizing $Y(d)$ as failure limit.

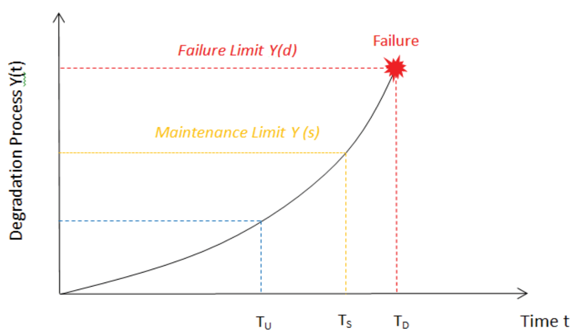


Figure 29 Assumed degradation process

In the case study, the following assumptions are used:

(1) The presumed equipment is a piece of mechanical equipment. The time to a dead event is Weibull distributed with an ageing parameter $\alpha = 2.6$.

(2) T_1 is referred as the time to an unwell state. T_2 is the time to a sick event. T_3 denotes the time to a dead condition. The sum $T_1 + T_2 + T_3$ has same expected value and standard deviation as for T_3. The mean time to the dead event $MTTF_3$ is assumed to be 100 days.

(3) It is assumed that the transition is chronologically from unwell to sick, and then dead without stepping back at any time.

6.3 Cost Model - Maintenance Optimization

This section constructs cost models for two situations with distinct maintenance strategies. As deduced in section 6.2: the first one does not perform regular inspections while the second one dose. Table 9 lists important elements to build the cost model and relevant assumed values.

Table 9 Cost elements with assumed values

Cost Model Elements	Assumed Value
Mean time to failure without maintenance	$MTTF_{WO}$=100 (days)
Ageing parameter, alpha	α =2.6
The (unavailability) cost per system failure	C_U =4000 (1000NOK)
The cost of preventive maintenance	C_{PM} =550 (1000NOK)
The cost of corrective maintenance	C_{CM} =800 (1000NOK)
The cost per inspection	C_I =5 (1000NOK)
The cost of renewing the system at state l	C_{RC} =500 (1000NOK)

These values are proposed dependent on the following arguments:

(1) C_{PM} is close to C_{RC}. C_{PM} in maintenance policy (a) is the cost of replacing a unit or performing a complete overhaul preventively. It is similar to C_{RC}, the renewal cost in (b). Even though replacing a 'sick' unit is costly than an 'unwell' one, C_{RC} on different states should be expected in the same order of magnitude with C_{PM}. This is due to the consideration that (i) preventive maintenance and renewal actions can all be planned in advance, for instance, plan for shutdown, make spare parts available and bring personnel for maintenance work; and (ii) both activities bring the item to a "as good as new" condition.

(2) C_{CM} is higher than C_{PM} and C_{RC}. C_{CM} is the corrective maintenance cost where cannot be planned and unexpected. The unit is perhaps in a state with severe damages. A repair is more demanding in this case.

(3) C_U is the highest. C_U is the unavailability cost related with the system failure. It is extremely costly in the O&G industry since the production is completely lost during the unexpected repair. $C_U = 5C_{CM}$ is utilized.

(4) C_I is the lowest since condition monitoring techniques could be used for inspection and that average cost is rather low.

Cost Model with No Inspection – Based on BRP

First consider a traditional maintenance strategy where no inspection is carried out. The block replacement policy (BRP) best fits the case taking into account the presence of minimal or imperfect repair. Let τ denotes the preventive maintenance interval. $\lambda_E(\tau)$ denotes the effective failure rate.

Total cost per unit time: $C(\tau) = C_{PM} / \tau + (C_{CM} + C_U) \times \lambda_E(\tau)$

The excel spreadsheet "BRPSImple.xls" given by course PK8207 is employed to get the result of τ and $C(\tau)$, see the result copy shown in figure 30. The preventive maintenance interval is 41 days with a total cost per unit time approximately 22 (1000NOK). The standard deviation in the time to failure = coefficient of variance$\times$ $MTTF_{WO}$=0.41314*100=41.314 and its variance is 1706.85, where the coefficient of variance is found by the same excel spreadsheet.

Parameter	Value
MTTF	100
alpha	2.6
PM-Cost	550
CM-Cost	800
SystCost	4,000
tau	41
$\lambda_E(\tau)$	0.001764393
PM	13.41463415
CM	1.411514755
System	7.057573774
Total cost	21.88372268
tau*	40.84134903
Coefficient of variance	0.41314

Figure 30 Result of cost per unit time without inspection

Cost Model with Inspection – Based on Markov State Model

The second maintenance strategy is considered to be improved and executed with inspections. With a finite number of states, Markov state model with inspections is utilized to demonstrate this policy.

Total cost per unit time: $C(\tau, l) = C_I / \tau + (C_{CM} + C_U) \times \lambda_E(\tau, l) + C_{RC} \times rr(\tau, l)$

The excel spreadsheet "MaintOp.xlsm" given by course PK8207 is employed to get the result of $\lambda_E(\tau, l)$, $rr(\tau, l)$ and $C(\tau)$, see the result copy shown in figure 31. The system is supposed to start in a perfect state and jumps to a higher state (y_i to y_{i+1}) with a time independent intensity λ_i where $i = 0,1,2$. τ under this policy refers as inspection interval. Let $V = \lambda_2 / \lambda_0$ to model the assumed the increasing ROCOF. The factor V is used to describe how much faster failure progression is just before failure in contrast with the initial (perfect) state. Let l to be the maintenance limit, where the system is replaced with a new one if the state at an inspection is greater or equal than the limit state. Practically there is a probability q to assess the performance of inspection. For simplicity, q is assumed to be 0. Let $\lambda_E(\tau, l)$ denotes the effective failure rate and $rr(\tau, l)$ signifies the renewal rate where their values are derived in an excel sheet.

In order to achieve the "correct" $MTTF_{WO}$ and its variance, the number of state r and factor V are varied. It is found that the variance of $T_1 + T_2 + T_3$ is close to the variance in the time to failure in BRP when r is set to be 7 and V is 4. The standard variance is coefficient of variance $\times$ $MTTF_{WO}$= 0.41467×100 =41.467 and the variance is 1719.51, where the coefficient of variance is derived by the same excel spreadsheet. Further the maintenance limit is considered to be 5. The previous "unwell-sick-dead" is not used since such situation generates a large variance compared to the one in BRP.

Parameter	Value	Parameter	Value
MTTF	100	$\lambda_E(\tau, l)$	0.00061
Tau	5	$rr(\tau, l)$	0.01124
V	4	Total Cost	9.53355
r	7	Cofficient of Variance	0.41467
l	5		
q	0		
CM-Cost	800		
SystCost	4,000		
Renew-Cost	500		
Inspection-Cost	5		

Figure 31 Result of cost per unit time with inspection

Maintenance Program

Table 10 presents the result comparison on two cost models. Maintenance strategy with inspections has the lower value and therefore is the cost-optimal alternative.

Table 10 Result comparison

Maintenance Strategy	Total cost per unit time
Without inspection	Approximately 22 (1000NOK)
With inspection	Approximately 10 (1000NOK)

The maintenance program is recommended to be built dependent on Markov state model with inspections. Its inspection interval is 5 days. The improved strategy with inspections contributes to nearly 50% cost savings.

6.4 Result Discussion

Seven states are considered to stick the Markov state model. These states can be determined by setting a specific monitoring value for each of them, for instance velocity and acceleration of rotating machinery. The lowest value indicates the best condition while the highest denotes the dead state. Equipment specialists are required to set these critical values. The inspection interval of 5 days is not realistic on condition that condition monitoring methods are employed. It is a challenge for the Markov state model to demonstrate this process with a finite number of states.

Since the procedures to establish the optimal maintenance program are dependent on assumed deterioration models and cost values, in practice, the program will vary on condition that distinct degradation models are applied as well as real costs are considered. It is expected that the maintenance strategy with inspections is the optimum since the inspection cost is rather low, particularly with applied condition monitoring techniques.

Chapter 7 Summary and Recommendations for Further Work

Chapter 7 summarizes the thesis and discusses some recommendations for future work.

7.1 Summary and Conclusions

In overall, it is concluded that the main objectives of this thesis have been realized. A brief summary of achievements is presented below related to each objective.

Objective 1 - Review the literature regarding various use of the term residual useful life as a basis for giving an explicit definition to be used through the work.

The various use of the term RUL is investigated and summarized in chapter 2, where a comprehensive literature review on RUL assessment is performed. Challenges within RUL assessment are indicated, followed by a terminology study to interpret RUL in different aspects. In maintenance engineering, the RUL links to diagnostics and prognostics. The purpose is to use automated methods to analyze the equipment degradation and calculate the acceptable remaining life before the critical failure; therein condition monitoring techniques and appropriate monitoring data processing methods are significant. The statistical perspective to describe RUL has two cases, one for repairable items, and the other for non-repairable items. Reliability models as well as statistical theory are critical elements in explaining RUL from this view. The state-of-the-art RUL assessment methods are presented in table B. 1 (pageTable B. 1 Summary of various RUL estimation methods 54).

An explicit definition of RUL is determined by measures applied to evaluate the usefulness of concerned equipment. Chapter 3 proposes a new approach to define RUL based upon this principle. Table 1 (page 17) provides a preliminary solution for evaluation of equipment usefulness. Figure 9 (page 18) shows a conceptual diagram applicable for RUL assessment.

Objective 2 - Identify two to three classes of critical equipment types as a basis for case studies. Such classes could be rotating equipment, static equipment and safety systems.

Rotating equipment has been chosen as the first type of production-critical equipment at the Kristin field for the pilot investigation as the results of discussions in the R&D project executed by SINTEF/NTNU. Electrical equipment also attracts the interests of Statoil, but was not handled in the thesis work due to project constraint and time limitation.

Objective 3 - For each of the identified classes the literature shall be revived with respect to which deterministic, probabilistic and combined models are proposed to link technical condition indicators and other degradation measures to RUL.

Deterministic, probabilistic and combined models that link degradation behavior to RUL are referred as RUL assessment methodologies. Chapter 4 carries out revived literature investigation on such methods with rotating equipment concentrated. Major failure causes are first reviewed. Analyzing vibration signals, lubrication oil condition and acoustic noise signals contribute to rotating machinery failure detection and RUL prediction.

Two phases are required to assess the RUL of rotating equipment. The first stage is to establish degradation model dependent on run-to-failure data. Signal processing techniques, for instance WT and FFT, are used to obtain the most monotonic degradation behavior during the run-to-failure tests. The time to failure can be determined by the point of time when the RMS hit the threshold value where could be set by equipment specialists. The second stage is to predict future health condition of the equipment based on established behavior models. Degradation behavior models have many branches developed through various experiments, for example ε -Support Vectors Regression model continuous, hidden Markov model and Gaussians hidden Markov models.

Objective 4 - Select one or two cases where models, methods and real condition data could be applied in the aging and life extension management.

Reaching an agreement with the supervisor and R&D project team, AC generators and gas turbines are targets for the case studies. Chapter 5 performs statistical analysis on SAP data of AC generators and vibration signal trend analysis on gas turbine B. The analytical methods are limited by the data type we get which is notification event data and sampled vibration data.

For AC generators, the analysis does not reveal any statistically significant ROCOF. The notifications are not demonstrating a systematic pattern. Without statistical significance, an extraordinary finding is that AC generator A has a decreasing ROCOF while AC generator B has an increasing one, whereas in reality they are in same type with identical maintenance strategy. The analysis principles are well demonstrated even though the result is not statistically significant.

The analysis of vibration signals of gas turbine B does not achieve any monotonic tendency. Some notification days record the increasing trend. A number of them show the decreasing trend. The others do not present any proneness. No strong and monotonic trend is obtained in signal change based on the sampled vibration data. This restricts the application of RUL assessment models proposed in chapter 4.

The quality of SAP and PI data is not sufficient to achieve any crucial results for RUL assessment. The main weakness in the current data is that specific systematic pattern within notifications cannot be derived. More efforts on improving reporting quality and assuring data completeness are expected as discussed in section 5.4 (page 41).

Objective 5 - The case studies shall demonstrate how the maintenance program will affect the technical condition on the equipment, and how to balance maintenance effort with other measures such as upgrading projects, renewal and modification.

In agreement with the supervisor, objective 5 is performed where limits to a theoretical case study through utilizing assumed deterioration models and cost values.

As summarized in objective 4, it is concluded that the data in case study is not sufficient for implementation of objective 5. Maintenance program is efficient for equipment with clear failure pattern. In particular, maintenance program is established in view of proper degradation modelling. With such considerations, chapter 6 carries out a case study on maintenance optimization following necessary assumptions. Block replacement policy and Markov state models with inspections are employed to construct cost models to optimize maintenance. The result of the principle case study shows that maintenance strategy executing inspections is the optimum. It is expected that the industry can draw on these valuable theoretical investigations as of contributions for optimal maintenance planning.

Statoil do have several upgrading projects, renewal and modification actions where are recorded. Nevertheless these notes are not open for the thesis and were not pursued.

7.2 Limitations of Approach

The approach of the thesis is subject to literature review and supervision. The literature review is limited by accessible resources with full text through NTNU library. RUL assessment is a relatively new research field where illustrates theories and experimental models as a majority. Most study papers are developed by carrying out specific laboratory tests and subsequent model trainings. With no experiments and no possibility to train any model, RUL assessment within the thesis is obviously more theoretical. Applications of assessment techniques require suitable data whereas the project team provides only event data and sampled monitoring data. The results of data analysis are not satisfactory where advanced assessment methods cannot be employed.

Several meetings with SINTEF project team and Statoil experts provide background information and sampled maintenance data of AC generators and gas turbines. The deadline of thesis is three months prior to the project 'Kristin Regularity'. This limits the prospect of retrieving more valuable information and data from Statoil.

7.3 Recommendations for Further Work

The thesis is performed with a limitation of restricted period of time as well as limited approaches discussed in section 7.2. It is recommended to further develop and improve the thesis work. A number of suggestions are given below.

Link to theoretical work (from academic perspective)

The new way to define RUL presented in chapter 3 is considered as a start for the industry to develop RUL assessment as a tool to optimize maintenance in ageing and life extension management. Further work in developing measurements for equipment evaluation is necessary and anticipated, for example, expand and apply Table 1 (page 17) with practical cases. The positive effects in using RUL assessment for optimal repair cannot be generated without clear criterion for evaluation of equipment usefulness. More efforts are required in such domain.

The conceptual diagram of RUL illustrated in figure 9 (page18) only considers one failure mechanism, fatigue, as an example. In reality equipment degradation are generally caused by several failure mechanisms. It is a challenging task to establish a realistic degradation process curve. For a specific piece of critical equipment, performing ageing tests to solve this challenge is believed to be an important step forward. The future work is advised to develop suitable methods to process test data as well as specific RUL estimation models.

Link to case study (from industrial perspective)

As previously demonstrated in section 5.4 (page 41), more efforts on RUL assessment of rotating equipment are expected in the future.

<u>What Statoil have done:</u>

The application of SAP and PI system provides a solid foundation for future RUL assessment as well as optimal maintenance planning. The failure classification is regarded as a start to identify available equipment states where Markov state model could be utilized. Condition monitoring of vibration on rotating equipment facilitate the early detection of failures.

<u>Recommendations:</u>

The failures are classified as three types: unwell, sick and dead. In reality such classification can be further developed to consider more states, in which fits the Markov state model in a better manner (section 6.4, page 46).

Lubrication oil condition is strongly recommended to be monitored for production-critical rotating machinery since this technique delivers roughly 10 times earlier warnings for machine failures compared to vibration based monitoring techniques (section 4.2.2, page 24). Noise signals can also be collected for RUL prediction and it allows for remote and non-contact monitoring of the machine in contrast with vibration analysis that requires a direct contact with the equipment (section 4.2.3, page 24).

The application of single processing techniques on acquiring mot monotonic degradation behavior is dependent on sufficient raw data collected from run-to-failure experiments (section 4.2.1, page 21). Deterioration models can be further trained and tested based on experiments in the coming performance (section 4.3, page 25). Provided with valid deterioration models and true maintenance costs, the optimal maintenance strategy could be determined as well as feasible maintenance programs.

The case study only considers rotating equipment. Electrical equipment is also crucial for safe and efficient oil and gas production. The following work could make some contributions in this aspect.

Appendix A Technical Background

This appendix gives a short and brief introduction of technical terminology demonstrated in the thesis where is probably not well known to readers. The relative sources that can provide an in-depth understanding of these terms, techniques and models are also indicated at the end of each part.

A.1 Empirical Mode Decomposition (Source: Wikipedia)

The empirical mode decomposition (EMD) method is the essential part of the Hilbert-Huang transform. A complicated data set can be decomposed into a finite and small number of components through using the EMD method. The EMD method reduces given data into a collection of intrinsic mode functions (IMF) where the Hilbert spectral analysis could be applied then.

The Hilbert-Huang analysis is a method to examine the IMF's instantaneous frequency data as functions of time which shows sharp identification of embedded structures. Its final result is an energy-frequency-time distribution, named as the Hilbert spectrum. More information about the EMD and Hilbert transform can be found: *Alexander D. Poularikas. 2010. Transforms and Applications Handbook, Third Edition. CRC Press.*

A.2 Paris Law Model (Source: Wikipedia)

Paris law is also designated as Paris-Erdogan law. It correlates the stress intensity factor to sub-critical crack growth within a fatigue stress regime. The basic formula is $\frac{da}{dN} = C\Delta K^m$, where a is the crack length, N is the number of load cycles, C and m are material constants, ΔK is the range of the stress intensity factor. It is extensively used to predict life for fatigue cracks. More information about Paris model can be found: *Xiong, J. J. and Shenoi, R. A. 2011. Fatigue and fracture reliability engineering. Springer, 22 Jan 2011. ISBN 978-0-85729-218-6.*

A.3 Grey System Theory (Source: Kayacan et al., 2010)

Grey models are developed to predict the future value of a time series. It is only dependent on a set of most recent data relying on the window size of the predictor. Two assumptions are within this theory. One is that all data values are assumed to be positive in this model. The second is that the sampling frequency of the time series is fixed. The main task of grey system theory is to extract realistic governing laws of the system with given data. A general grey model is $GM(n,m)$, where n is the order of the difference equation and m is the number of variables. More information about grey system theory can be found: *Liu, S. F., J. Forrest and Y. Lin. 2011. Grey systems, theory and applications. Springer. ISBN 978-3-642-16157-5.*

A.4 Diffusion Process (Source: Wikipedia)

A diffusion process is to solve a stochastic differential equation. Its mathematical definition is given as "*a Markov process with continuous sample paths for which the Kolmogorov forward equation is the Fokker-Planck equation*". Examples of diffusion processes are Brownian motion, reflected Brownian motion and Ornstein-Uhlenbeck processes. Si et al. (2012) indicate that diffusion processes are capable of describing random degradation among stochastic process-based models; therein Brownian motion with a linear drift becomes popular to model degradation recently. More information about diffusion process and its applications can be found: *Fuchs, C. 2013. Inference for diffusion processes. Springer. ISBN 978-3-642-25969-2.*

A.5 Nonlinear autoregressive exogenous model (Source: Wikipedia)

A nonlinear autoregressive exogenous model is a nonlinear autoregressive model with exogenous inputs in time series modeling. The model links the current value of a time series to past values of the same time series and current and past values of the exogenous series. It can be demonstrated as $y_t = F(y_{t-1}, y_{t-2}, y_{t-3}, \ldots, u_t, u_{t-1}, u_{t-2}, u_{t-3}, \ldots) + \varepsilon_t$. y is the interested variable which we intend to predict and u is the variable determined externally. Here ε is the error term (or noise). The function F can be a neural network, a wavelet transform, etc. More information about this model can be found: *Nelles, O. 2001. Nonlinear system identification. Springer. ISBN 978-3-662-04323-3.*

A.6 Artificial Neural Network (Source: Wikipedia)

Artificial neural networks are computational models that are able of machine learning and pattern recognition. The networks are commonly demonstrated as systems of interconnected 'neurons' which computes values from inputs by feeding information through the network. This method is used to solve tasks that are difficult to find solutions using ordinary rule-based programming. More information can be found: *B. Yegnanarayana. 2009. Artificial neural networks. PHI Learning Pvt. Ltd., 14. Jan. 2009.*

A.7 Levenberg-Marquardt Algorithm (Source: Wikipedia)

The Levenberg-Marquardt algorithm is also designated as the damped least-squares method. It is used to solve problems facing non-linear least squares. This algorithm is known as a popular approach to solve generic curve-fitting problems. For instance, given a set of m empirical datum pairs of independent and dependent variables, (x_i, y_i), the sum of the squares of the deviations $S(\beta) = \sum_{i=1}^{m} [y_i - f(x_i, \beta)]^2$ will be minimal if the parameters β of the model curve $f(x,\beta)$ is optimized. The other application of Levenberg-Marquardt algorithm lies in solving nonlinear inverse problems. More information about this theory and its implementation can be found: *Naveen, M., S. Jayaraman, V. Ramanath and S. Chaudhuri. 2010. Modified Levenberg Marquardt Algorithm for Inverse Problems. Lecture notes in computer science volume 6457, pp 623-632.*

A.8 ε-Support Vector Regression (Source: Loutas et al., 2013)

The concept of 'support vector machines' is introduced by Vapnik(1995) for solving classification and regression problems. Given a set of n observations, generally, each of them lies in an M-dimensional space, $x_i \in R^M, i = 1,...,n$. For each observation vector, a required mapping is presented. It is further assumed that a set of target values $y_i \in R$ contains the vector of mappings. The objective of regression is to find a transformation f, which fulfills $X_{NxM} \xrightarrow{f} Y_{Nx1}$ in the best way. The support vector context gives a good answer to this problem:

Given a parameterization $f(x) = \mathrm{w}^T \mathrm{x} + b$, find w that minimizes $\min\limits_{\mathrm{w}} \left\{ \frac{1}{2}\mathrm{w}^T\mathrm{w} + \mathrm{C}\frac{1}{n}\sum_{i=1}^{n} \max(|y_i - f(\mathrm{x}_i)| - \varepsilon, 0) \right\}$. ε-SVR comes from the second term of the function, which is an ε-intensive cost function. Details concerning the application of support vector regression can be found in the book *Christmann and Steinwart, 2008. Support Vector Machines. Information Science and Statistics. Springer, ISBN:978-0-387-77241-7.*

A.9 Principal Component Analysis (Source: Wikipedia)

Principal component analysis (PCA), a statistical procedure, uses orthogonal transformation to transfer a number of observations that are possibly correlated variables into a set of linearly uncorrelated variables, named principal components. Mathematically, PCA is an orthogonal linear transformation that converts the data to a new coordinate system. The first principal component has the greatest variance by some projection of the data. Correspondingly, the second coordinate has the second greatest variance, and so forth. Further knowledge about PCA could be found: *Jolliffe I.T. Principal Component Analysis, Series: Springer Series in Statistics, 2nd ed., Springer, NY, 2002, XXIX, 487 p. 28 illus. ISBN 978-0-387-95442-4*

Appendix B Tables

Table B. 1 Summary of various RUL estimation methods

RUL estimation methodology	Reference/Article No.	General topics	Specific system/component
Physics based methodology for RUL estimation			
Physical Model	Ghiocel (2003) **(1)**	Using probabilistic physics-based model to predict RUL including uncertainties in maintenance activities.	-Aircraft jet engines
	Huang et al. (2010) **(2)**	RUL estimation by analyzing empirical mode decomposition.	-CNC feed drive system
	Coppe et al. (2012) **(3)**	Using Paris law model to estimate RUL considering adjustment of model parameters.	-Plate
	Hao et al. (2012) **(4)**	Finite element model with crack. Predict RUL of the gear with crack.	-Gearbox
	Lorton et al. (2013) **(5)**	RUL estimation using online information. Modeling deterioration using Markov process.	-Pneumatic valves
	Zhu et al. (2013) **(6)**	RUL estimation of the particle contaminated lubrication oil based on physical models.	-Wind turbine
Hazard Rate (Proportional hazard rate)	Wang et al. (2002) **(7)**	Failure behavior modeling.	-Automobile components
	Lloyd et al. (2005) **(8)**	Framework for reliability estimates.	---

RUL estimation methodology	Reference/Article No.	General topics	Specific system/component
Hazard Rate (Proportional hazard rate)	Gupta and Gupta (2007) **(9)**	Monotonic (non-monotonic) hazard rate. Reliability data analysis.	---
	Xia et al. (2009) **(10)**	RUL prediction based on grey system theory and PHM.	-Bearings
	Suwan et al. (2010) **(11)**	RUL estimation using PHM based on economically optimal replacement times of pipes.	-Water pipes
	Ge et al. (2012) **(12)**	RUL estimation through using PHM. Spare part issues.	---
	Ghodrati et al. (2012) **(13)**	Conditional reliability function. Operational influencing factors.	-Hydraulic jack unit (Mining equipment)
	Zhou et al. (2012) **(14)**	Detection of reliability problems.	-Automobiles
Nonlinear Dynamics	Gasperin et al. (2012) **(15)**	Using a dynamical state-space model to predict RUL.	-Gearbox
	Si et al. (2012) **(16)**	RUL estimation based on adaptive and nonlinear drift-based diffusion process.	---
	Santoso et al. (2013) **(17)**	Using nonlinear autoregressive with exogenous model to estimate RUL.	-Bearings
Data-driven methodology for RUL estimation			
	Mahamad et al. (2010) **(18)**	RUL estimation based on Feed forward Neural Network with Liebenberg Marquardt of training algorithm.	-Bearings

RUL estimation methodology	Reference	General topics	Specific system/component
Neural Network	Yan et al. (2011) **(19)**	RUL prediction based on a neural network and a new performance degradation index.	-Rotor unbalanced test bed
	Ahmadzadeh and Lundberg (2013b) **(20)**	Using artificial neural network to estimate RUL.	-Grinding mill liners
	Candelieri et al. (2013) **(21)**	Using artificial neural networks for RUL estimation combined with finite elements simulation.	-Aircraft structures
Support Vector Machine	Scanlon and Bergin (2007) **(22)**	RUL estimation based on support vector machine and analysis of acoustic noise signal.	-Bearings
	Tran et al. (2012) **(23)**	RUL estimation based on support vector machine associated with time-series techniques.	-Low methane compressor
	Benkedjouh et al. (2013) **(24)**	RUL estimation based on isometric feature mapping reduction technique and support vector regression.	-Bearings
	Zhang et al. (2013) **(25)**	Review of applications of using support vector machine to predict RUL.	---
Bayesian Network	Ferreiro et al. (2011) **(26)**	RUL estimation based on a Bayesian network. Discussion of maintenance strategies.	-Aircrafts
	Tobon-Mejia et al. (2012) **(27)**	RUL estimation based on dynamical Bayesian networks.	-CNC tool
	Mosallam et al. (2013) **(28)**	Prediction of RUL using a Bayesian approach.	-Batteries

RUL estimation methodology	Reference	General topics	Specific system/component
Bayesian Network	Peng et al. (2013) **(29)**	RUL estimation based on Lamb wave-based damage detection technique and a Bayesian updating method.	-Fuselage lap joints
Hidden (Markov, Semi Markov)	Zhang and Kang (2010) **(30)**	Using hidden Markov and an inference algorithm to estimate RUL.	-Bearings
	Peng and Dong (2011) **(31)**	Hidden Markov. Ageing factors. Hazard Rate.	-Hydraulic pumps
	Dong and Peng (2011) **(32)**	Segmental hidden semi-Markov. Ageing factors.	-Hydraulic pumps
	Tobon-Mejia et al. (2011) **(33)**	Estimation of RUL based on mixture of Gaussians Hidden Markov Models.	-Bearings
	Kobayashi et al. (2012) **(34)**	Using hidden Markov models to forecast the deterioration process.	-Infrastructures
	Yu (2012) **(35)**	Using hidden Markov model and contribution analysis method to assess the machine health degradation.	-Bearings
Hybrid approach for RUL estimation			
Statistical Model	Boskoski et al. (2012) **(36)**	RUL estimation based on Gaussian process models.	-Bearings
	Goto and Kenta (2012) **(37)**	RUL evaluation based on a deterioration model. Model parameters are estimated by using the exponentially weighed recursive least squares method.	-Rotating equipment in a thermal power plant.
	Sankararaman et al. (2013) **(38)**	RUL estimation using inverse first-order reliability method.	-Aerospace components

RUL estimation methodology	Reference	General topics	Specific system/component
Statistical Model	Lorton et al. (2013) **(39)**	Probabilistic prognosis used to predict RUL.	---
	Xi et al. (2013) **(40)**	RUL estimation based on health index systems and Copula-based models.	-Electric cooling fans
Computational intelligence techniques (Fuzzy Logic, Genetic Algorithms etc.)	Zio and Maio (2010) **(41)**	RUL estimation using a fuzzy similarity-based approach.	-Accelerator driven system
	Ishibashi and Junior (2013) **(42)**	RUL estimation based on genetic fuzzy rule-based system supported by a decision tree.	-Aeronautical engines
	Zein-Sabatto et al. (2013) **(43)**	RUL estimation based on nonlinear exponential prediction method and fuzzy logic inference systems.	-Turbofan engine components
Wavelet Transform Analysis with Statistical Model	Wang and Miao (2010) **(44)**	Using wavelet lifting scheme and hidden Markov model to describe RUL of gearbox.	-Gearbox
	Tobon-Mejia et al. (2011) **(45)**	RUL estimation based on Wavelet Packet Decomposition and the mixture of Gaussians Hidden Makrov Models.	-Bearings
	Loutas et al. (2013) **(46)**	RUL estimation based on ε-support vector regression.	-Bearings
Dynamic wavelet with neural network	Gebraeel and Layley (2008) **(47)**	RUL estimation based on dynamic wavelet neural network and Bayesian approaches.	---
Fourier transform with neural network	Hongmou and Zein-Sabatto (2001) **(48)**	RUL estimation based on spectral analysis using Fourier Transform and monitored vibration signals.	-Bearings

Table B. 2 Comparison various approaches for RUL assessment (summarized from Ahmadzadeh & Lundberg, 2013a)

	Physics based methodology	Experimental approaches	Data-driven approaches
Advantages	• Very accurate if the system has consistent physics of models. • Fewer data is required in contrast with data-driven techniques.	• Reliable results through accelerating tests can be obtained. • Available to perform the trend analysis dependent on the experimental data.	• Do not require to assume and estimate physics parameters. • Able to have a better understanding of the degradation process. • The calculation and prediction of future states are easy. • A well-constructed theoretical basis. • The utilization of more complete information increase estimation accuracy.
Disadvantages	• Only give overall estimates for identical units, not suitable for units operating individually. • Expensive for computation. • The examination of simplifying assumptions is required. • Normally too stochastic and complicated to model the defect.	• Theoretical models are needed to be verified all the time. • Model parameters varied easily in constrained conditions. • Experiments are costly. • The significance of the experiments might be reduced by scaling problems.	• Require large amount of data to be accurate. • Can lead to inaccurate times of change forecasts. • Have a short prediction horizon. • Perform poorly with high dimensional data. • Hard to fit domain.

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Curriculum Vitae

Personal Information

Name:	Bin Lu
Gender:	Male
Date of birth:	8, February 1989
Address:	Herman Krags Vei 08-42
Nationality:	Chinese
Email (1):	binlv@stud.ntnu.no
Email (2):	binlv89@gmail.com
Telephone:	+47 45170655

Education

01.2012-06.2014	Master of Science – RAMS (Reliability, Availability, Maintainability and Safety) Program *Norwegian University of Science and Technology (NTNU), Trondheim, Norway*
09.2007-07.2011	Bachelor of Engineering – Machine Design Manufacturing and Automation *Harbin University of Science and Technology (HUST), Harbin, China*

Language Skills

Chinese:	Native Speaker
English:	Proficient User
Norwegian:	Basic Learner

Computer Skills

CARA Fault Tree Program:	Fault tree analysis
MINITAB:	Software for statics, process improvement, Six sigma and quality improvement
Matlab:	Language of technical computing
Autodesk CAD:	2D and 3D design engineering software
CATIA:	Solution for product design and innovation. Dassault Systems S.A.
Microsoft Office:	Office suite
GRIF:	System analysis software platform for determining the essential indicators of dependability: Reliability-Availability-Performance-Safety