Risk-Based Evaluation of Pitting Corrosion in Process Facilities

by

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Dedicated to
my husband and my parents
for their patience and faith

ABSTRACT

Pitting is one of the most challenging forms of corrosion to study and model due to complex pit behavior. Pitting can occur in different engineering alloys and can lead to catastrophic consequences. Pits are usually latent or difficult-to-detect and resulting degradation often causes in-service failure of process equipment. Therefore, the ability to predict pit behavior is key to design and maintenance of assets. In particular, pitting corrosion is a significant challenge in marine environments and offshore operations due to remoteness of operations and hidden damage under insulations. Thus, the ability to assess risk and estimate remaining life of assets affected by pitting corrosion is necessary for timely maintenance and safe operation of assets.

This thesis proposes a methodology to assess and dynamically update the risk of pressurized components affected by pitting corrosion. To take into consideration the time-dependent growth of pits, the application of non-homogenous Markov process is proposed to model the maximum pit depth. The integration of the developed maximum pit model into a pressure-resistance model is proposed to predict the failure probability of affected components. An economic consequence analysis model is developed to estimate both business and accidental losses due to failure of the affected component. Then, risk is estimated by integrating models developed for probability of failure and associated consequences. The application of Bayesian analysis is proposed to update estimated risk as new inspection data gets available and also as economic condition of the process evolves. This work also proposes a risk management strategy including corrosion prevention, control and monitoring measures to make effective decision related to pitting corrosion. The application of the proposed methods is demonstrated using different case studies.

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ABBREVIATIONS AND SYMBOLS

Acronyms and Abbreviations

AL	Asset loss
APD	Average pit density
AD	Anderson-Darling test
CDF	Cumulative density function
CPM3	Corrosion Prevention, Monitoring, Maintenance and Management
CUI	Corrosion Under Insulation
EV	Extreme value
ECC	Environmental clean-up cost
FFS	Fitness-for-service
FOSM	First order second moment
GDP	Gross Domestic Product
HHL	Human health loss
MCMC	Markov Chain Monte Carlo
M–H	Metropolis–Hasting
MPD	Maximum pit depth
MTTR	Mean time to repair
NBS	National Bureau of Standards
PDCA	Plan-Do-Check-Adjust
PDF	Probability density function
PERT	Program Evaluation Review Technique
RBI	Risk-based inspection
RSF	Remaining strength factor
SMTS	Specified minimum tensile strength
VSL	Values of statistical life

English letters

A	Parameter for pit density Equation
a_d	Damage area
AF_{CPM3}	CPM3 adjustments factor
$B(\bullet)$	Beta function
BL	Business loss
B_i	Parameter for business losses during downtime equation
B_i'	Parameter for business losses during recovery periods equation
$BL_{dt}^{(\cdot)}$	Business losses during downtime
$BL_{rp}^{(\cdot)}$	Business losses during recovery periods
C_u	The process unit replacement cost
C_{hh}	the unit human health
C_{ec}	The environmental clean-up cost
d_p	The population density
D	Outside diameter of the pipe
f	Inflation rate per year
f_L	Lang factor
f_e	Estimated fraction of material evaporating
f_u	Ultimate tensile strength
f'_{MPD}	Prior MPD distribution
f''_{MPD}	Posterior MPD distribution
$F_\chi(x)$	Cumulative distribution function of the parameter χ
i	Morkovian states
IR	Insurance recovery
l	Length of the pitted area
$L(\|)$	likelihood function
m	Number of pits on the surface

m_{dm}	Discharge mass of the released fluid
n	Total number of Morkovian states
N'	Number of pits between time t_1 and t_2
OL'	Overall loss in actual monetary value
OL	Adjusted overall loss
OL_0	The overall loss based on today's monetary value
P_{corr}	the maximum allowable pressure of the corroded component
P_f	Failure probability
P_{op}	Operating pressure
POF_0	Original probability of failure
POF	Adjusted POF
R	Risk
t	Time past since the component commissioning
t_k	Initiation time of pits
t_{design}	The design life of the equipment
v_{PERT}	Shape parameter for PERT distribution
w_{PERT}	Shape parameter for PERT distribution
w	Parameter for pit density model
w_1	Shape parameter in the Weibull distribution
w_2	Scale parameter in the Weibull distribution
x_{ob}	set of observations (inspection data)
$x(t)$	Random variable denoting the process characteristic at time t
$Z(t)$	State function

Greek letters

α_{AF}	Shape factor of AF_{CPM3}
β	Reliability index
γ_{PERT}	Parameter for PERT distribution
γ_d	Partial safety factor for the pit depth

γ_m	Partial safety factor for the longitudinal corrosion model prediction
$\Delta\tau_{dt}$	Downtime period
Δd	Thickness intervals in the Markov process
$\Delta\tau_{rp}$	Mean value of the recovery period
ε_d	Factor for defining a fractile value for the pit depth
η	Parameter to estimate the pit density
$\boldsymbol{\theta}$	Vector of Markov model parameters
$\Theta_H(t,i)$	Cumulative distribution of the maximum pit depth
λ_i	The intensity rate in the Markov process
$\mu_{(.)}$	Mean of the normal distribution
μ_{Pcorr}	Mean of the burst pressure distribution
$\pi(\theta\|x)$	Posterior distribution of θ
$\pi(\theta)$	Prior distribution of θ
ρ_l	Liquid density at storage or normal operating conditions
$\sigma_{(.)}$	Standard deviation of the normal distribution
τ	Component thickness
$\phi(\cdot)$	The normal cumulative distribution function
χ	Parameter (with the dimension of distance) to estimate the number of transited states in the Markov model
ψ	Parameter to estimate the pit density
ω	Parameter to estimate the number of transited states in the Markov process

1. INTRODUCTION

1.1. Overview

1.1.1. Background

DNV-RP-C302 [1] reported that 60% of the world's offshore structures have passed their theoretical design life of 20 years; many more approaching the end of their design life. Offshore structures often are being kept in operation for a prolonged period of time beyond their design life [1]. There is a need to manage material deterioration to ensure the ongoing integrity and safety of these aging structures. The process components in offshore operations are usually insulated to conserve energy and protect equipment against external environment. The insulation adds an extra level of complexity to the integrity management of these assets due to potential initiation and growth of corrosion under insulation, such as pitting corrosion.

Pitting is defined as localized regions of metal loss that is characterized by a pit diameter on the order of the plate thickness or less, and a pit depth that is less than the plate thickness [2]. Pitting is one of the most destructive forms of corrosion as it is hard to detect and predict. Small pits can remain undetected using traditional visual inspection methods as corrosion products and equipment insulation cover the pits. More advanced inspection methods such as ultrasonic and radiography inspections may also be unable to effectively detect pits as small narrow pits have minimal metal loss. Undetected pits can result in the failure of engineering systems, with subsequent threats to people, assets and the environment.

In offshore structures, pitting usually occurs in materials that are coated or naturally protected by their passive layers [3]. Pitting corrosion damage is identified by Engelhardt et al. [3] as a three stage process including:

i. Stage 1: Nucleation: in this stage, pits are initiated (nucleated)

ii. Stage 2: Propagation: here, some pits begin to grow

iii. Stage 3: Re-passivation: this stage includes pits that cease to continue to grow

Stage 1 of the pitting mechanism is nucleation. Steel alloys, such as stainless steel and aluminum alloys, are comprised of a passive oxide layer that can form on the metal surface [4], [5]. For other types of steel, such as carbon steel, a protective coating is used for corrosion protection. However, such passive films or protective coatings are often susceptible to localized damages. A damage in the protective layer, either natural or applied, provides a nucleation point for the formation of pits in the presence of an electrolyte containing an aggressive anion [6]. The breakdown layer can be due to salt particles in the solution or due to other factors including chemical or physical heterogeneity at the surface, including second phase particles, inclusions, solute-segregated grain boundaries, flaws, mechanical damage or dislocations [7]–[9].

Pit propagation is the second stage of pitting mechanism. Pitting growth is an autocatalytic reaction; once a pit starts to grow, the local conditions are altered so that further pit growth is promoted [10], [11]. Figure 1.1 shows the pitting growth mechanism on the metal, M, in a marine environment that contains Cl^-. Dissolution of iron reaction occurs along with oxygen reduction. Fe^{2+} ions attract negative ions (Cl^-) and as the result of the hydrolysis reaction, $Fe(OH)_2$ cap is created over the pit and the pH of the electrolyte inside the pit decreases. This creates a self-propagating system where the increased acidity in the pit cavity accelerates pitting corrosion of the steel walls [9], [12].

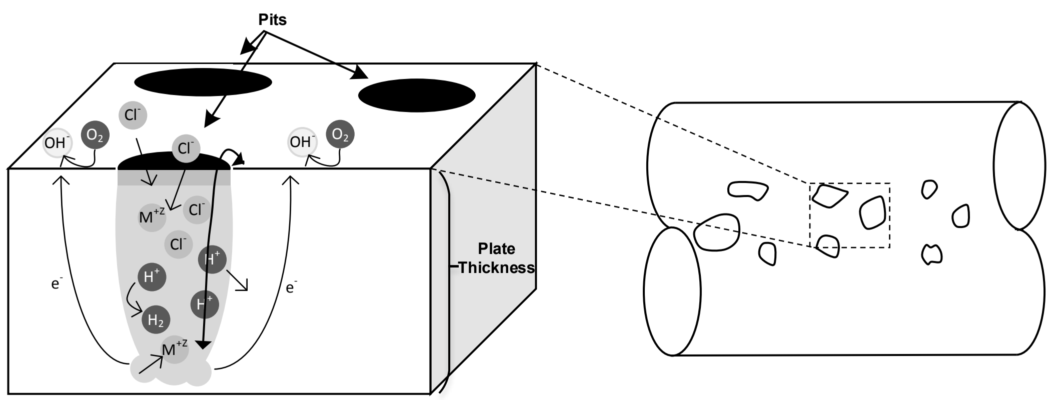


Figure 1.1. Autocatalytic process occurring in a corrosion pit; adopted from [11] and modified by the author

All pits that are initiated do not always continue to propagate. Pits can re-passivate and stop growing in materials that have a naturally produced passive layer such as stainless steels. According to Novak [13], the reason for pit re-passivation is an increase in the internal resistance of the local cells within the pit, due to the pit filling with corrosion products, the drying out of the surface and the reaction being limited by passive film of the cathode [9].

Pitting corrosion is one of the most expensive and challenging forms of corrosion to prevent by design. As discussed earlier, pits can attack carbon steel as well as the expensive engineering alloys, such as stainless steels and aluminum alloys. They can lead to accelerated failure of structural components by perforation or by acting as an initiation site for cracking [14]. Moreover, the occurrence of pits and their relative size in a region of a component are typically random and poorly understood [2]. Consequently, pitting corrosion has been an active area of research to better understand and predict pitting behaviour.

The charts in Figure 1.2 shows the cumulative trend of the journal and conference publications over time in the domain of pitting corrosion. This cumulative trend can be used as an index of the importance of pitting corrosion. The area charts in Figure 1.2 show the trend of pitting corrosion publications in different disciplines. It is evident from Figure 1.2 that the number of publications focusing on pitting corrosion has increased significantly in recent decades, especially in the period of 1990 to 2010. In particular, engineering and material science fields have seen a sharp increase in the number of publications. This substantial increase can be attributed to the industries' increased awareness of the importance of shifting from traditional reactive interval-based inspections and maintenance to proactive methods by understanding and predicting corrosion mechanisms and potential failure.

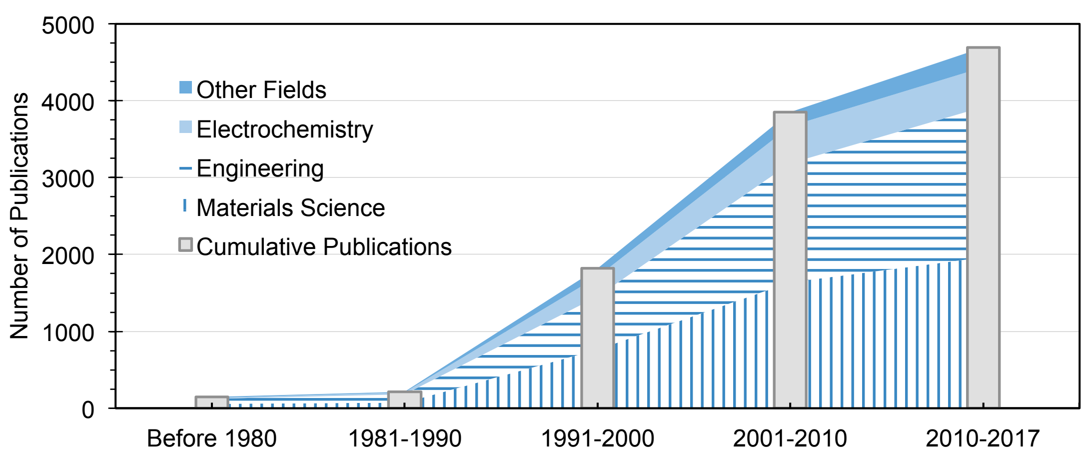
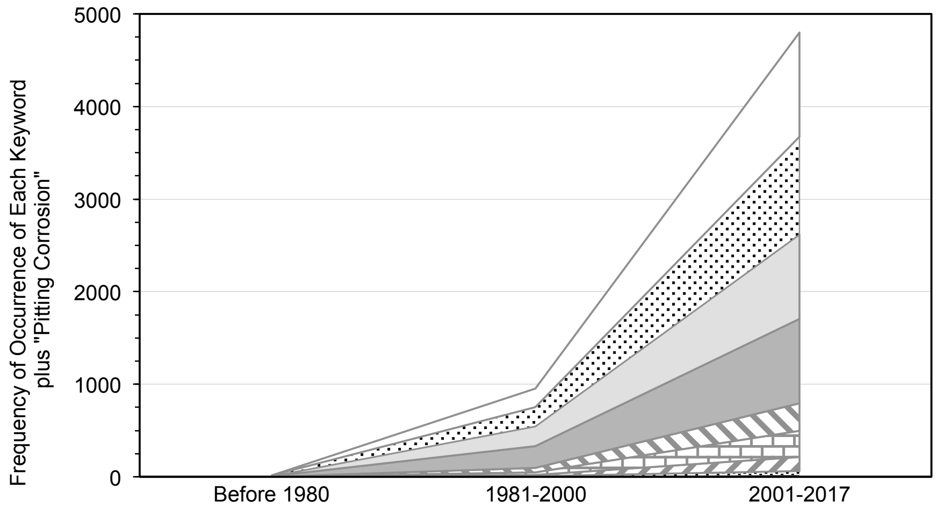


Figure 1.2. The trend of publications in the domain of pitting corrosion over time

Figure 1.3 provides a holistic view of the pitting corrosion knowledge evolution over time. Figure 1.3 is developed by collecting publications from the Web of Science (www.webofknowledge.com) and the Scopus databases (www.scopus.com) in which the keywords identified in Figure 1.3 and “pitting corrosion” have co-occurred. As shown in Figure 1.3, the number of co-occurrences of keywords such as modelling, mechanisms and growth has increased sharply over the past two decades. This shows that researchers have responded to the industry’s need to develop more proactive integrity management methods by focusing on pitting mechanisms understanding and modelling. Other keywords such as “prediction” and “monitoring” have also been popular fields of research during this period. An important observation from Figure 1.3 is that topics such as “remaining life estimation”, “risk assessment” and “fitness-for-service assessment” of assets susceptible to pitting corrosion were almost unknown before the 1990s. These research areas have shown a very slow increase in popularity amongst researchers in the past decade. This observation highlights an important knowledge gap in pitting corrosion literature. Bridging this knowledge gap requires a shift toward risk-based integrity assessment methods to increase safety and prioritize inspection and maintenance resources.



	Before 1980	1981-2000	2001-2017
Model(l)ing	1	204	1128
Mechanisms	10	202	1053
Growth	2	219	913
Initiation	3	234	910
Monitoring	0	46	302
Prediction	0	32	283
Consequence Analysis	0	12	151
Remaining Life	0	2	38
Risk Assessment	0	3	18
Fitness for Service	0	0	5

Figure 1.3. The number of co-occurrences of "pitting corrosion" and some important keywords in journal and conference papers

Following the increased awareness of industries about the advantages of risk-based techniques, Risk-Based Inspection (RBI) standards such as API 580 [15] and API 581 [16] were introduced in the early 2000s. Also, design codes such as ASME B31.3 [17] for piping and ASME Section VIII [18] for pressure vessels accepted the application of risk-based techniques in inspection scheduling. Accordingly, inspection codes such as API 510 [19] for pressure vessels, API 570 [20] for piping, and API 653 [21] for storage tanks adopted the application of RBI for the oil and gas industry. The rest of this chapter provides a detailed review of existing literature in the field of pitting corrosion risk assessment and fitness-for-service assessment.

1.1.2. Pit Modeling

The rate of pit growth can be used for predicting pitting behaviour of assets susceptible to pitting corrosion. Different corrosion growth rate models such as [22]–[29] have been developed to model the pitting rate. Table 1.1 provides a list of available pit growth rate models in the literature along with their characteristics and related references.

Table 1.1. A list of major recommended pit growth rate model in the literature

Model	Characteristics	Related References
Single-Value Corrosion Growth Rate model	• Constant value for pit growth rate • Growth rate is independent of age of asset and depth of corrosion feature • Deterministic model	[29], [30]
Linear Corrosion Growth Rate Model	• Inline inspection (ILI) data should be available • Deterministic model	[28], [31]
Non-linear power law model	• Deterministic approach • Inline inspection (ILI) data should be available	[23], [30]
Power law (Temperature and Stress Dependency)	• Empirical model • Time independent	[24], [30]
Markov model	• Requires the initial pit-depth distribution and soil-pipe parameters	[32], [30]
Generalized Extreme Value Distribution (GEVD) model	• Suitable for a generic textural soil • Complicated equations	[28], [30]
Gaussian model	• The mean pit depth of the distribution, increased at a rate less than linear with time	[27], [30]
Gamma Process	• Inline inspection (ILI) data should be available	[26], [30]
Bayesian network	• Probabilistic model for the long-term pitting corrosion depth in marine environment	[33]

Although pit growth rate and pit depth are important to evaluate the condition of an asset affected by pitting corrosion, the study of the deepest pits in large scale engineering structures is considered to be more relevant as it is the deepest pits that actually cause the system failure [34]. The Markov process [35] and Extreme Value Theory [36] are the two primary approaches which are often used in the literature to model maximum pit depth. While models based on extreme value theory have advantages such as simple practical applications, they have the major limitation of being static. To address this limitation, models based on the Markov process are introduced in the literature. In the Markov process, the material thickness is discretized in non-overlapping intervals, which correspond to the n possible Markov states i ($i = 1, \ldots, n$). The assumption of the Markov process is that the probability of a pit growing deeper only depends on its current state.

Besides the maximum pit depth, pit density (i.e. the number of pits in the unit area at each time) is another pit characteristic that is essential to estimate the overall risk for equipment affected by pitting corrosion. A comprehensive review of different maximum pit depth models, the Markov process, and pit density models are provided in Chapter 2.

1.1.3. Fitness-for-Service Assessment

Design codes are less useful to evaluate in-service degradation that may be found during subsequent inspections as they usually cover defects found during equipment fabrication [1]. The fitness-for-service (FFS) assessment, which is defined as "quantitative engineering evaluations that are performed to demonstrate the structural integrity of an in-service component that may contain a flaw or damage" [2], has been developed to tackle this challenge by (i) evaluation of the current stage of damage, (ii) extrapolation from the current state to estimate the remaining safe and serviceable life [3], and (iii) providing guidelines to make "run, rerate, repair, or replace" decisions about equipment under pressure affected by damage and corrosion [37]. Research conducted and knowledge gained during the last couple of decades have led to the formulation of international standards and procedures for conducting FFS assessments such as BS 7910 [38], API 579-1/ASME FFS-1 [2], FITNET [39], SINTAP [40], B31.G [17], R5 [41], R6 [42] and RSE-M [43]. Among these standards, only API 579-1/ASME FFS-1 covers assessments of equipment susceptible to pitting corrosion. However, the FFS assessment in API 579-1/ASME FFS- 1 [2] is based on current pitting damage characteristics [37].

1.1.4. Risk-Based Remaining Life Estimation

The importance of using risk-based methods to schedule inspection and maintenance activities is now recognized by the industry to ensure safety while prioritizing limited resources. A risk-based approach can also provide a framework for remaining life evaluation and informed decision-making [44]. Several quantitative, semi-quantitative and qualitative models have been developed to help engineers to make risk-based decisions about damaged equipment [44]–[49] .

Qualitative risk approaches assign subjective scores to the different factors that are thought to influence the probability and consequences of failure [50]. These scores are then combined using simple formulas to give an index representing the level of risk.

Semi-quantitative approaches use semi-quantitative models for consequence estimation as well as failure probability calculations [48], [50]–[52]. These approaches provide a tool to ascertain whether the estimated risk of failure satisfies a predetermined acceptance criterion [50]. Quantitative risk approaches such as [44], [53]–[57] estimate the level of risk based on direct estimates of the probability and consequences of failure.

Risk is defined as the combination of three attributes: what can go wrong, how bad could it be, and how often might it happen. For risk estimation, both deterministic and probabilistic approaches are used in the literature to estimate failure probability due to corrosion. For instance, Race et al. [46] developed a deterministic corrosion scoring model based on corrosion susceptibility and severity [46]. In this study, the probability of failure is estimated using failure probability related to coating, cathodic protection and uncoated pipe. However, deterministic approaches are unable to incorporate the uncertainty associated with probability estimation. To address this shortcoming, probability distributions are usually used in the literature. In the case of corrosion, different studies have focused on developing probabilistic methods to estimate the failure probability in risk estimation, such as [58]–[66]. For example, in a study by [47] the authors used the thinning failure function proposed by Khan et al. [50] to assess failure of insulated piping. In this analysis, the variables are assumed to be random and follow normal distribution with a known mean and standard deviation [9].

Reliability assessment based on limit state function analysis has been another approach to probability assessment of corroded equipment. Hasan et al. [26] reviewed different burst pressure estimation models and provided guidelines to choose the best model based on different factors such as component type, age, and type of service. Using burst pressure and state function, they estimated the failure probability for a corroded pipeline. The main shortcoming of the aforementioned models is that they are static models and the dynamic nature of a corrosion mechanism is not taken into consideration. The application of Bayesian network analysis has received increased attention in recent years to enable a dynamic estimation of failure probability [26], [67]–[69].

Risk analysis also requires analyzing the consequences of failure. Traditional consequence assessment techniques usually involve a variety of mathematical models, such as source and dispersion models that predict the release rate of hazardous materials, fire and explosion models, impact intensity models and toxic gas models [44], [70]–[74]. In these models, the consequences are usually estimated deterministically as a function of affected areas, ignoring the uncertainty associated with affecting parameters, which can lead to imprecise consequence analysis.

1.1.5. Dynamic Risk Management

The importance of using risk-based methods to schedule inspection and maintenance activities is now widely recognized by researchers and the industry to ensure safety while prioritizing the allocation of limited resources. Numerous quantitative, semi-quantitative and qualitative models have been developed to help engineers to make risk-based decisions about damaged equipment [44]–[49]. Most corrosion risk assessment methods discussed in the previous section have the common shortcoming of being static. However, pitting corrosion is a complex process and pit behaviour changes over time due to different causes including, but not limited to, operational changes, feed variability, varying external environment and changes in asset conditions [9], [11]. Hence, it is essential to use a dynamic risk assessment approach which considers ‘prior’ knowledge of the pitting corrosion process along with inspection data and new information from the system in order to calibrate the model over time [75].

Several studies have been conducted to investigate pit behaviour and models for pitting corrosion. These models are used in a variety of methods to predict failures, optimize maintenance and inspection schedules, and aid in material selection [56], [57], [65], [76]–[80]. Pit models are also used in risk assessment to assess failure risk, remaining life estimation and risk-informed decision-making [44]. Moreover, there have been several efforts in dynamic corrosion risk assessment such as [44]–[49], [82]–[87]. However, this review observes that there is no model available for ‘dynamic risk assessment’ of pitting corrosion. The existing efforts in the field of dynamic evaluation of pitting corrosion are limited to updating pit behaviours [34], [75], [88]–[90] or the failure probability [90]–[93]. A detailed review of the related literature is provided in Chapter 6 of this thesis.

There is a need to develop a dynamic risk assessment model that can update pit behaviour and failure probability and use this information to update risk of failure due to pitting corrosion. Moreover, risk management strategies including prevention, control and mitigation measures should also be integrated with the developed dynamic risk assessment model to develop a risk management framework for pitting corrosion. A risk management approach is important for corrosion management to ensure appropriate resources and procedures are allocated with specific tasks to manage pitting corrosion.

Development of a dynamic risk management framework is one of the main objectives of this research.

1.2. Knowledge Gap Analysis and Research Motivation

As discussed earlier, pit density and maximum pit depth have been identified by most researchers as the key parameters to describe pit behaviour. There have been several attempts to model these pit characteristics. Also, risk-based assessments of corroded equipment have been investigated by several researchers for specific industries and components. However, in the case of pitting corrosion, it is observed that there has been a limited work on developing dynamic risk-based assessment methods; the majority of the existing works have covered pit modelling [34], [75], [88]–[90] or probability assessment [90]–[93]. Having evaluated the existing pitting evaluation and risk-based remaining life assessment methods, the following knowledge and technological gaps are identified:

i. The effect of pitting characteristics such as pit depth and pit density on failure probability is not fully understood. There is a need to find an appropriate method to model and incorporate time-dependent pit behaviour in probability estimation.

ii. The existing remaining life evaluation models are usually based on pit growth rates and the reduction of maximum allowable working pressure of corroded equipment. The application of a risk-based method for remaining life evaluation of an asset attacked by pitting corrosion is crucial to ensure consideration of both the probability and consequences of failure in decision-making.

iii. The current FFS assessment methods are based on known pitting damage and the procedure cannot be used for predictive FFS assessment and estimation of the pitting progression rate. Moreover, the uncertainties associated with input data, such as pit depth and pit density, are not taken into consideration.

iv. Most existing pit models and risk assessment techniques are static in nature. There is a need to develop dynamic pit evaluation and dynamic risk assessment models to update estimated pit depths, and the estimated remaining life, based on system information such as inspection data.

v. To estimate the consequences of failure, traditional approaches ignore the uncertainty associated with loss estimations when using deterministic values for losses. Moreover, the current methods do not consider the time value of money when estimating future losses based on the current dollar value.

vi. There is a lack of a dynamic risk management framework for pitting corrosion to incorporate the effect of management measures in the risk assessment process.

1.3. Objectives and Scope

The proposed models in this thesis perform the required pitting evaluation by answering these questions:

1. What is the probability of failure of an affected asset by pitting in future?
2. How does inspection data affect the estimated probability?
3. If failure happens, what will be the consequences?

4. What will be the effect of a corrosion remediation technique on a susceptible asset?

To answer these questions, the following research objectives are identified for this research (illustrated in Figure 1.4):

1. To develop a dynamic probabilistic pit evaluation methodology and study the importance of different parameters in modeling the pitting.
2. To develop a predictive Fitness-For-Service (FFS) assessment for pitting corrosion.
3. To develop a methodology for risk-based remaining life evaluation of assets affected by pitting corrosion.
4. To integrate an economical consequence analysis model for assets susceptible to pitting corrosion with corrosion prevention, monitoring and management methods.
5. To develop a dynamic risk management framework for pitting corrosion.

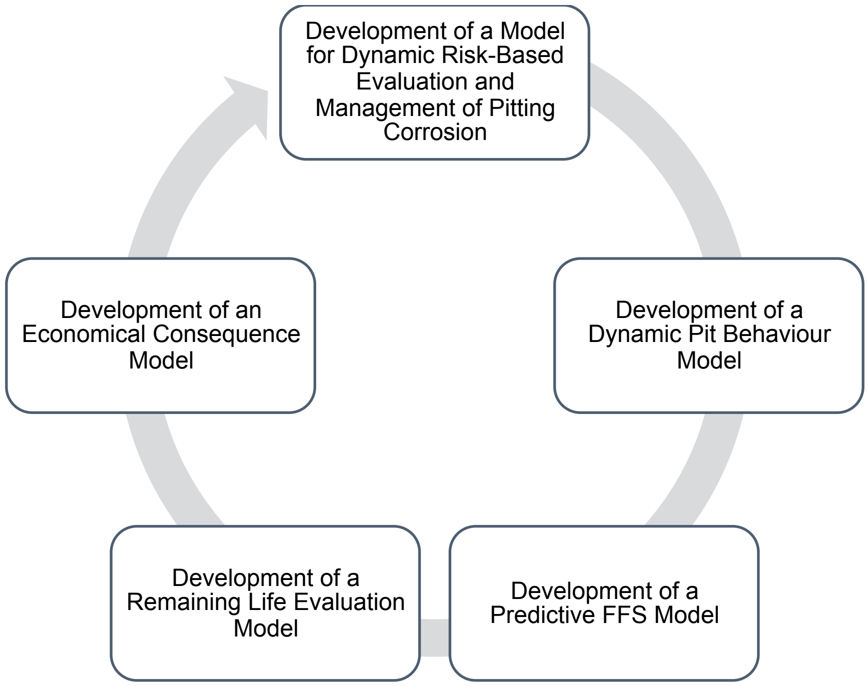


Figure 1.4. Research objectives

The scope of this research covers pitting modelling and a predictive risk-based evaluation of pitting corrosion in process facilities which may result in the release of chemicals or energy and cause loss of productivity. The models developed in this work are best suited for risk assessment of assets susceptible to pitting corrosion, such as those for offshore oil and gas development in harsh environments, where accurate risk estimation is required to ensure overall safety.

1.4. Contributions

This section highlights the contributions and significance among existing research efforts in the area of risk-based evaluation of pitting corrosion. A detailed description of each contribution is provided in the respective chapters.

1.4.1. Probabilistic Modelling of Pitting Corrosion

The ability to predict pitting behavior is key to designing and maintaining equipment safely in offshore environments. In most conventional pit models, pit depth and pit density are considered to be deterministic. Chapter 2 of this thesis proposes a probabilistic pit evaluation methodology to take into consideration the uncertainties associated with these pit characteristics. In the proposed methodology, the Non-homogeneous Poisson process is used to model pit generation and a Markov model is developed to model the dynamic nature of maximum pit depth over time. The practical application of the proposed models is demonstrated using a pressure vessel case study.

1.4.2. Predictive FFS Assessment

As discussed earlier, the existing pitting corrosion FFS assessment methods are not predictive and are based on known pitting damages. Moreover, the uncertainty of the input data for main pit characteristics is not taken into consideration. One of the contributions of this thesis is to tackle these limitations by developing a new predictive FFS assessment for pitting corrosion in Chapter 3. The proposed method uses predicted pit density, maximum pit depth and maximum allowable pressure of the defected component to conduct FFS assessments.

1.4.3. Updating Predicted Pit Behaviour

Existing maximum pit depth models use either experimental data or expert knowledge to estimate model parameters, without the ability to revise the model parameters for a specific application. These methods do not consider the use of inspection data to update the maximum pit depth and revise the estimated remaining life. However, it is important to incorporate inspection data into models to predict the pit growth rate and estimate the maximum pit depth. The novelty of this research is the development of a hybrid method for pitting evaluation by integrating the Markov process with Bayesian analysis to provide a dynamic probabilistic framework, while overcoming the major limitation of the Markov process. This contribution is presented in Chapter 4.

1.4.4. Risk-based Economic Impact Analysis

As mentioned earlier, in most of the current consequence assessment methods, the consequences are estimated using the affected area [44], [70]–[74]. These methods usually use deterministic values and the uncertainties associated with loss estimations are ignored. Also, the mitigating effects of corrosion prevention, monitoring and management on estimated losses are not considered. Moreover, the time value of money is not considered in loss estimation. Another contribution of this work (Chapter 5) is the development of risk-based economic impact analysis of pitting corrosion. The proposed model considers the uncertainty associated with loss estimations, the time value of money, and the mitigating effect of corrosion prevention, monitoring and management of estimated losses.

1.4.5. Dynamic Risk Management of Pitting Corrosion

As mentioned earlier, the limitation of most of the current risk assessment methods for pitting corrosion is that these are static models and the dynamic nature of corrosion mechanisms is not taken into consideration. In Chapter 6, a methodology is developed to assess and dynamically update the risk for pressurized components that have been affected by pitting corrosion and subjected to regular inspection. Another contribution of the corresponding chapter is the evaluation of different risk management strategies including, prevention, control and mitigation measures to make effective decisions related to pitting corrosion.

1.5. Organization of the Thesis

This thesis is written in a manuscript format (paper-based). Overall, the outcomes of this thesis are published in five peer-reviewed journal papers, two conference papers and two conference abstracts. Figure 1.5 shows the structure of this PhD thesis. As shown in this figure, Chapters 2 to 6 of this thesis are developed based on the paper submissions to peer-reviewed journals.

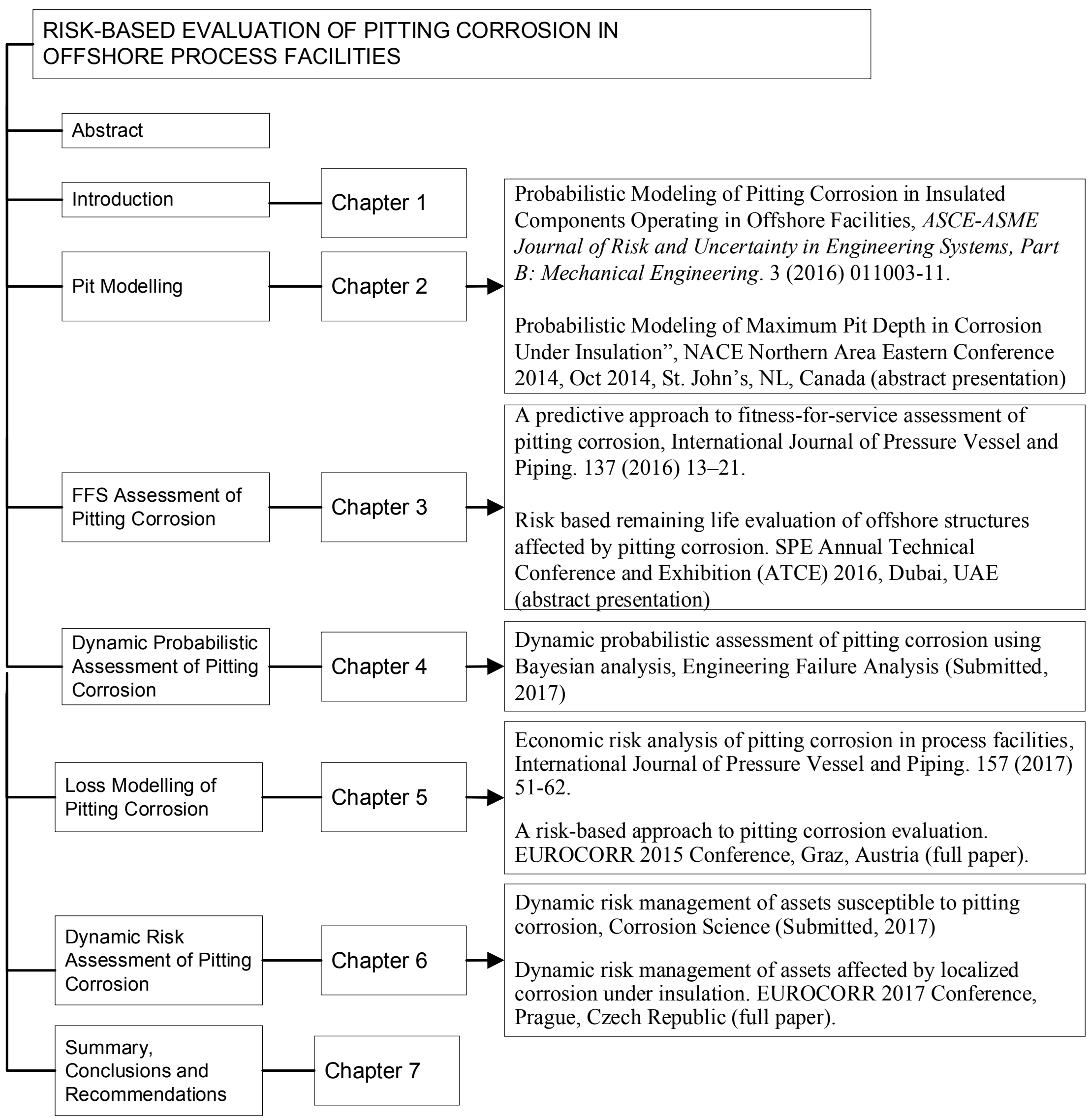


Figure 1.5. Structure of the PhD thesis and related publications

Chapter 2 reviews the models for pit characteristics and investigates the factors affecting pit initiation and pit growth on equipment under insulation operating in offshore environments. A methodology is proposed for studying the pitting CUI characteristics including pit initiation time, pit density and maximum pit depth over time.

Chapter 3 presents a predictive fitness-for-service (FFS) assessment methodology for process equipment using pit characteristics to track and predict pitting corrosion. In this method, the uncertainties in input data, such as pit depth and pit density, are taken into consideration.

Chapter 4 presents a hybrid method for pitting evaluation by integrating the Markov process with Bayesian analysis to provide a dynamic probabilistic framework. This method updates the remaining life estimates based on inspection data.

Chapter 5 presents a predictive probabilistic model to estimate the overall economic impacts of pitting corrosion by considering both the corrosion costs and significant losses that may occur if failures occur because of pitting corrosion.

Chapter 6 proposes a methodology to assess and dynamically update the risk of pressurized components affected by pitting corrosion. This chapter also evaluates different risk management strategies including prevention, control and mitigation measures to make effective decisions related to localized corrosion.

Chapter 7 reports the summary of the thesis and the main conclusions drawn through this work. Recommendations for future work are presented at the end of Chapter 8.

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2. PROBABILISTIC MODELING OF PITTING CORROSION IN INSULATED COMPONENTS OPERATING IN OFFSHORE FACILITIES[1]

Preface

A version of this manuscript has been published in the ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems Part B: Mechanical Engineering. I am the primary author of this paper. Along with the co-authors, Faisal Khan and Salim Ahmed, I developed the conceptual models for pit characteristics in insulated equipment. I carried out the literature review and the comparison of pitting models. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback and also the peer review process. The co-author Faisal Khan helped in developing and testing the concepts/models, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Salim Ahmed contributed through support in the development, testing and improvement of the models. Salim Ahmed also assisted in reviewing and revising the manuscript.

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Abstract

Pitting corrosion under insulation is one of the challenging issues for safe operation of offshore facilities. Degradation usually remains hidden causing the inspection of insulated assets to be equally challenging. The modeling of the pitting corrosion under insulation (CUI) helps to better understand the current state of the asset and predict failure. This paper investigates the factors affecting the pit initiation and pit growth on equipment under insulation operating in offshore environments. A methodology is proposed for studying the pitting CUI characteristics including pit initiation time, pit density, and maximum pit depth over time. The proposed methodology provides a practical and more effective asset life management approach when supported by inspection data. The practical application of the proposed methodology is demonstrated in this paper using a pressure vessel case study in an offshore platform.

Key words: corrosion under insulation; Markov model; pit depth; pit density; offshore operation

2.1. Introduction

Corrosion under insulation (CUI) is defined as a type of corrosion that happens in piping, pressure vessels and structural components resulting from water trapped under insulation or fireproofing. CUI can occur at -12^{o}C to 177^{o}C, the operating temperature range for most offshore applications [1]. Moreover, CUI affects different types of steel including carbon steel, alloy steel, 300 Series stainless steel, and duplex stainless steel [1]. It is reported that CUI accounts for 40-60% of piping maintenance costs in ExxonMobil facilities [2]. Fathi [3] reported that CUI was the main cause for 10% of the total annual maintenance cost of fixed equipment and has been the main challenge in 17 out of 30 process plants operated by Saudi Aramco. In another study, DuPont Company estimated that the direct costs of CUI repairs and replacements exceed $10 million per year for its facilities. These costs do not include normal preventative maintenance costs and indirect costs such as loss of production and revenue [4].

CUI is typically difficult to identify because it remains hidden under insulation material, often until it becomes a serious problem [5]. Besides uniform corrosion and stress corrosion cracking, pitting corrosion is a dangerous form of CUI, which requires specific consideration for insulated equipment due to the technical difficulties in pitting detection and prevention. Pitting corrosion is a localized form of corrosion that occurs when one area of a metal surface becomes anodic with respect to the rest of the surface. It can also happen when highly localized changes in the corrodent in contact with the metal cause accelerated localized attack [6]. This type of CUI can lead to serious consequences. For instance, small pits can progress through equipment wall thickness and lead to a loss of containment of process materials or act as an initiation site for stress corrosion cracks. If pitting develops such that the strength of the material is affected, brittle failure can also occur [7].

In marine applications, pitting usually occurs in coated or naturally protected materials. For other types of steel, such as carbon steel, corrosion protection is sometimes due to an applied protective coating. Although these protective layers prevent corrosion over the bulk of the equipment, defective or inappropriate coating can cause localized pitting corrosion [7].

Pitting corrosion can be considered as a combination of two physical processes: pit generation and pit depth growth. Both processes are random and cannot be adequately modeled by deterministic models [8]. The pit density is another characteristic of pitting corrosion that affects the stress distribution and load capacity of a component. From a practical point of view, in addition to pit density, quantification of the maximum pit depth is also important, since the deepest pit will cause the failure of the equipment [9]. As a result, along with the depth of the pit, pit density affects the structural integrity of components in marine environments.

The ability to predict pitting behavior is key to designing and maintaining equipment safely in offshore environments [7]. In conventional life estimation methods, pit depth and pit density are considered to be deterministic. However, in reality, significant uncertainties are associated with these parameters [10]. To take these uncertainties into consideration, it is rational to employ a probabilistic framework to analyze the pitting. The modeling of pitting phenomena for insulated components is challenging. The insulation adds an extra level of complexity as the pitting corrosion remains hidden and is hard to inspect or maintain. In an earlier work, the authors developed a pit characterization and fitness-for-service (FFS) assessment methodology [11]. However, a comprehensive review of the literature shows that there is no specific study on probabilistic modeling of pitting CUI in marine environments.

The objective of this paper is to address the pitting CUI challenge in offshore applications and marine environments by proposing a probabilistic pit evaluation methodology. The first contribution of this paper is the investigation of different parameters and their importance in modeling pitting CUI. Furthermore, this paper proposes a methodology to integrate the pit initiation and pit density models in order to assess the maximum pit depth. The organization of this paper is as follows: Section 2.2 discusses the factors affecting the modeling of the pit characteristics in insulated components in offshore applications using comparative study of related works. Section 2.3 presents a methodology for probabilistic assessment of pitting CUI in marine environments. Finally, Section 2.4 presents the practical application of the illustrated methodology using a case study, followed by some concluding remarks.

2.2. Pitting Corrosion Under Insulation

Pitting in insulated equipment can occur when moisture penetrates the insulation and aids to create a corrosion cell. Average pit density and maximum pit depth are two important pit characteristics that need to be quantified for any quantitative evaluation of pitting corrosion [11]. The purpose of this section is to investigate the factors that should be taken into consideration to model pitting CUI in insulated equipment.

Modeling pit characteristics in an insulated area adds an extra level of complexity into the stochastic process due to the hidden nature of corrosion. It results in difficulty in monitoring and inspection, which sometimes causes the degradation to remain undetected until failure. Therefore, the model used for pit characteristics in CUI should be flexible enough to consider the inspection difficulty as well. Other important parameters that can affect the pitting CUI are discussed in the following sections and the results are summarized in Table 2.1.

Insulation: Pitting in insulated equipment occurs in many ways including insulation damage or wicking, atmospheric wetness, or poor installation. Some insulation materials contain water-leachable salts that may contribute to corrosion, and some foam may contain residual compounds that react with water to form an acidic environment. Also, insulation can act as a transporter, as the movement of moisture from one area of insulation to another area causes spread of this phenomenon [12]. The water retention, permeability, and wettability properties of the insulation material also influence the pitting CUI [13].

Coating: For coated equipment under insulation, breaks or holidays in the coating cause the underlying metal to be exposed to moisture trapped under insulation. Damage to the protective coating and discontinuities in the protective coating are the critical factors for pit initiation. The coating specification that can affect the pit initiation includes surface preparation of the material, choice of coating, quality of the coating, and the maintenance activities [14].

Chloride ion: Insulated equipment located in marine environment is exposed to chloride ions. The chloride acts as an important role for pit growth as an autocatalytic process [7, 13]. The migration of chloride ions to the active corroding area can help to stabilize pitting corrosion. A study by Frankel et al. [15] states that pitting corrosion will only occur in the presence of aggressive anionic species which are usually chloride ions.

Temperature: Temperature is another factor that can accelerate the autocatalytic pit growth process. Temperature greatly influences the corrosion behavior of steels in seawater and offshore-insulated structures. Increasing temperature results in higher current transients and increases the conversion of metastable pits into stable pits. Temperature also has a relation to chloride ions. The increase in temperature in a chloride environment usually cause an increase in the growth rates of pits [14].

Table 2.1. Factors affecting pitting CUI

Parameter	Important Attributes	Effect on Pit Mechanism	Effect on Pitting CUI Modeling	References
Insulation	• Water retention • Permeability • Wettability • Compounds	Affects pit initiation due to providing annular space and wicking and/or absorbing of water	Affects average pit density and transition state parameters in the Markov model by creating a corrosion cell in the presence of water.	[12, 13]
Coating	• The surface preparation of the material • Type and quality of the coating	Affects pit initiation if coating breaks down	Affects parameters of the pit initiation time and average pit density model by speeding up the pit generation rate, in case of coating failure.	[7, 14]
Chloride Ion	Concentration	Affects pit growth if Cl^- penetrates the film due to its high diffusivity	Affects average pit density and transition state parameters in the Markov model due acceleration of autocatalytic corrosion reactions.	[7, 13, 15, 16]
Temperature	Safe operating window	Affects pit initiation by converting the metastable pits into stable growing pits and also by affecting the pitting potential	Affects the transition state parameters in Markov model.	[14, 17]

From Table 2.1, it can be concluded that a methodology to model pit characteristics must be flexible enough to consider the effect of the contributing parameters in pitting CUI. For this purpose, the model should include parameters enabling the modeling of complex non-linear pit behaviors. Moreover, as will be discussed later, a methodology should be in place to estimate the model parameters based on the insulation, coating, and marine environment, as well as operational conditions.

2.3. Methodology for Modeling Pit Characteristics

Figure 2.1 shows the proposed methodology to evaluate pitting CUI. As shown in Figure 2.1, the methodology involves modeling of three characteristics of the pit- pit density, pit initiation time and maximum pit depth- as a part of an overall methodology to estimate probability of failure and associated risk. The scope of this study includes the pit evaluation and maximum pit depth estimation as the main characteristics in pitting risk assessment. A review of related works and different steps of the proposed methodology are discussed in the subsequent sections.

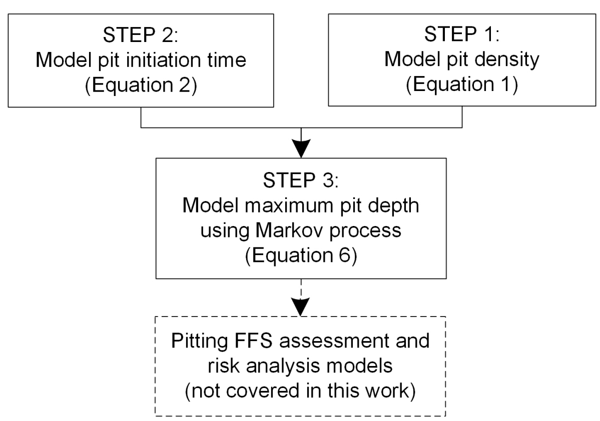


Figure 2.1. The methodology for evaluation of pitting CUI modeling

2.3.1. Step 1: Average Pit Density Modeling

2.3.1.1. Related Works

Pits randomly initiate on the surface of metal. The initiation rate varies due to different composition of alloys and changes in the environment. The number of pits per unit area of metal, referred to as pit density in this work, can be predicted from the average number of estimated pits over an area of interest.

Elola et al. [18] conducted field tests on aluminum alloy 1050 in different exposure times and presented a linear distribution with respect to time for the average pit density. However, Pride et al. [19] conducted tests on aluminum loop and concluded that pits generated rapidly at first but the generation rate slowed down with time and provide an exponential model for pit generation. In studies by Workman [20] and Zhao [21], a generalized average pit density model is presented, which combines the non-linear model in Pride et al. [19] with the linear model in Elola et al. [18] to determine the average pit density. In order to predict the pit density distribution Workman [20] and Zhao [21] integrate the non-homogenous Poisson distribution with their combined averaged pit density model to estimate the probability of specific number of pits in an area at a given time. Using this method, the inverse of the average pit density model is used to estimate the pit initiation times.

In another study, Nuhi et al. [22] investigate the effect of temperature and stress on pit density of API 5L samples. They observe that the average pit density follows a lognormal distribution, and they show logarithmic dependency of pit generation with temperature and time.

Datla et al. [23] introduce a probabilistic model of steam generator tube pitting corrosion based on inspection data from a nuclear generating station. They present a time-dependent model for the average pit density based on the non-homogeneous Poisson process.

Table 2.2 summarizes the models for pit density reviewed in this section.

Table 2.2. Pit density models

Reference(s)	Average pit density model	Remarks
Elola et al. [18]	Linear model	Based on lab experiments on aluminum alloy 1050.
Pride et al. [19]	Exponential model	Based on experiments on an aluminum loop.
Workman [20], Zhao [21]	Combination of linear and exponential model	Based on lab test data from the published literature.
Nuhi et al. [22]	Lognormal distribution	Based on experiments on API 5L carbon steel samples to consider the effect of temperature and stress.
Datla et al. [23]	Power law model	Based on inspection data from a nuclear power generation station.

2.3.1.2. Methodology for Modeling Pit Density

In this section, a methodology is presented to model pit density for insulated equipment. The rate of pit initiation varies with the corrosive environment and the type of material considered and therefore must be considered as a random phenomenon [9]. To tackle the problem of random generation of pits under insulation, application of a non-homogeneous Poisson model is identified as a suitable approach to model pit density distribution. When selecting the intensity function and estimating the mean of non-homogeneous Poisson model in insulated equipment, the material properties, environmental conditions, process and operational conditions, and other factors such as the effect of insulation and coating should be considered.

The model presented by Workman [20] and Zhao [21] is used in this work to estimate average pit density (APD) as it has the ability to represent both linear and non-linear behaviors:

$$APD(t) = \frac{A}{\psi}\left[1 - e^{-\psi t}\right] + wt^{\eta} \tag{2.1}$$

where A, w, ψ, and η are the parameters that could depend on time, allowing for changes in environmental conditions to be considered and t is time [20]. These parameters make the model adaptable to consider the parameters affecting the potentially complex pit generation mechanism in insulated equipment.

Failure history analysis from similar processes and the expert's knowledge can be used to estimate the starting value of the model parameters. Data analysis of accelerated corrosion test results for pitting corrosion in marine environment, recently proposed by Caines et al. [24], can also be used to estimate the model's parameters. The Bayesian approach can be used to update the model parameters as new evidence from the inspection data and failure records become available. This is an interesting subject for future research.

2.3.2. Step 2: Pit Generation Modeling

2.3.2.1. Related Works

A pit initiates due to a local breakdown of the passivation layer or coating on a metal's surface. The pit generation on the metal surface can be considered as a random phenomenon [20]. In real life problems pitting can be considered as a stochastic non-homogenous process since pit generation is not always constant over time. Mears and Brown [25] were among the first who used the Poisson distribution to model pit generation on the surface.

In a study by Tsukaue et al. [26], using experimental data, the pit initiation time is determied to be exponentially distributed. Based on these results, the stochastic pit generation phenmoena is considered to follow a homogeneous Poisson process and the pit generation is considered to have occured randomly in time with a constant generation rate.

Shibata and Suko [27] suggest analytical probabilistic models for pitting including a model based on exponential distribution for pit generation. They argue that the rate of pit generation and its re-passivation is a function of applied potential. In another study, Shibata [28] verifies this relationship by using experimental data and Monte Carlo simulations. Later, Shibata et al. [29] present two models for pit generation: pure birth stochastic models, which consider only pit generation events and birth and death stochastic models, which assume stochastic pit generation and subsequent pit re-passivation processes. They prove that the exponential model for pit generation may not be suitable as the second model, the birth and death stochastic model, is fitted better for experimental data from different case studies [30].

Valor et al. [31] use a non-homogeneous Poisson process to model pit initiation. Based on the experiments in [32], they conclude that the initiation rate is not uniform with respect to time and most pits are generated at beginning. In this way, Valor et al. [31] use two interpretations for the initiation time for each of m pits generated on the surface: the time of the first failure of each part of the system and the time of the first failure each of m non-homogeneous Poisson processes. They argue that in both cases, the Weibull distribution is the best distribution to simulate pit nucleation times. They conclude most pits generated at beginning.

In Workman [20] and Zhao's studies [20, 21], given that m pits initiate at time t by assuming all pits initiate in order at times $t_1, t_2, \ldots, t_m$, they obtain the initiation time t_k for each pit by calculating the inverse of the pit density function so that $t_k = APD^{-1}(k)$.

Table 2.3 summarizes the pit generation models, which are discussed in this section.

Table 2.3. Pit generation models

References	Pit generation model	Remarks
Tsukaue [26]	Exponential distribution	Based on experimental tests on 304 and 316 stainless steels in wet air.
Shibata and Suko [27]	Exponential distribution	Based on experimental tests on aluminum.
Shibata [29]	Empirical model	Based on experiments on stainless steels, zirconium, and titanium. Assumed pitting process as birth and death of pits and proposed models to consider stochastic pit generation and pit re-passivation.
Valor et al. [31]	Weibull distribution	Based on lab test data from the published literature, including [32].
Workman [20], Zhao [21]	Inverse of average pit density model	Based on lab test data from the published literature.

2.3.2.2. Methodology to Model Pit Generation

As can be clearly seen in Table 2.3, although there is a general agreement in all the models about the necessity of considering pit generation as stochastic processes by considering probability distributions for the pit generation models, different probabilistic methods are used throughout the literature. In fact, choosing a proper model is a case-specific task which requires consideration of the material properties, environmental conditions, process and operational conditions, and other factors such as internal (process side) pitting versus external pitting as well as the effect of insulation and coating.

Pit generation under insulation can be considered to follow a non-homogeneous Poisson process, as pit generation is not constant with time. Other models such as Weibull distribution assumes that most of pits are generated at early time, as a result it cannot be fit to experimental data as intuitively as the Poisson parameters can [20].

To estimate the initiation times of pits in insulated equipment, it is supposed *APD*(t) is the result of curve fitting equation (2.1) to a data set. If t is the desired stopping time of the model predictions and *APD* at time of t is m, by assuming all pits initiate in order at times $t_1, t_2, \ldots, t_m$, the pit birth times t_k for $k = 1, 2, \ldots, m$ are found by solving the equation $APD(t_k) = k$ [20, 21].

$$t_k = APD^{-1}(k) \qquad \text{, for } k = 1, 2, \ldots, m \tag{2.2}$$

As discussed in Step 1, expert knowledge estimates based on available literature and similar processes can be used as starting values for the model parameters. Then, analysis of inspection data and accelerated corrosion test data can be applied to revise the initial model parameters.

2.3.3. Step 3: Maximum Pit Depth Modeling

2.3.3.1. Related Works

In large-scale engineering structures, limited resources can make the measurement of pit depth un-affordable [30]. Thus, it is more practical to study only the deepest pits since it is the deepest pits that actually cause the system failure. As a result, most of the existing literature has focused on modeling the maximum pit depth using both deterministic and probabilistic methods [31, 33-35].

Modeling the depth of a corrosion pit requires understanding the corrosion growth rate. Traditionally, deterministic approaches have been used to model the pitting growth rate [10, 36, 37]. For example, Romanoff [37] presents pit growth with the use of a simple power law. However, the deterministic models are unable to handle variability and uncertainties associated with alloy composition, microstructure, temperature and non-homogeneity of the surrounding media [10]. The stochastic approach is, therefore, preferred due to its ability to represent the variability of the contributing factors in pit growth.

To model the maximum pit depth, the extreme value statistics developed by Gumbel [38] are widely used [39- 42]. Sheikh [43] modeled pitting corrosion as a time-dependent damage process by exponential or logarithmic pit growth. Time dependence of the maximum pit depth is characterized by random functions of time, either by a logarithmic law or exponential law. Weibull extreme value is also used to model the time-to-first-leak for the pipeline.

Shibata [39] reviews extreme value statistics and its application to the engineering area. In Shibata's study, extreme value distributions are used for evaluating the maximum depth of corrosion penetration and the minimum time for corrosion failure. The parameter estimation is accomplished using a minimum variance linear unbiased estimator (MVLUE) method.

More recently, based on inspection data from a nuclear generating station, a probabilistic model for pitting of steam generator tubes has been presented by Datla et al. [23]. Their model is based on inspection data of pits with a depth greater than 50% thickness. In this model, the distribution of the largest pit among all generated m pits in time interval $(0, t)$ is expressed using the generalized Pareto distribution.

Although conventional methods of the extreme value statistical theory have been used for a long time, they have some limitations. The first limitation of extreme value theory is the static nature of methods based on this theory as time variable is not involved [30]. Furthermore, methodologies based on extreme value theory assume that the pit process is homogenous. In other words, such models assume that pits occur with the same frequency in time, however, it has been demonstrated that pitting corrosion is a stochastic process mainly related to its initiation stage [44].

Recently, Melchers [34] studied the pitting corrosion of mild steel in a marine immersion environment and presented new field data. A multiphase phenomenological model was proposed for general pit depth as a function of period of exposure. Later he found that a bi-modal probability distribution might fit the data better. This finding casts doubts on the conventional use of extreme value theory in representing the uncertainty associated with maximum pit depth [45]. He suggested high dependence of maximum pit depth should be the major reason for such a contradiction.

Melchers [33] studied the pitting corrosion of mild steel in marine immersion environments. He proposed a multiphase model for pit depth as a function of exposure time. In a subsequent study [45], Melchers presented a bi-modal probability distribution for maximum pit depth. This result challenged the conventional use of extreme value theory in representing the uncertainty associated with maximum pit depth [30]. Melchers concluded that the reason for this inconsistency is that pit depths are highly inter-dependent. He further showed that it is not entirely appropriate to use the Gumbel distribution which is a conventional method to derive the extreme value statistics for maximum depth of pits in pitting corrosion [9]. The key issue is that the underlying population of pit depths typically used in this analysis is not homogeneous. Except for very short exposures, it consists of a bi-modal distribution [9].

In another study, Melchers [46] presents a distribution for long-term exposures of steel in seawater. It is argued that for long-term exposures of steel to seawater the pitting process changes with exposure time and eventually becomes controlled by the rate of bacterial metabolism. He concludes that the Fréchet extreme value distribution can be used as the candidate distribution for maximum pit depth.

One of the assumptions made for pitting corrosion is that it retains no memory of the past, so only the current state of the damage affects its future development [35]. This important characteristic allows pitting corrosion to be categorized as a Markov process, an alternative method from extreme value theory to model maximum pit depth. The discretization of the pit depth space in a finite or countable set of non-overlapping states makes pitting corrosion a good fit for Markov chain modeling [47]. The assumption of

Markov process is that the probability of a pit growing deeper only depends on its current state. This means that the probability calculation for maximum pit depth is not affected by previous states of a pit or its growth rate into its current state [20].

Provan and Rodrguez [48] are among the first who used the Markov stochastic to model pit depth growth. In their model, the thickness along with pit depth is divided into discrete, non-overlapping states and Kolmogorov's forward equations are used to represent the transition probabilities P_{ij} between damage states i and j:

$$\frac{dp_{ij\,(t)}}{dt} = \begin{cases} \lambda_{j-1}(t)\, p_{i,j-1}(t) - \lambda_j(t) p_{i,j}(t), j \geq i+1 \\ \lambda_i(t) p_{i,j}(t) \end{cases} \tag{2.3}$$

The main limitation of this model, according to Valor et al. [31], is that the results of this study are not reproducible and the physical meaning of the expression for $\lambda_j(t)$ are not discussed.

Morrison and Worthingham [49] also applied the Markov process to determine the reliability of high-pressure corroding pipelines. To calculate the probability distribution function of the load-resistance ratio, the space of the load-resistance ratio was divided into discrete states and the Kolmogorov's equations numerically solved. Hong [36] improved Morrison and Worthingham's study [49] by integrating the Poisson-distributed initiation model and Provan and Rodriguez's [48] Markov propagation model. In this non-homogeneous model, the Kolmogorov's equations were solved analytically to evaluate the probability transition matrix and the probability of failure. To derive the parameters of the model, the sum of the squared differences between the estimated and observed means of the maximum pit depths were minimized [31]. The main disadvantage of Hong's model is that the extreme distributions do not fit with the probability distribution of the maximum pit depth [31]. Moreover, the analytical solution of Hong's model was determined using constant growth rates for pit propagation. The problem, however, the pit growth rate from one depth to another is not always constant over time [20].

Valor et al. [31] improve Hong's [36] and Provan's [48] models by applying a non-constant growth rate. To determine the transition probability from the first state to any j_{th} state during a given time interval, Kolmogorov's equations are solved analytically. From this solution, on the assumption that a pit is in state 1 at time t = 0, Valor et al. [31] show that the probability that the pit depth is equal or less than state i after a time increment (t - t_k) is:

$$F(i, t - t_k) = 1 - \{1 - \exp[-\rho(t - t_k)]\}^i,\ i = 1, \ldots, n \tag{2.4}$$

where n is the total number of states in the Markov chain and t_k is the pit initiation time modeled by Weibull distribution. $\rho(t)$ is the number of transited states by a corrosion pit and is assumed to be a power function:

$$\rho(t) = \chi(t - t_k)^{\omega} \tag{2.5}$$

where χ has dimensions of distance over the ωth power of time and ω is less than one. Once the number of pits per unit area is determined, the cumulative distribution function of maximum pit depth for single pit determined from Equation (2.4) must be combined to estimate the distribution of the deepest pit, based on the assumption that pits nucleate and grow independently. In such a case, Valor et al. [31] propose a model to estimate the probability that the deepest pit is in a state less than or equal to a specific state at a given time.

Valor et al. [31] prove that their proposed model follows extreme value statistics theory, which validates the model by confirming that small samples of pit depths can be induced to predict larger areas of pit propagation. One of the limitations of the Valor et al.'s [31] model is its inability to model growth of metastable pitting [20]. However, it can be updated given the proper data.

In addition to the analytical solution for Kolmogorov's equations, some authors [20, 21, 50] present numerical solutions of Kolmogorov's equations in the Markov model. In Workman's study [20], the model used relies upon the non-homogeneous Markov chain system to describe the propagation of pit depths throughout a discretized set of states. Workman's study examines the flexibility of the model with respect to the probabilistic transition rates used in the Markov system. They consider factors such as the effect of cyclical changes, abrupt shifts in environmental parameters, and corrosivity in the expression of the transition rate of Markov process.

Table 2.4 summarizes the maximum pit depth models discussed in this approach.

Table 2.4. Maximum pit depth modeling methods

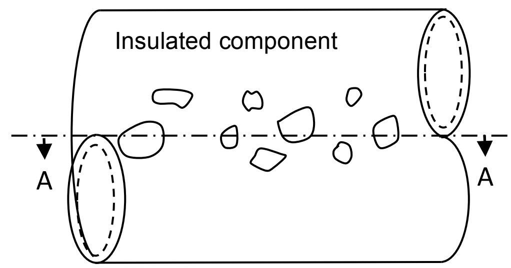
Reference	Maximum pit depth modeling approach	Remarks
Sheikh et al. [43]	Weibull distribution (Extreme value method)	Based on data from water injection pipeline systems and the published literature.
Datla et al. [23]	Generalized Pareto distribution (Extreme value method)	Based on inspection data of pits with a depth greater than 50% of thickness.
Melchers [45]	Bi-modal probability distribution	Based on experimental data on mild steel in marine immersion environment. Their lab results cause doubt in the suitability of Extreme value theory application for maximum pit depth modeling.
Melchers [46]	Fréchet extreme value distribution	Based on long-term exposures of steel in seawater in the presence of bacterial activity.
Provan and Rodrguez [48]	Markov process	Assuming pit mechanism as a memory less process. The model failed to provide a physical interpretation for Markov transition rate.
Hong [36]	Markov process	Based on analytical solution of Kolmogorov's forward equations using constant growth rates for pit propagation.
Valor et al. [31]	Markov process	Based on analytical solution of Kolmogorov's forward equations using non-constant growth rates for pit propagation.
Workman [20]	Markov process	Based on numerical solution of Kolmogorov's forward equations.

2.3.3.2. Methodology to model maximum pit depth

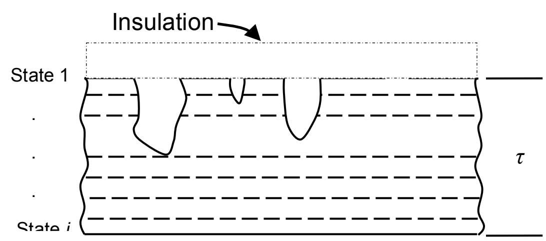
As shown in Table 2.4, the extreme value theory [46, 51] and the Markov process [20, 21, 31, 35], are two main approaches used in the literature to describe the growth of the maximum pit depth in pitting corrosion. Because of its stochastic nature, the Markov chain method is used in this study as the preferred approach to model the pitting mechanism in insulated equipment as a function of time. To model the maximum pit depth, by assuming the future growth rate is independent of its past growth, the time-dependent pit growth rate is assumed to follow a non-homogeneous Markov process. The analytical solution for Markov process proposed by Valor the transition rate for Markov process, as proposed by Valor et al. [31], has flexibility for a combination of affected factors on CUI pitting. In this study, Valor's model [35] is improved by using the average pit density in Equation (2.1). The pit density model proposed by Workman [20] and Zhao [21] is applied to estimate m, as it has the ability to represent both linear and non-linear behaviors. Initiation times also are estimated using Equation (2.2). Figure 2.2 provides a schematic representation of the Markov states in a cylindrical component. Accordingly, by combination of the cumulative distribution function of maximum pit depth for single pit (Equation (2.4)) and the average pit density (Equation (2.1)), the probability that the deepest pit is in a state less than or equal to state *i* at time *t* is estimated as:

$$\theta_H(i,t) = \prod_{k=1}^{m=APD} 1 - \{1 - \exp[-\rho(t - t_k)]\}^i. \tag{2.6}$$

where the number of pits (m) and initiation time (t_k) are determined from Steps 1 and 2, respectively. The number of transited states by a corrosion pit, $\rho(t)$, is assumed to be power function $\rho(t) = \chi(t - t_k)^{\omega}$. The parameters of the transition rate must reflect the environmental factors affecting the growth of pits on insulated equipment.



(a) A cylindrical component containing pits



(b) Section A-A

Figure 2.2. Schematic representation of maximum pit growth in an insulated component using Markov process

To show the applicability of the proposed model for representing maximum pit depth, an example data set previously published by Aziz [32] is used to test the model. The maximum pit depth in each coupon was measured using optical microscopy. In this experiment the maximum number of pits is considered 350 pits. Similar to Zhao's study [21], using the pit density model in Equation (2.1), the parameters for the model are chosen A = 18.320, ψ = 0.020, η = 1.000, and w = 0.

To model maximum pit depth, Equation (2.6) is curved to fit the data from Aziz's study [32]. The values of the resulting parameters for the analytical solution for the Markov process proposed by Valor [31] are χ = 0.940 and ω = 0.102. The wall thickness of the sample is discretized into 100 possible Markov states. A plot of the maximum pit depth data and proposed model for average maximum pit depth are displayed in Figure 2.3. As demonstrated, the model proposed in this paper, corresponds very closely with Aziz's experimental data.

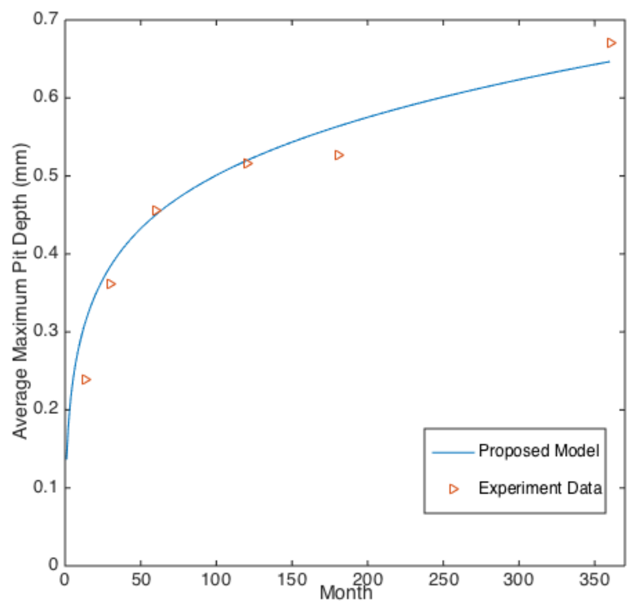


Figure 2.3. The estimated mean distributions and observed values of maximum pit depth reported by Aziz's pitting corrosion test [32]

2.4. Case Study

The practical application of the pit density and maximum pit depth models presented in Section 2.3 are demonstrated using a case study on the cylindrical shell section of a pressure vessel. The vessel was constructed to the ASME B&PV Code, Section VIII Division 1, 1986, and was newly installed on topside facilities of an offshore platform. The probability of internal corrosion is considered to be negligible due to the application of corrosion inhibitors and internal lining. However, external corrosion is expected as a result of marine conditions and trapped moisture under insulation. The vessel had no fabrication and/or corrosion defects at the installation time (t = 0). The vessel design information is shown in Table 2.5.

Table 2.5. Pressure vessel design information and basic assumptions

Description	Design Value
Material	SA − 516 Grade70 Year 1986
Internal Pressure	2.4 MPa
Inside Diameter	2.133 m
Wall Thickness	10 mm
Coating	Single coat epoxy
Insulation	Calcium silicate

Due to the difficulty in removing the insulation and remoteness of the facility, frequent periodic inspections to detect pitting corrosion are not feasible. Thus, the application of a predictive model for the pitting corrosion is required to determine the optimal inspection dates to ensure the safety and integrity of the vessel during service while considering the economical and operational constraints. To achieve this purpose the average pit density model and the probability of maximum pit depth evolving over time are estimated using Equations (2.1) and (2.6), respectively.

The model parameters and assumptions, which are shown in Table 2.6, are determined from the expert's knowledge, which is inevitable for new installations with no operational and inspection histories. As discussed in Section 2.3, these estimated model parameters can be updated over time.

Table 2.6. Parameters used to evaluate pitting corrosion in the case study

Characteristic	Equation	Parameter
Pit density	$APD(t) = \frac{A}{\psi}\left[1 - e^{-\psi t}\right] + wt^{\eta}$	$A = 35.00$, $\eta = 1$, $\psi = 0.09$ and $w = 0$
Number of transited states	$\rho(t) = \chi(t - t_k)^{\omega}$	$\chi = 4.20$ and $\omega = 0.09$
Maximum pit depth	$\theta_H(i,t) = \prod_{k=1}^{m=APD} 1 - \{1 - \exp[-\rho(t - t_k)]\}^{i}.$	$i = 1800$

2.4.1. Step 1: Average Pit Density

Figure 2.4 illustrates the average pit density for a period of 15 years, determined from the proposed methodology in Section 2.3.1.2 and Equation (2.1).

As can be seen in Figure 2.4, pits are generated right after the commissioning of the vessel and continue to increase in a relatively exponential order. As time passes, more pits are generated on the surface and the number of pits per unit area increase, those pits generated close to each other combine together and cause even bigger pits [19]. This decreasing rate in the average pit density over time has also been reported in several studies based on experimental data, as seen in [19].

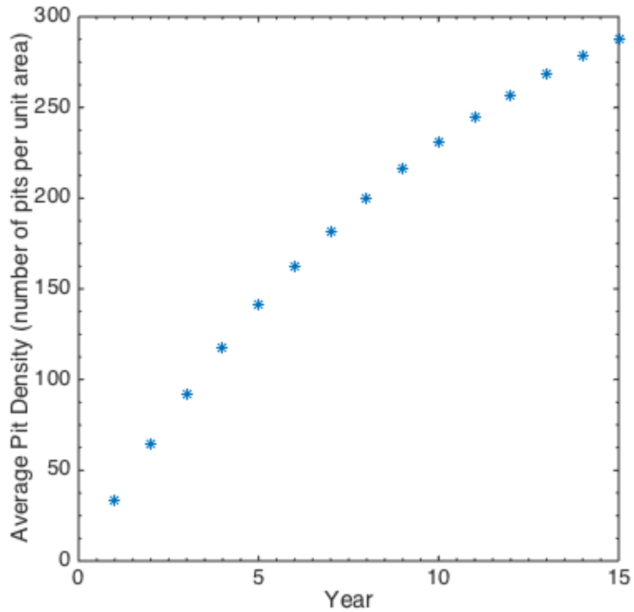


Figure 2.4. Average pit density for 15 years

2.4.2. Steps 2 and 3: Pit Generation and Maximum Pit Depth

The cumulative distribution function (CDF) of maximum pit depth and the probability density function (PDF) are determined using the methodology presented in Section 2.3.3 and Equation (2.6). As shown in Figure 2.5, the CDFs and PDFs shift to the right over time, this depicts the increase in the probability of deeper pits.

Maximum pit depth growth over a period of 15 years is shown in Figure 2.6, and is estimated using Equation (2.6). Considering the stochastic nature of pitting corrosion, one of the advantages of developing the probability distribution of the maximum pit depth is the ability to investigate the uncertainty involved in the model outputs. In Figure 2.6, both the mean and 95th percentile of the estimated maximum pit depth distribution are shown over time. Based on the conservatism of the study and sensitivity of the operation one can use the mean, 95th percentile, or any other statistic from the estimated maximum pit depth distribution.

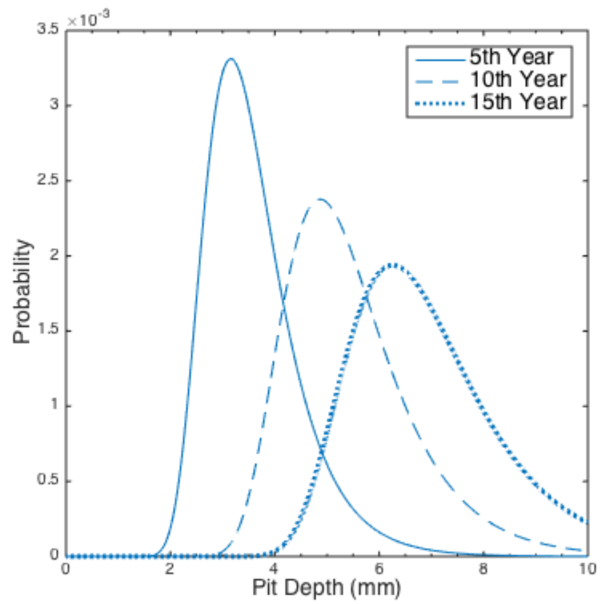


Figure 2.5. The probability density function of maximum pit depth in different years

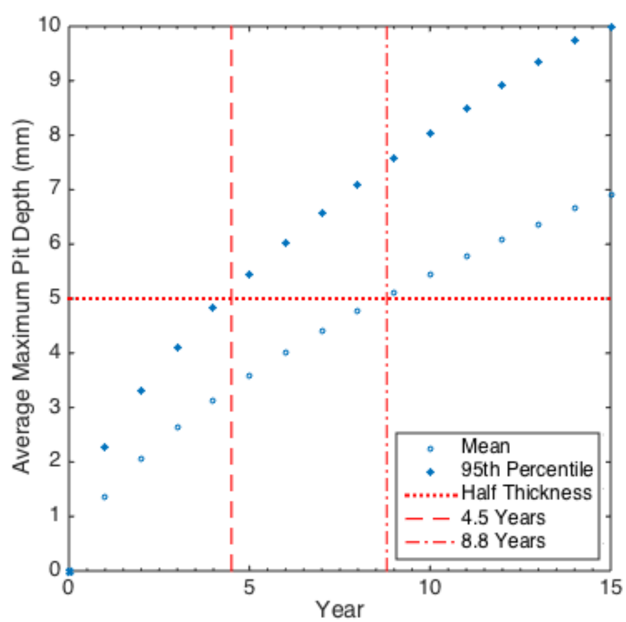


Figure 2.6. Maximum pit depth for 15 years

2.4.3. Sensitivity Analysis

2.4.3.1. Effect of APD

As different environments, coatings and insulations may cause different pit initiation rate affecting the average pit density, it can be useful to study the effect of uncertainty on estimated pit density on the mean maximum pit depth. As mentioned above, using different parameters the average pit density model in Equation (2.1), has the flexibility to consider different behaviors for pit initiation rates and hence pit density such as linear and exponential [21]. These results are shown in Table 2.7. The parameters for each model are determined using the assumption that after 10 years, the number of pits on the surface reaches 230 pits.

Table 2.7. Parameters for different APD models

Model	Parameter values in Equation (2.1)	Resulted equation
APD1	$A=0$, $\eta=1.00$, $\psi=1.00$ and $w=23.00$	$APD1(t) = wt$
$APD2$	$A=36.40$, $\eta=1.00$, $\psi=0.10$ and $w=0$	$APD2(t) = \frac{A}{\psi}\left[1 - e^{-\psi t}\right]$

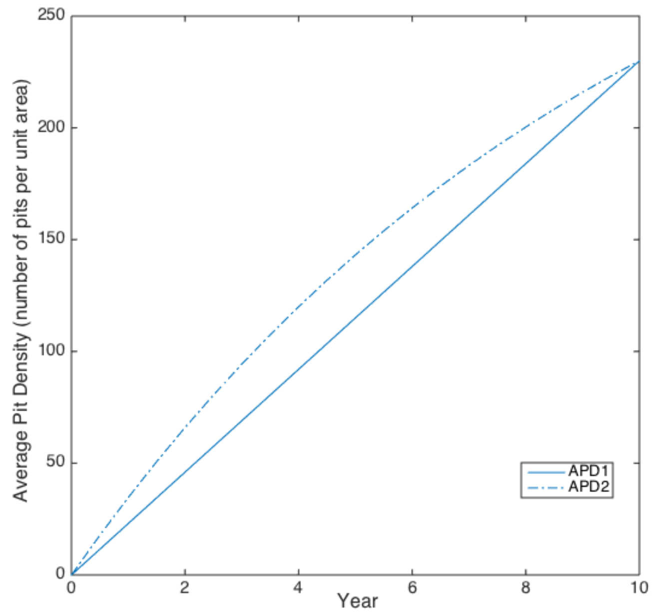


Figure 2.7. Average pit density models

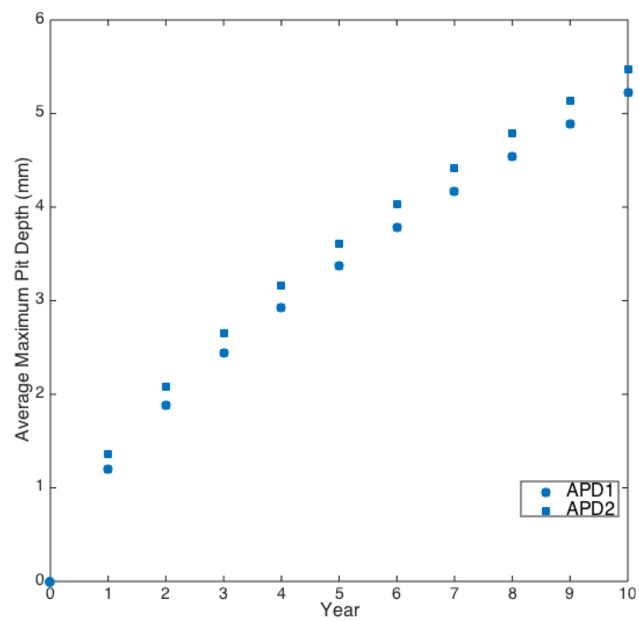


Figure 2.8. Average maximum pit depth for different APD models

As can be seen in Figure 2.7, the pits in model APD2 initiate quickly at an early time, and this can be used to represent aggressive environments. Thus, by changing the parameters, the average pit density model in Equation (2.1) has the flexibility to represent different environmental, coating and insulation conditions.

In Figure 2.8, APD2 model has the highest mean maximum pit depth in comparison with APD1 through the whole time since it has the faster pit initiation rate. As seen in Figure 2.8, although the variation of pit density does not affect significantly the maximum pit depth, the higher pit initiation rate results in deeper pit and faster pit growth rate.

2.4.3.2. Effect of Transited States' Parameters

A sensitivity analysis is also conducted to investigate the effect of changing the parameters of the ρ, number of transition states, on maximum pit depth. As was mentioned above, ρ has two parameters: χ and ω, which are less than one. In the first part of this sensitivity analysis, χ is assumed to be constant and ω has values $\omega = 0.09$, $\omega = 0.09 \times (1 \pm 5\%)$ and, $\omega = 0.09 \times (1 \pm 10\%)$.

In the second part, ω is assumed to be fixed and ρ has five different values, $\chi = 4.20$, $\chi = 4.20 \times (1 \pm 5\%)$ and $\chi = 4.20 \times (1 \pm 10\%)$, to see the effect of this parameter on maximum pit depth.

As shown in Figures 2.9 and 2.10, while increasing ω, the maximum pit depth variation is not significant, however, a slight change of χ causes a considerable difference for the mean maximum pit depth. In larger χ values, the pit growth is faster, but in greater ω values pit growth mostly remains the same. Thus, χ is the parameter that can be affected more in aggressive environments resulting in faster pit depth growth and higher probability of failure [21].

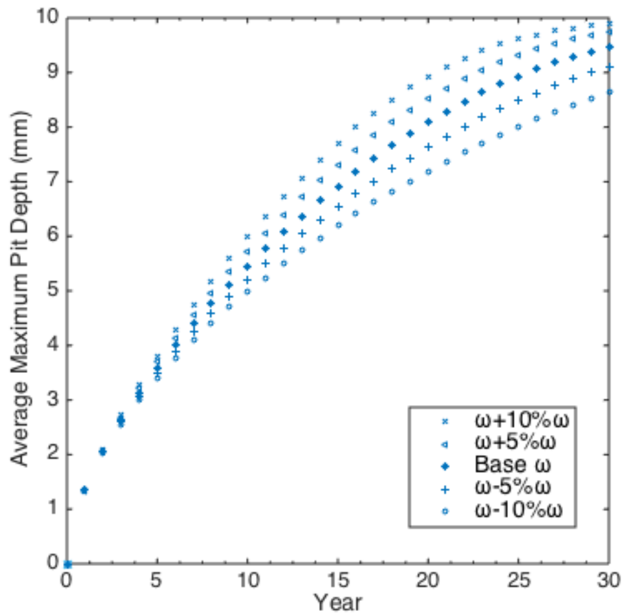


Figure 2.9. Mean Maximum Pit Depth in different values of *ω*

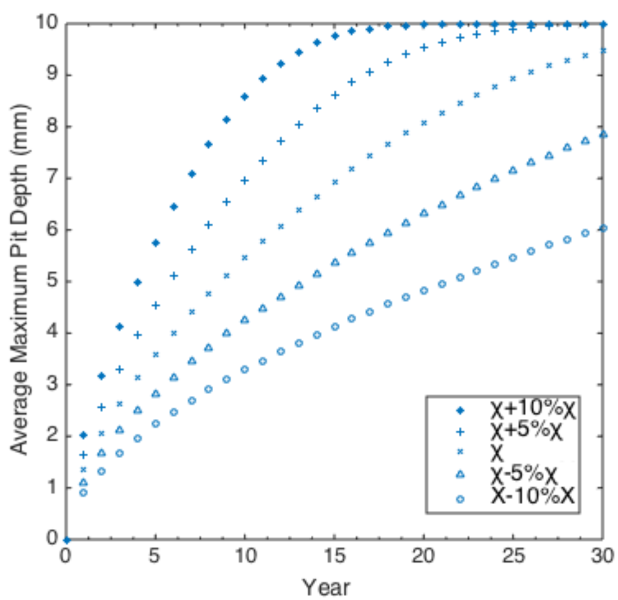


Figure 2.10. Mean Maximum Pit Depth in different values of χ

2.4.4. Potential Applications

The ability to predict pitting behavior is key to designing and maintaining assets in processing industries. As important equipment such as pressure vessels, piping, and storage tanks become older and maximum pit depth increases, the plant operator must decide if they can continue to operate safely and reliably enough to avoid injuries to personnel and to the public, environmental damage, and unexpected shutdowns.

As shown in Figure 2.6, using the proposed model, the maximum pit depth-over-time plots can be used for remaining life evaluation of insulated equipment susceptible to pitting corrosion. For example, according to API 510 [52], when the maximum pit depth exceeds half of the pressure vessel thickness, the damaged component should be repaired or replaced. As a result, the remaining life of the component and its failure time can be determined as the time when the maximum pit depth curve will intersect half of the component thickness. A methodology for remaining life assessment of equipment susceptible to pitting using probabilistic maximum pit depth models is proposed in Shekari et al [11]. Using the estimated remaining life, inspections can be made at proper time intervals to ensure that pitting damage is detected and mitigated before failure happens.

Fitness-for-service (FFS) assessment is another potential application of the presented pitting models. It can help engineers by: (i) Assessment of the current state of the (damaged) structure, and (ii) providing guidelines to make decision regarding running, rerating, repairing, or replacing aging pressure components and structures containing defects. As a result, developing a predictive FFS assessment for insulated equipment affected by pitting in future studies using the presented maximum pit depth can help to predict the failure time and make decisions about affected components [11].

Figure 2.11 is a schematic representation of the expected pitting damage predicted using the pit density and maximum pit depth model after 5 and 15 years. Actual pitting damage dimensions, determined using inspections, should be compared with the model predictions to verify the model results and adjust model parameters. As discussed above, integration of the presented models in this work with the Bayesian approach to revising model parameters using inspection data could be a subject for future research. For this purpose, the model parameter updating approach would deal with the pit generation and pit growth in a systematic way and their parameters will be revised using a Bayesian methodology.

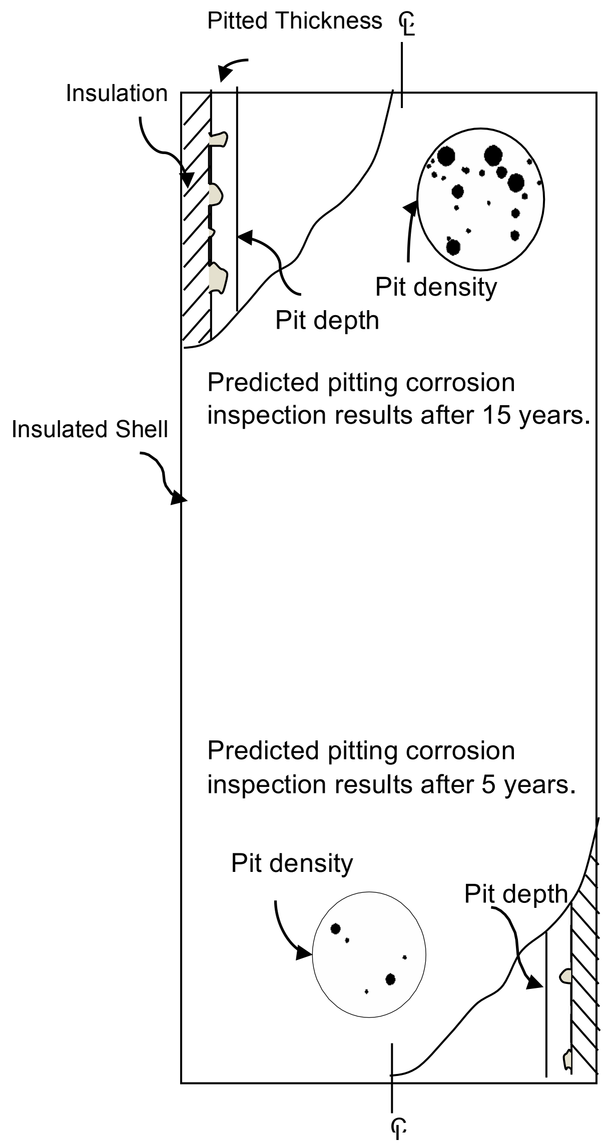


Figure 2.11. Schematic representation of the expected pitting damage after 5 and 15 years

2.5. Conclusions

Pitting corrosion in insulated equipment is a form of CUI that occurs stochastically in an extensive range of metals and environments. This paper provides a comparative study of the methods and models for different pit characteristics including pit initiation, pit growth rate, and maximum pit depth. Non-homogeneous Poisson process is found as a preferred approach to model pit generation under insulation as pits occur non-uniformly in time with variable generation rate. It is shown that the Markov process is an adequate method to model the dynamic nature of maximum pit depth over time. Moreover, for the case of pitting under insulation, the parameters and transition rate of the Markov model can illustrate the impact of the insulation and coating type. The practical application of the proposed models is demonstrated using a pressure vessel case study. The case study highlights the ability of the proposed methodology to track and predict pitting corrosion in insulated equipment, which is very difficult to inspect in real life problems, especially for the case of offshore facilities.

In future work, different aspects of coating and insulation impacts on the behavior of pitting corrosion should be further analyzed using experimental lab results. A risk assessment using the pit characteristic models will be developed to help engineers make decisions about pitting corrosion using the proposed models.

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3. A PREDICTIVE APPROACH TO FITNESS-FOR-SERVICE ASSESSMENT OF PITTING CORROSION[2]

Preface

A version of this manuscript has been published in the International Journal of Pressure Vessels and Piping. I am the primary author of this paper. Along with the co-authors, Faisal Khan and Salim Ahmed, I developed the conceptual model for Fitness-for-Service assessment of pitting corrosion. I carried out the literature review, case study, data collection and analysis. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback and also the peer review process. The co-author Faisal Khan helped in developing the concepts/models and their testing, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Salim Ahmed contributed through support in the development, testing and improvement of the model. Salim Ahmed also assisted in reviewing and revising the manuscript.

Abstract

Pitting corrosion is a localized corrosion that often causes leak and failure of process components. The aim of this work is to present a new fitness-for-service (FFS) assessment methodology for process equipment to track and predict pitting corrosion. In

[2] Shekari et al. International Journal of Pressure Vessels and Piping 2016; 137:13-21

this methodology, pit density is modeled using a non-homogenous Poisson process and induction time for pit initiation is simulated as the realization of a Weibull process. The non-homogenous Markov process is used to estimate maximum pit depth, considering that only the current state of the damage influences its future development. Subsequently, the distributions of the operating pressure and the estimated burst pressure of the defected component are integrated with Monte Carlo simulations and First Order Second Moment (FOSM) method to calculate the reliability index and probability of failure. This methodology provides a more realistic failure assessment and enables consideration of uncertainty associated with estimating pit characteristics. The practical application of the proposed model is demonstrated using a piping case study.

Keywords: Pitting corrosion; fitness-for-service (FFS) assessment; maximum pit depth; probability of failure.

3.1. Introduction

Pitting is defined as localized regions of metal loss that can be characterized by a pit diameter on the order of the plate thickness or less, and a pit depth that is less than the plate thickness [2]. Small pits can progress through wall thickness and lead to a loss of containment of process facilities. Pits may also act as initiation sites for stress corrosion cracks or affect the component strength, causing brittle failure [3].

The ability to predict pitting behavior, and any other damage mechanism, is key to designing and maintaining assets in process industries. Pitting corrosion can lead to catastrophic consequences in marine applications [3]. Design-code-focussed methods of structural analysis generally have specific (and usually tight) damage tolerances and their application for damage assessment during the operational life is likely to produce unduly conservative assessments [4]. Design codes do not provide rules to evaluate equipment that degrades while in-service, and deficiencies due to degradation or from original fabrication that may be found during subsequent inspections [2]. Fitness-for-service (FFS) assessment method has been developed in recent years to tackle this challenge by (i) assessment of the current state of the (damaged) structure, (ii) extrapolation from the current state to estimate the remaining safe and serviceable life [4], and (iii) providing guidelines to make run, rerate, repair, or replace decisions about ageing pressure components and structures containing defect. API 579-1/ASME FFS-1 [2] defines FFS as "quantitative engineering evaluations that are performed to demonstrate the structural integrity of an in-service component that may contain a flaw or damage."

The stochastic nature of the pitting corrosion has been recognized in the literature and several models have been presented to understand pitting in different material-environment combinations [3–6]. However, a comprehensive review of the literature shows that other than API 579-1/ASME FFS-1 [2], no other FFS assessment methodology has been proposed for pitting corrosion. This methodology is applied when pitting corrosion has been found during an inspection to help make decisions about the possibility of continued service of the damaged asset. However, estimating the pitting rate and its application in remaining life assessment of the attacked assets is not covered in API 579-1/ASME FFS-1. Overall, to the best of the authors' knowledge, there is no existing predictive FFS method to assess pitting corrosion.

Traditionally, the difficulty in choosing a suitable variable that can be measured quantitatively and treated mathematically has been the main challenge in the study of pitting corrosion [8]. Moreover, the model verification is another challenge for pitting study. From a practical point of view, the maximum pit depth (MPD) is usually used in pitting analysis since the deepest pit will cause the first perforation [4]. It is the depth of a pit that will affect the containment and structural integrity of pipes and other components in marine environments [3]. This is why much of the existing literature has focused on modeling the maximum pit depth [5,8–10]. The pit diameters and the distance among pits (i.e., the pit density) is another important characteristic of pitting corrosion that affects the stress distribution and load capacity of a component. It is recognized in this study that both MPD and pit density are time-dependent random variables. The importance of using a probabilistic analysis to address the uncertainty of MPD(t) and pit density, as well as the necessity of estimating the future pit progression rate, are recognized in API 579-1/ASME FFS-1, however, its methodology does not address these aspects.

In this paper, models are presented to estimate the distributions of MPD and average pit density (APD) as a function of time. Then, a methodology is provided to estimate the distribution of the future maximum allowable pressure for a component containing defects using the estimated MPD(t) and APD(t) through Monte Carlo simulations. The estimated maximum allowable pressure and the operating pressure of the component are then used to develop the performance function and estimate the failure probability. In Section 3.3.3, determination of the maximum pit depth and pit density are discussed, and the proposed FFS method is presented. A case study is used in Section 3.3.4 to demonstrate the application of the method.

3.2. Overview of FFS Methodologies

Worldwide regulatory requirements entail that the FFS assessment must be based on recognized and generally accepted good engineering practices. Research conducted and knowledge gained during the past years have led to the formulation of international standards and procedures for conducting FFS assessments. Table 3.1 provides a list of major FFS procedures along with the addressed failure mechanisms and related industry sector.

Table 3.1. Comparison of major FFS procedures

				Failure/damage mechanisms addressed								
Procedure	Reference	Status	Industry sector	Pitting	Pitting (growth rate)	Fracture	Fatigue	Creep rupture	Metal loss	Environment assisted cracking	Mechanical damages	Fire damage
BS 7910	[12]	UK national procedure, published by BSI	General	N†	N	Y	Y	Y	Y	Y	Y	N
API 579-1/ASME FFS-1	[2]	Joint API/ASME standard	Downstream oil and gas facilities	Y	N	Y	Y	Y	Y	Y	Y	Y
FITNET	[13]	European document, superseded by BS 7910:2013	General	N	N	Y	Y	Y	Y	Y	Y	N
SINTAP	[14]	European document, superseded by FITNET	General	N	N	Y	Y	Y	Y	Y	N	N
B31.G	[15]	ASME Standard	Pipeline transportation	N	N	N	N	N	Y	N	Y	N
R5	[16]	Maintained by the UK nuclear industry	General	N	N	Y	Y	Y	N	N	N	N
R6	[17]	Maintained by the UK nuclear industry	General	N	N	Y	Y	N	N	Y	N	N
RSE-M	[18]	French design code	Nuclear power	N	N	Y	Y	Y	N	N	N	N

† Note: N: No, Y: Yes.

As can be seen from Table 3.1, the API 579-1/ASME FFS-1 is the only one that specifically addresses FFS assessment of pitting corrosion. API 579-1/ASME FFS-1 includes two levels of FFS assessment for pitting corrosion. In level 1 assessment, observed pit damages are classified by using standard pit charts and wall thickness ratio to determine the associated remaining strength factor (RSF). Then, the actual RSF is compared with the allowable RSF to qualify the attacked asset for continued service. Level 2 assessment provides a better estimate of RSF for pitting damage in a component subject to pressure and supplemental loadings. For this purpose, a representative site is chosen for stress analysis and then procedure accounts for the orientation of the pit-couple with respect to the maximum stress direction. In API 579-1/ASME FFS-1, the FFS assessment is based on known pitting damages and the procedure cannot be used for predictive FFS assessment and estimation of pitting progression rate. Moreover, the uncertainty in input data, such as pit depth and pit density, are not taken into consideration.

3.3. The FFS Assessment Methodology

Figure 3.1 shows the flow chart of the proposed methodology for the evaluation procedure of components with pitting. The details of the assessment procedure are provided in the following sections.

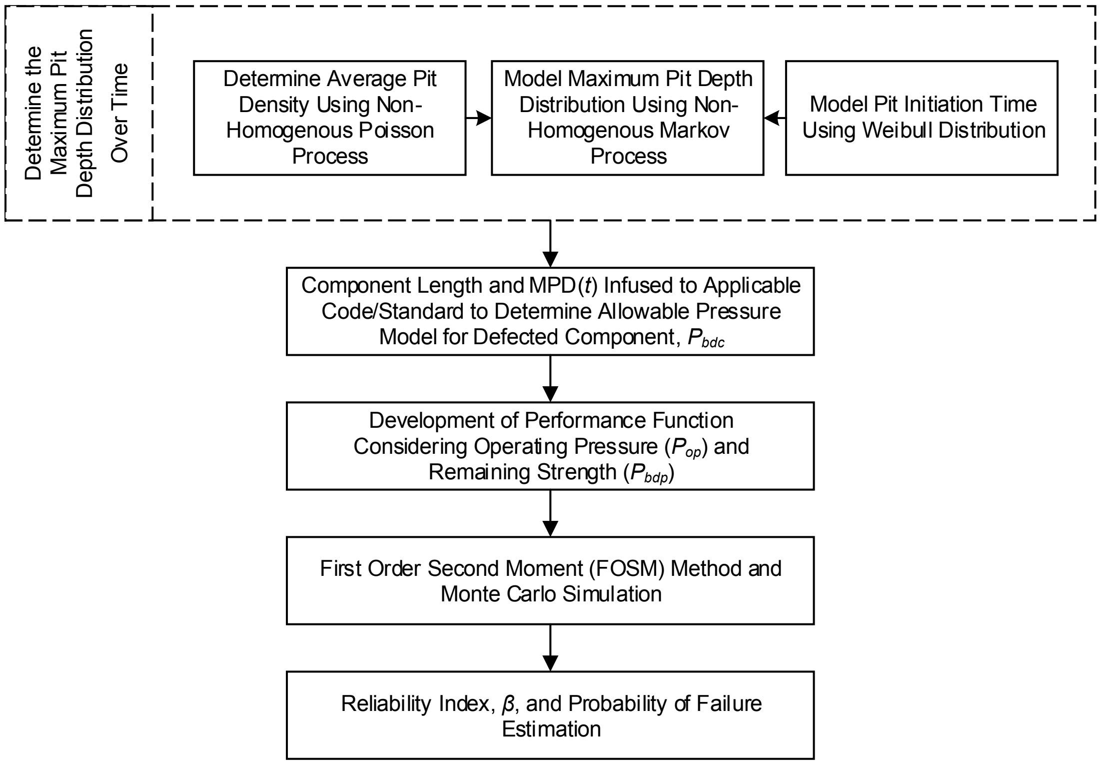


Figure 3.1. The predictive FFS assessment methodology

3.3.1. Maximum Pit Depth Model

The extreme value theory [4,17,18] and the Markov process [5,10,19,20] are two main approaches used in the literature to describe the maximum pit depth distribution in pitting corrosion. Because of its stochastic nature, the Markov chain method serves as an excellent approach to model the progression of corrosion [23] by considering pitting mechanism to be time and depth dependent. A Markov process assumes that the pit depth is examined at different time intervals, and that the depth in a future time interval relies only on the depth at the present time [21]. A review of the application of Markov process in modelling of pitting corrosion and the comparison of different pit models can be found in Workman [22] and Zhao [21]. The predictive FFS method presented in this work is built upon the pit growth (Markov chain) and pit initiation model suggested by Hong [7] and Valor et al. [6] to track and predict the maximum pit depth. To generalize the model presented by Valor et al. [6], a non-homogeneous Poisson distribution is used to determine the pit density. Then, the expected value of the future generated pits is combined with the maximum pit depth model to determine the probability distribution of the depth of deepest pit.

For a single pit generated at time t, a non-homogeneous Markov process is used to model the of pit depth over time. As shown in Figure 3.2, the material thickness is discretized in non-overlapping intervals Δd, which correspond to the n possible Markov states i (i =1, ..., n). For example, a pit in state i has a depth between $(i-1)\times\Delta d$ and $i\times\Delta d$. On the assumption that a pit is in state 1 at time t = 0, Valor et al. [6] showed that the probability that the pit depth is equal to or less than state i after a time increment (t - t_k) is as follows:

$$F(i,t-t_k)=1-\left\{1-\exp\left[-\rho(t-t_k)\right]\right\}^i, \quad i=1,...,n \tag{3.1}$$

where n is the total number of states in the Markov chain and t_k is the pit initiation time. The number of transited states by a corrosion pit, or the pit depth, is denoted by $\rho(t)$ and is assumed to follow a power function:

$$\rho(t)=\chi(t-t_k)^{\omega} \tag{3.2}$$

where χ has dimensions of distance over the ωth power of time and ω is less than 1.0. Derivation of Equation (3.1) can be found in Valor et al. [6] and is skipped here to avoid repetition. In Equation (3.1), the pit initiation time (t_k) is considered to follow a Weibull distribution with shape parameter v and scale parameter ε:

$$F(t_k) = 1 - \exp[-(t_k / \varepsilon)^v] . \tag{3.3}$$

Equation (3.3) reduces to the exponential distribution when $v = 1$, representing pit initiation with constant occurrence time, or can represent more complex time-to-failure by changing v.

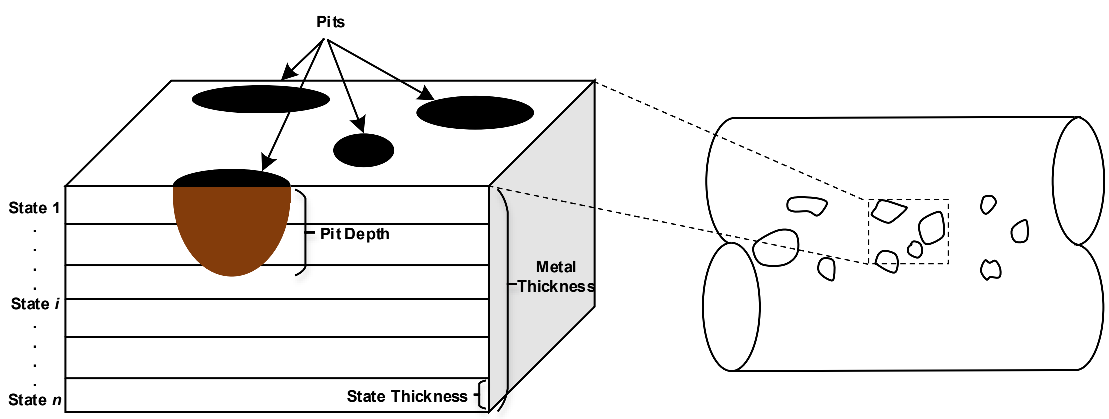


Figure 3.2. The states of a Markov process for pitting on a metal surface

Equation (3.1) is used to predict the probability that the maximum damage state is less than or equal to a given value for a time increment when multiple pits are considered, and each one of them is nucleated at a different time t_k. When m pits are generated at different times t_k, Equation (3.1) holds for each one of them.

Elola et al. [24] showed that pit density can follow a linear distribution with time, using field tests on 1050 aluminum. However, Pride et al. [25] showed that during pitting corrosion tests on aluminum loop, the pits nucleated rapidly but the initiation rate slowed down with time. Combining models from Elola et al. [24] and Pride et al. [25], Zhao [21] and Workman [22] proposed the following generalized equation to determine the average pit density:

$$APD(t) = \frac{A}{\psi}\left[1 - e^{-\psi t}\right] + wt^{\eta} \tag{3.4}$$

where A, Ψ, w, and η are the parameters that could depend upon time, allowing for changes in environmental conditions to be considered [22]. The parameters should be chosen in a way to best reflect data from literature or historical data. In order to predict the pit density in the future, a non-homogenous Poisson distribution is used. Using Equation (3.4), the probability of m pits in an area at time t is estimated by

$$\Pr[m] = \frac{1}{m!}[-APD(t)]^{m}.\exp[-APD(t)], \tag{3.5}$$

It can be noted that the expected value of the Poisson distribution in Equation (3.5) is $APD(t)$, which is an important simplification made to the combined model.

Once the number of pits per area is determined, the cumulative distribution function of maximum pit depth for each single pit determined from Equation (3.1),

$F_k(i, t-t_k),\ k=1,...,m$, must be combined in order to estimate the distribution of the deepest pit, under the assumption that pits nucleate and grow independently. In such a case, Valor et al. [6] proposed that the probability that the deepest pit is in a state less than or equal to state *i*, at time *t*, can be estimated using the expression:

$$\theta_H(i,t) = \prod_{k=1}^{m} \{1-[1-\exp(-\rho(t-t_k))]^i\}. \tag{3.6}$$

The product of the expected value of Equation (3.6) and the thickness of each state gives the mean maximum pit depth. Mean *MPD* and the 95th percentile of the *MPD* distribution are used in the proposed FFS assessment methodology to determine the maximum allowable working pressure of the corroded component.

3.3.2. Allowable Pressure Model for Defected Component

The strength of process components deteriorate due to pitting corrosion, and they generally become weaker with increasing age. Hence, the remaining strength of the component is required to be estimated by adopting any suitable method. In this work, the burst pressure of the defected component (P_{corr}) is used as an indication of the reduced strength due to the presence of pitting corrosion. Hasan et al. [26] reviewed different burst pressure estimation models and provided some guidelines to choose the best model based on different factors such as component type, age, and type of service.

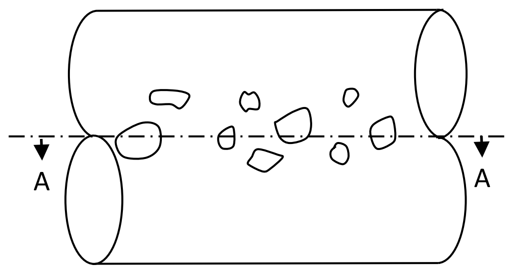
As an example, the P_{corr} model in DNV F-101 [27] for corroded pipelines is adopted in this work, where the effective equipment thickness is determined after subtracting the maximum pit depth from the original equipment thickness. To simplify the model, an idealized rectangle is considered as the equivalent of the defect profile related to pitting (see Figure 3.3). The P_{corr} for a component with pitting corrosion can be determined as follows:

$$P_{bdc}(t) = \gamma_m \frac{2\tau f_u (1-\gamma_d \left(MPD(t)/\tau\right)^*)}{(D-\tau)\left(1-\frac{\gamma_d \left(MPD(t)/\tau\right)^*}{Q}\right)} \tag{3.7}$$

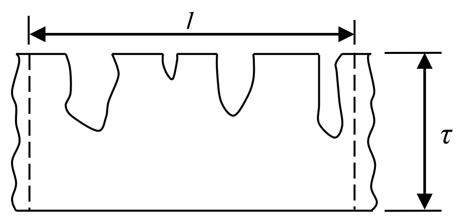
where $P_{corr}(t)$ is the burst pressure of the defected component as a function maximum pit depth over time, $Q=\sqrt{1+0.31\left(l/\sqrt{D\tau}\right)^2}$ and $\left(MPD(t)/\tau\right)^* = \left(MPD(t)/\tau\right) + \varepsilon_d StD\left[MPD(t)/\tau\right]$. If $\gamma_d \left(MPD(t)/\tau\right) \geq 1$, then the P_{corr} value should be considered as zero [27]. In Equation (3.7), the parameters are defined as follows: D is the outside diameter of the pipe; l is the length of the pitted area and is assumed to be the total length of the component (pipe segment) under analysis; γ_d is the partial safety factor for pit depth; ε_d is a factor for defining a fractile value for the pit depth; τ is the component thickness; f_u is the ultimate tensile strength; $MPD(t)$ is the time dependent maximum pit depth determined as the expected value, or 95th percentile, of Equation (3.6); γ_m is the partial safety factor for longitudinal corrosion model prediction;

and $StD[MPD/\tau]$ is the standard deviation of the random variable (MPD/τ). The values of γ_d, γ_m, and ε_d are provided in DNV RP-F101 [27]. It is important to point out that the partial safety factor, γ_d, as well as the ratio (MPD/τ), depend on the accuracy of the applied method of inspection. Thus, partial safety factors are given to account for uncertainties associated with the sizing of the defect depth and the material properties.

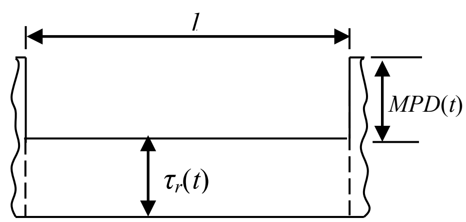
When using Equation (3.7), the component is considered to have sufficient material toughness. Temperature and/or process conditions that result in material embrittlement are discussed in API 579-1/ASME FFS-1 [2]. If there is uncertainty regarding the material embrittlement during operation due to temperature and/or the process environment, FFS assessment should also evaluate the brittle fracture, which is outside the scope of this study. Moreover, supplemental loads are assumed to be negligible and the component is considered to be subjected to internal pressure only with a uniform, through-wall stress distribution.



(a) A cylindrical component containing pits



(b) Section A-A



(c) The idealized rectangle considered as the equivalent of the defect profile

Figure 3.3. The rectangular projection of pitting

Once the maximum pit depth distribution is determined using Equation (3.6), the Monte Carlo simulation is integrated with Equation (3.7) to determine the distribution of the burst pressure of the defected component. Probability distributions can also be considered for other parameters of Equation (3.7), if available.

For other component types, such as pressure vessels and storage tanks, the P_{corr} models from applicable codes/standards and individual models can be adopted (similar to

Equation 3.7) by replacing the corroded thickness with the maximum pit depth. A listing of the P_{corr} formulations from different codes/standards can be found in Hasan et al. [26].

3.3.3. Probability of Failure

Based on the limit state analysis, the performance function of the corroded component is calculated using the $P_{corr}(t)$ and the operating pressure, P_{op}:

$$g(t) = P_{corr}(t) - P_{op}. \tag{3.8}$$

where $P_{corr}(t)$ is evaluated as burst pressure of the defected component. Operating pressure, P_{op}, can be characterized by a Gumbel distribution as per CSA Z662-07 [28] recommendation. $P_{corr}(t)$ is considered as the resistance and the P_{op} is considered as the load in the limit state function [26]. When $g(t)$ is less than zero, failure will happen.

Using the First Order Second Moment (FOSM) reliability method and the limit state equation, Equation (3.8), one can now determine the reliability index, β, as a function of time from load and resistance variables [26]:

$$\beta(t) = \frac{\mu_{P_{corr}(t)} - \mu_{P_{op}}}{\sqrt{\sigma^2_{P_{corr}}(t) - \sigma^2_{P_{op}}}} \tag{3.9}$$

Once the reliability index, β, is calculated, the failure probability (P_f) as a function of time can be calculated using Equation (3.10):

$$P_f(t)=\phi[-\beta(t)]=1-\phi[\beta(t)]. \quad (3.10)$$

The proposed approach provides an estimate of the probability of failure for the time of assessment or a time in the future.

3.3.4. Remaining Life Assessment

Figure 3.4 shows a schematic representation of *MPD* distribution in different time periods. As *MPD* increases, failure probability also increases due to reduced allowable pressure of the effected component. Accordingly, the remaining life can be determined from a plot of the burst pressure of the defected component, failure probability, or remaining thickness versus time. In this work, it is suggested that the component-remaining-life to be considered as the minimum of the remaining life determined from the following approaches:

i. According to API 579-1/ASME FFS-1 [2], the time at which the allowable pressure curve, $P_{corr}(t)$, intersects the design allowable pressure, P_d, is defined as the remaining life of the component. The design allowable pressure is to be determined from the component construction code.

ii. The remaining life can also be obtained as the intersection time of a threshold limit and the component failure probability determined from Equation (3.10). The minimum value of reliability index, β, in Equation (3.9) is assumed to be zero (it can be negative, but logically not correct), which corresponds to a highest failure probability of 0.5 for the limit state analysis [26]. Therefore, the threshold value of the failure probability can be considered as 0.5, or it can be selected based on expert knowledge.

iii. API 510, Pressure Vessel Inspection Code [29], API 570, Piping Inspection Code [30], and API 653, Storage Tank Inspection Standard [31], do not accept scatter pits during inspections if the remaining thickness below the pit is less than one-half the required thickness. They also have requirements for the length of the damaged area. Accordingly, the remaining life of the component can be determined as the time when the maximum pit depth curve (expected value of Equation 3.6) intersects half of the component thickness.

For a given equipment, the remaining life is taken as the smallest value of the remaining life determined from above criteria for individual components.

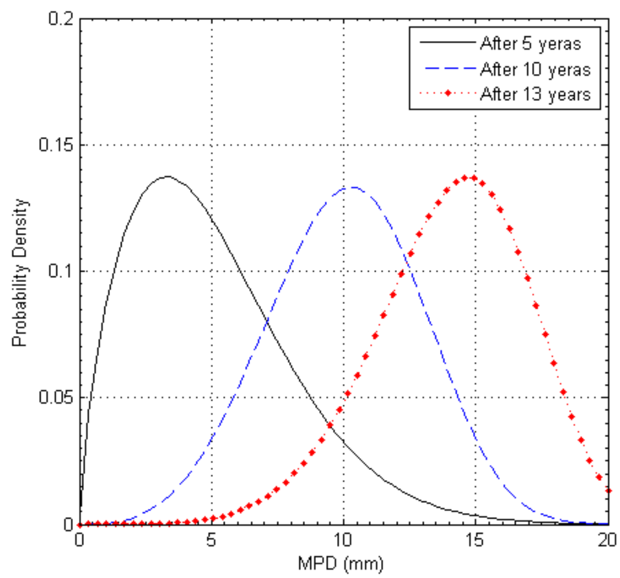


Figure 3.4. An example representation of shift in MPD distribution over time (numbers provided are for illustrative purposes only)

3.3.5. Decision Making

As a rule of thumb provided in inspection codes [25–27], inspection should be conducted, at maximum, half of the estimated component-remaining-life, unless a risk-based inspection (RBI) planning provides a different inspection date. Periodic inspections are critical to verify the maximum pit depths estimated by the model. Inspection results and in-service monitoring can also be used to qualify the assumption made to establish the remaining life [2] and to calibrate the model by adjusting the model parameters. The application of Bayesian approaches is a subject for further research to incorporate the inspection data and new evidence from the system to revise the model parameters.

If pits are found during an inspection, the associated allowable pressure, P_{corr}, and failure probability can be used by a FFS practitioner to make decisions about the possibility of continued service or the need for remediation (rerate, repair or replacement of the damaged component). In such cases, applicable alteration and repair codes and standards [25–27] should be followed.

3.4. Case study: Piping

3.4.1. Case Study Description

The practical application of the proposed model is demonstrated using a hypothetical piping case study. The pipe under study is considered as a newly installed cylindrical straight section of an insulated piping component on topside facilities of an offshore platform. The piping has no fabrication and/or corrosion defects at the installation time ($t = 0$). The section of the piping under study is away from major structural discontinuities (such as branches, supports, and girth welds). Therefore, there are no supplemental loads on this section of the piping.

Pitting corrosion is expected due to water trapping under insulation and reported pitting damage in similar services. Due to the difficulty in removing the insulation and remoteness of the facility, frequent periodic inspections to detect pitting corrosion are not feasible. Thus, the application of a predictive FFS assessment model for the pitting corrosion is required to ensure the safety and integrity of the piping during the service.

Based on the proposed methodology in Figure 3.1, application of the FFS model on this case study involves the following steps:

1. Estimating the average pit density over time using Equation (3.4) and the probability of maximum pit depth evolving over time using Equation (3.6).
2. Estimating the allowable pressure for the defected component (P_{corr}) based on Equation (3.7).
3. Determining the failure probability versus time (Equation 3.10).
4. Remaining life assessment using the guidelines in Section 3.3.4.

The description of parameters and their estimated values used in this case study are provided in Tables 3.2 and 3.3. The pipe thickness is discretized into 100 states of equal depth, Δd = 19.10×10^{-2} mm. For instance, a pit in state 1 has a depth between 0 and 19.10×10^{-2} mm, a pit in state 11 has a depth between 1.910 mm and 2.101 mm, and a pit in state 100 implies a perforated pipe shell.

The model parameters and assumptions are determined from expert knowledge and related literature [10,19,20], which is inevitable for new installations with no operational and inspection histories. However, as more information from the operation, inspection, and maintenance of the piping system become available over time, such data can be used to adjust the initial model parameters. Alternatively, the data from accelerated tests can be used to estimate the initial values of the model parameters. The design and implementation of accelerated pitting corrosion tests for insulated equipment operating in marine environments is discussed in Caines et al. [32].

Table 3.2. Parameters used for FFS assessment of piping case study

Symbol	Description	Estimated Value
n	Number of Morkovian states. The thickness is divided into n layers to develop the Markov model.	100
A	Parameter for pit density in Equation (3.4)	18.3192
η	Parameter for pit density in Equation (3.4)	1
ψ	Parameter for pit density in Equation (3.4)	0.0596
w	Parameter for pit density in Equation (3.4)	0
v	Shape parameter in Weibull distribution in Equation (3.3)	4.79
ε	Scale parameter in Weibull distribution in Equation (3.3)	17.27
χ	Parameter in transited states equation of Markov process in Equation (3.2)	0.9152
ω	Parameter in transited states equation of Markov process in Equation (3.2)	0.1069

Table 3.3. Probabilistic models of the basic variables of the pipe [22,29]

	Tensile strength	Thickness	Diameter	Operating Pressure	Length
Distribution Type	Normal	Normal	Normal	Gumbel	Length = 200 mm
Mean	Design tensile strength for API 5L X65 (530.9 N/mm^2)	Nominal thickness (19.10 mm)	Nominal diameter (812.8 mm)	1.05 $MAP^{\dagger}$ (15 bar)	-
Coefficient of Variation	0.01	0.03	0.01	0.03	-

† MAP: Maximum allowable pressure

3.4.2. Result and Discussion

Figures 5 and 6 show the average pit density and maximum pit depth over a period of 20 years. As can be seen from Figure 3.5, pits are generated immediately after commissioning of the piping and continue to increase exponentially. As shown in Figure

3.6, considering the stochastic nature of the pitting corrosion, one of the advantages of developing the probability distribution of the maximum pit depth is the ability to investigate the uncertainty involved in the model outputs. In Figure 3.6, both the mean and 95th percentile of the estimated maximum pit depth distribution are shown over time. Obviously, 95th percentile values provide more conservative estimate of the maximum pit depth and represent a worst-case scenario.

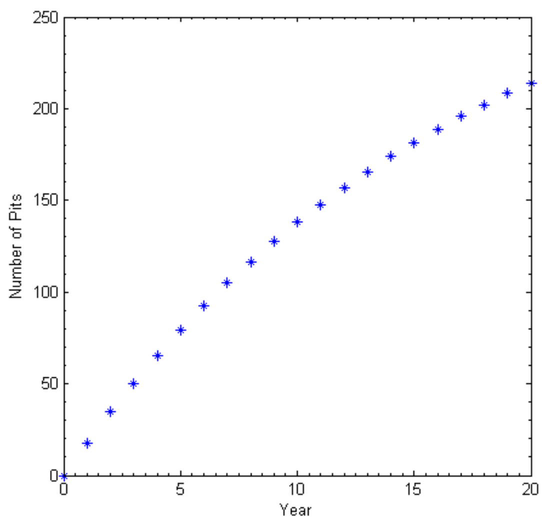


Figure 3.5. Number of pits over time

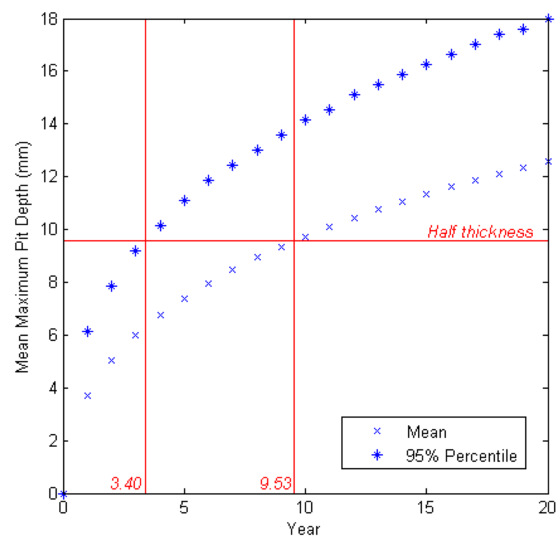
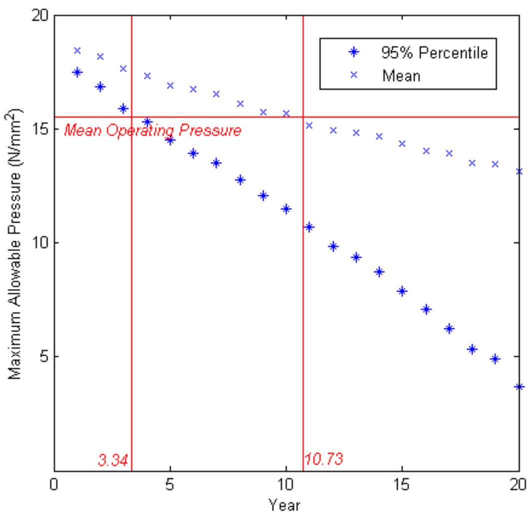


Figure 3.6. Maximum pit depth over time

The maximum allowable pressure values for the defected pipe (P_{corr}) over time are estimated using Equation (3.7) and the results are shown in Figure 3.7. As can be seen in Figure 3.7, as pits grow over time, the maximum allowable pressure of the defected pipe is decreased accordingly. Both mean and 95th percentile values of the maximum allowable pressure are shown in Figure 3.7 to account for the uncertainty.



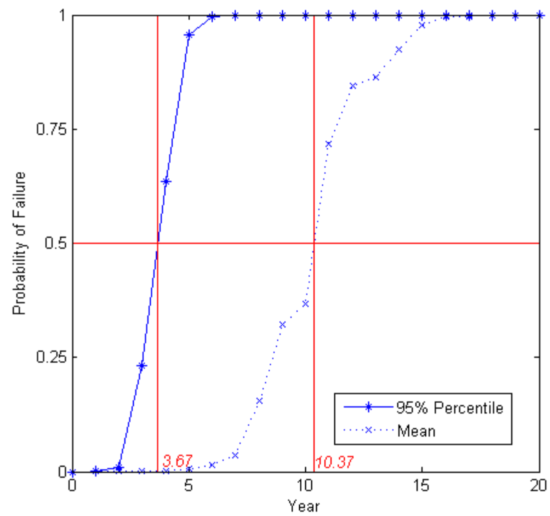


Figure 3.7. Maximum allowable pressure for the defected pipe over time

Figure 3.8. Probability of failure of the defected pipe over time

The estimated maximum allowable pressure and the operating pressure are then used to estimate the reliability index according to the performance function provided in Equation (3.9). Finally, the failure probability as a function of time is estimated using Equation (3.10). The mean and 95th percentile of the estimated failure probability over time are shown in Figure 3.8. These statistics, along with the three criteria introduced in Section 3.3.4, are used to evaluate the remaining life of the pipe:

i. Considering the intersection of the maximum pit depth curve and the half thickness of the pipe as the estimated life, Figure 3.6 shows the estimated remaining life of the pipe. Using the mean and the 95th percentile of the maximum pit depth values, the remaining life of the pipe is estimated as 9.53 and 3.40 years, respectively.

ii. Figure 3.7 shows the estimated remaining life of the pipe, determined as a point of time when the maximum allowable pressure of the defected pipe intersects the operating pressure. Using the mean and the 95th percentile of the maximum, the remaining life is estimated as 10.73 and 3.34 years, respectively.

iii. Considering the failure probability of 50% as the threshold limit, Figure 3.8 shows the remaining life using the mean and the 95th percentile of the failure probability curve, which are 10.37 and 3.67 years, respectively.

Table 3.4 summarizes the estimated remaining life values using different criteria. As discussed in Section 3.3.4, the remaining life can be considered as the minimum of the values estimated from the above three criteria. Therefore, the remaining life for the pipe using the mean and 95th percentile statistics is determined as 9.53 and 3.34 years, respectively.

Table 3.4. Estimated remaining life values for the piping case study

	Criterion Used			**Minimum of All Criteria**
	MPD	**MAP**	**POF**	
Remaining Life (years) Using 95th Percentile	3.40	3.34	3.67	3.34
Remaining Life (years) Using Mean	9.53	10.73	10.37	9.53

MPD: Maximum Pit Depth; MAP: Maximum Allowable Pressure; POF: Probability of Failure

Based on the quality and quantity of the data available and the severity and sensitivity of the service, an FFS practitioner may use the estimated remaining life based on other statistics besides the mean and 95th percentile. Having estimated the remaining life values, as discussed in Section 3.3.5, inspection using a proper technique should be done, at maximum, half of the estimated remaining life to verify the maximum pit depth values estimated using the model. Alternatively, risk-based inspection (RBI) can be performed to determine the inspection schedules.

3.5. Conclusions

A new predictive FFS assessment for pitting corrosion is proposed, which uses pit density, maximum pit depth, and maximum allowable pressure of defected component to predict the failure time due to pitting corrosion. The model relies upon a non-homogenous Markov chain system in order to describe the propagation of pit depths throughout a discretized set of states. Then, the burst pressure of the defected component is calculated by adopting the maximum allowable pressure models and using the estimated maximum pit depths. The burst pressure and operating pressure are then used to develop the limit state equation (performance function). Using FOSM, the reliability index is then calculated based on the burst pressure and operating pressure variables and used to determine the probability of failure.

The methodology is implemented on a piping case study where mean and 95th percentile of the maximum pit depth and failure probability are used to determine the remaining life of the defected pipe. The results of the case study show the importance of choosing the remaining thickness and failure probability threshold limits when evaluating the remaining life. Moreover, the case study highlights the importance of implementing periodic inspections to verify the estimated maximum pit depths and to adjust the model parameters. Some guidelines and criteria are provided to choose threshold limits and estimate the remaining life and inspection schedules of the defected component.

The purpose of the presented methodology is to track and predict pitting corrosion for places with restricted availability to implement frequent inspections, such as offshore process facilities. In such facilities, however, piping and equipment are usually insulated to conserve energy and protect components. The existence of insulation adds an extra level of complexity to the model. Thus, to improve the flexibility of the presented FFS approach, model modification will be conducted in a future work to consider the type, condition and maintenance quality of the insulations. Application of Bayesian approaches is also a subject for further research to incorporate the inspection data and new evidence from the system to revise the model parameters. Moreover, the model will be extended into a risk-based approach to consider both the probability and consequences of pitting corrosion in FFS assessments.

3.6. References

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4. DYNAMIC PROBABILISTIC ASSESSMENT OF PITTING CORROSION USING BAYESIAN ANALYSIS[3]

Preface

A version of this manuscript has been submitted to the Engineering Failure Analysis journal. I am the primary author of this paper. Along with the co-authors, Faisal Khan and Salim Ahmed, I developed the conceptual model. I conducted the literature review and proposed a methodology to conduct dynamic probabilistic analysis of pitting corrosion. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback. The co-author Faisal Khan helped in developing and testing the concepts/models, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Salim Ahmed contributed through support in the development, testing and improvement of the models. Salim Ahmed also assisted in reviewing and revising the manuscript.

Abstract

This paper presents a methodology to evaluate and update the remaining life of pressurized components that have been affected by pitting corrosion and subjected to inspection. The methodology incorporates the Non-homogeneous Markov process, which

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models the maximum pit depth, and a pressure resistance model to estimate the failure probability of affected components. To update the probability of failure and hence the remaining life of the pitted components, Bayesian updating is used. Markov Chain Monte Carlo (MCMC) simulation in conjunction with the Metropolis–Hastings (M–H) algorithm are employed to carry out the Bayesian updating. A case study involving a selected pipe of the gas condensate (GC) system in the North Sea is used to validate the proposed model and illustrate the application of the methodology. The results of the case study highlight the importance of the incorporation of inspection data using Bayesian analysis to update Markov model predictions over time.

4.1. Introduction

Pitting is a typical form of localized corrosion, which is prone to be very destructive due to its concentrated damage, with the potential to cause catastrophic failures [1]. Compared to periodic inspections, a potentially more viable and economical approach for controlling pitting corrosion is to predict the timing and severity of its effects [2]. This is especially useful for corrosive processes that are not easily accessible, such as those in remote operations and offshore facilities. Therefore, it is important to develop a methodology to predict pitting behaviour for remaining life evaluation and structural integrity assessment of process equipment. Moreover, utilizing the information from the inspection data to develop a realistic pit model is of great importance to the process industry.

The stochastic nature of pitting corrosion has been recognized in the literature and several models have been presented to understand pitting in different material-environment combinations [3–7]. The extreme value theory [3,8,9] and the Markov process [2,4,10,11] are two predominant approaches used in the literature to describe the maximum pit depth distribution in pitting corrosion. In an earlier work by authors [12], these methods were investigated and the Markov process was found to be the preferable approach to model the progression of corrosion because the pitting mechanism is considered to be time and depth dependent. More discussion on the advantages of using the Markov process in modeling pitting corrosion can be found in Shekari et al. [12].

More recently, Shekari et al. [13] presented a predictive remaining life evaluation method for a pitted area. They improved the non-homogenous Markov process from Valor et al. [11] to estimate maximum pit depth. Subsequently, they presented a time dependent equation for burst pressure and estimated the predictive failure probability of components affected by pitting corrosion [13]. The presented model in Shekari et al. [13] and most of the other models that apply the Markov process use either experimental data or expert knowledge to estimate model parameters, without the ability to revise the model parameters for a specific application. More specifically, none of these methods consider the effect of inspection data to update the maximum pit depth model and revise the estimated remaining life. However, it is important to incorporate inspection data for developing models to predict the pit growth rate and estimate maximum pit depth [14]. In addition, the Markov process suffers from some serious limitations such as lack of memory and lack of adaption of new evidence/data.

To address this challenge, the application of Bayesian analysis has been an active area of research to handle inspection data of different corrosion defects [15–21]. Bayesian analysis has received increased attention from industrial practitioners as it provides an updating mechanism to revise predictions provided by expert knowledge [20]. Zhang et al. [16] and Qin et al. [19] developed models for corrosion defect depth and updated the model parameters using the Bayesian framework. However, none of these methods are developed specifically to model pit characteristics such as the maximum pit depth, which is essential for evaluating the remaining life of components affected by pitting corrosion. In the context of pitting corrosion, for instance, Mao [22] presented a probabilistic model that considers the uncertainties of the in-service inspection. Mao's model utilizes a Markov Chain Monte Carlo (MCMC) simulation-based Bayesian method for estimating the model parameters. However, Mao considered a static pit density and maximum pit depth [22]. Therefore, there is still a need to develop a model that is able to simultaneously capture the time-dependent pit characteristics' behaviour and use inspection data to revise model parameters.

Considering the aforementioned need, the objective of the present study is to develop a holistic methodology to: (i) develop a probabilistic method for remaining life evaluation using maximum pit depth predictions; and (ii) update the remaining life estimates based on inspection data. The chief contribution of this study is to develop a hybrid method for pitting evaluation by integrating the Markov process with Bayesian analysis to provide a dynamic probabilistic framework while overcoming the major limitation of the Markov process, which is the lake of adaptation of new data to update model parameters. The proposed methodology in the next section has three parts. Part one includes a non-homogeneous Markov process to model the maximum pit depth. The second part uses Monte Carlo simulations to estimate the future maximum allowable pressure and probability of failure for the affected component using the estimated maximum pit depth (MPD) and average pit density (APD). Part three uses a Markov Chain Monte Carlo (MCMC) simulation to carry out the Bayesian updating to revise the Markov process model parameters using collected inspection data. Finally, a case study is provided to demonstrate the practical application of the method.

4.2. Methodology

Figure 4.1 shows the proposed three-step methodology for evaluating the components susceptible to pitting corrosion. As shown in Figure 4.1, the methodology starts with the estimation of the prior distribution of maximum pit depth (MPD) using the Markov process. In Step 2, MPD distribution is used to estimate the maximum allowable pressure, which is subsequently used to obtain the probability of failure and the remaining life of the component. Step 3 uses Bayesian analysis to estimate the posterior distribution of MPD by incorporating inspection data over time. The posterior MPD is then used to revise the probability of failure and the remaining life of the component. Details of each step are discussed in the following sections.

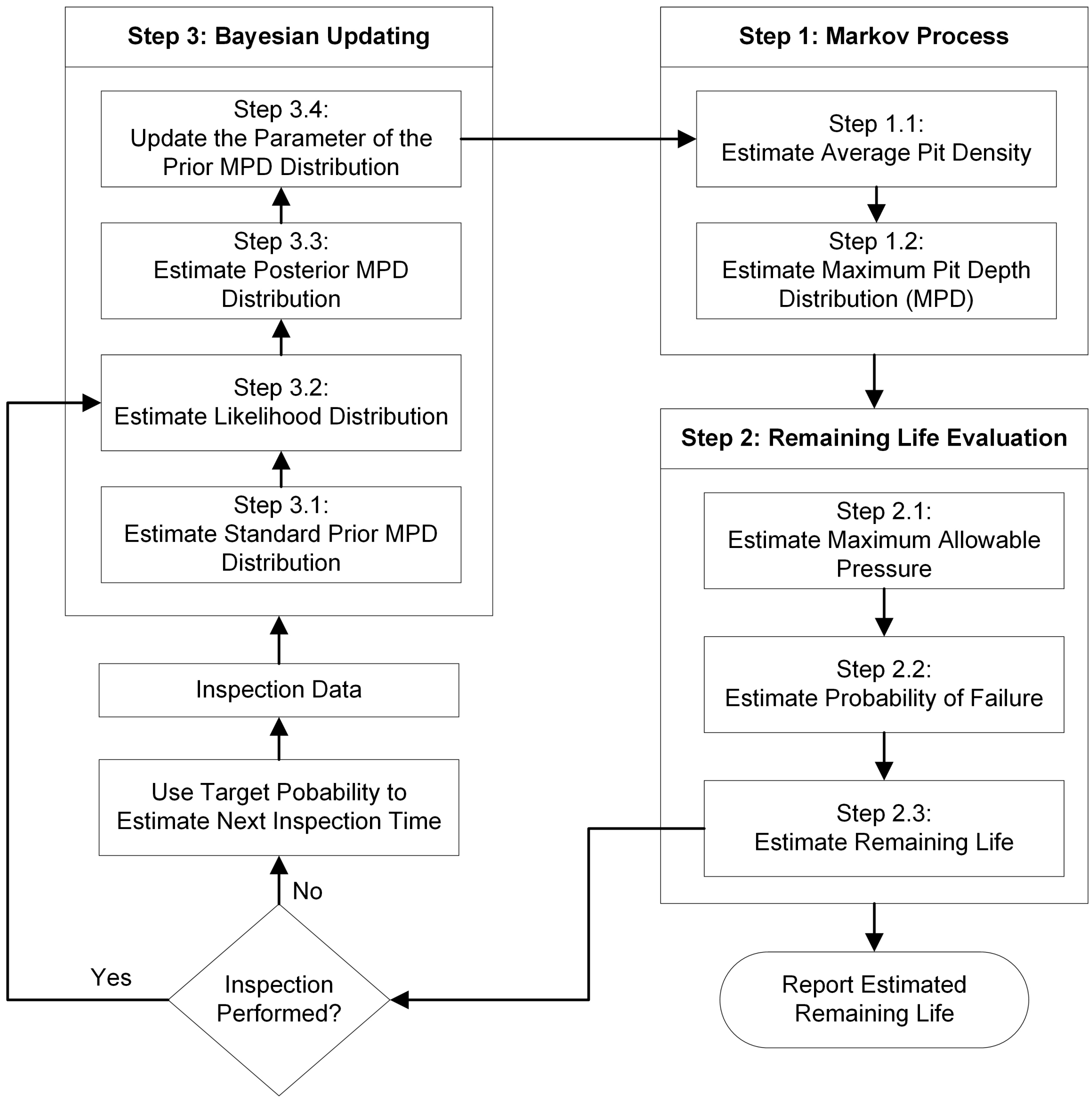

Figure 4.1. Proposed methodology for assessment of pitting corrosion

4.2.1. Step 1: Estimation of MPD Prior Distribution Using Markov process

4.2.1.1. Step 1.1: Average Pit Density

The number of pits per unit area of metal, referred to as average pit density (APD) in this work, can be predicted from the average number of estimated pits over an area of interest. A review of the pit density models is presented in Shekari et al. [12]. A combination of exponential and power models, proposed by Zhao [10] and Workman [2], is used in this work to determine the average pit density as it is flexible enough to represent potentially complex pit behaviours:

$$APD(t) = \frac{A}{\psi}\left[1 - e^{-\psi \mathrm{t}}\right] + wt^{\eta} \tag{4.1}$$

where A, w, ψ, and η are the model parameters. The distribution of pit density is considered to follow a non-homogenous Poisson process. Thus, using APD as the mean of the intensity function for the non-homogenous Poisson process, the distribution of pit density can be estimated by:

$$P\{APD(t_2) - APD(t_1) \ = \ N') = e^{-[\mathrm{APD}_{N'}]} \frac{[\mathrm{APD}_{N'}]^{N'}}{N'!} \ , \ N' \geq 0, t_2 > t_1 \tag{4.2}$$

where

$$APD_n = \int_{t2}^{t1} A\left[e^{-\psi \mathrm{t}}\right] + w\eta t^{\eta-1}\, dt \tag{4.3}$$

4.2.1.2. Step 1.2: Maximum Pit Depth Model

In this study, the maximum depth of pitting corrosion on a structure at time t (years), denoted by *MPD*(t), is characterized by a non-homogeneous Markov process, where $t = 0$ represents the installation time of the equipment [2,4,10,11]. A Markov process assumes that the pit depth is examined at different time intervals and that the depth in a future time interval relies only on the depth at the present time [10]. In this model, it is assumed that the pits initiate and grow independently, as pit depth dependency could only be assumed if the dissolution reactions that happen at one pit depend on what is taking place at other pitting sites. However, the stable pit growth process is affected by the autocatalytic reaction for the pit, where a low pH pit solution with a high concentration of Cl^- ions is required to sustain the pit growth [23].

Let $\Theta_i(i| X, \omega)$, $i = 1, \ldots, n$, denote the probabilities that the deepest pit is in a state less than or equal to state i, at time t, defined by X, dimensions of distance and ωth power of time. In fact, X and ω define $\rho(t)$, which is the number of transited states of corroded pit and is assumed to be a power function [4]:

$$\rho(t) = \chi(t - t_k)^{\omega}. \tag{4.4}$$

Then, the Cumulative Distribution Function (CDF) of the maximum pit depth can be estimated using the expression:

$$\theta_H(i, t|\chi, \omega) = \prod_{k=1}^{m}\{1 - [1 - \exp(-\rho(t - t_k)]^{i}\} \quad i = 1, \ldots, n \tag{4.5}$$

where t is the time of assessment (year), t_k is the initiation time of pits, n is the total number of states in the Markov chain, m is the average pit density (APD) at time of assessment and $\rho(t\text{-}t_k)$ is the number of transited states of a pit that grow in a short time interval (t_k, t). Equation (4.5) provides a predictive model that can be used to estimate the CDF of maximum pit depth in different years. The derivation of Equation (4.5) can be found in Valor et al. [4] and is omitted here to avoid repetition. Then, the probability distribution function can be estimated using:

$$f_i(i(t)|X, \omega) = \frac{d\theta_{H_i}}{di} \simeq \frac{\theta_{H_i} - \theta_{H_{i-1}}}{1}. \tag{4.6}$$

In this study, Valor's model [4] in Equation (4.5) is further developed by its integration with the average pit density model in Equation (4.2). By assuming all pits initiate in order at times t_1, t_2, ..., t_m, the initiation time t_k for each pit , k = 1, ..., m, can be estimated by calculating the inverse of the pit density [2,10]:

$$t_k = APD^{-1}(k), k = 1, \ldots, m. \tag{4.7}$$

4.2.2. Step 2: Remaining Life Evaluation

4.2.2.1. Step 2.1: Maximum Allowable Pressure

In this work, the maximum allowable pressure of the corroded component (P_{corr}) is used as an indication of the reduced strength due to the presence of pitting corrosion. Hasan et al. [24] reviewed different burst pressure estimation models such as CSA Z662-07 [25], AMSE B31G [26], the model of Netto et al. [27] and DNV F-101 [28] and provided guidelines to choose the best model based on different factors such as component type, age and type of service. Shekari et al. [13] adopted the P_{corr} model in DNV F-101 [28] for pitting corrosion in a pipeline and presented a time dependent modification of the model. This model is used in this work, where the effective equipment thickness is determined after subtracting the time-dependent maximum pit depth from the original equipment thickness. To simplify the model, an idealized rectangle is considered as the equivalent of the defect profile [13]. This conservative assumption simplifies the model by replacing the pitted area with a rectangle, where the length of the rectangle is the length of the pitted area and the width is the depth of the deepest pit. Accordingly, the P_{corr} for a component with pitting corrosion can be determined as follows:

$$P_{corr}(t) = \gamma_m \frac{2\tau f_u \left(1-\gamma_d \left(\frac{MPD(t)}{\tau}\right)^*\right)}{(D-\tau)\left(1-\frac{\gamma_d \left(\frac{MPD(t)}{\tau}\right)^*}{Q}\right)} \tag{4.8}$$

where P_{corr} (t) is the maximum allowable pressure of the defective component as a function of maximum pit depth, $Q=\sqrt{1+0.31\left(l/\sqrt{D\tau}\right)^2}$ and $\left(MPD(t)/\tau\right)^* = \left(MPD(t)/\tau\right) + \varepsilon_d StD\left[MPD(t)/\tau\right]$. If $\gamma_d\left(MPD(t)/\tau\right) \geq 1$, then the P_{corr} value should be considered as zero [28]. In Equation (4.8), the parameters are defined as follows: *MPD (t)* is the maximum pit depth determined as the expected value of maximum pit depth distribution using Equation (4.5); D is the outside diameter of the pipe; l is the length of the pitted area and is assumed to be the total length of the component (pipe segment) under analysis; γ_d is the partial safety factor for pit depth; ε_d is a factor for defining a fractile value for the pit depth; τ is the component thickness; f_u is the ultimate tensile strength; γ_m is the partial safety factor for longitudinal corrosion model prediction; and $StD[MPD/\tau]$ is the standard deviation of the random variable (MPD/τ). The values of γ_d, γ_m, and ε_d are provided in DNV RP-F101 [28].

4.2.2.2. Step 2.2: Probability of Failure

Different deterministic and probabilistic methods have been developed in the literature to predict the remaining strength and assess the reliability of equipment affected by corrosion [29]. As the traditional design code-focused deterministic methods are unable to predict the failure probability of corroded components at a given time, a probabilistic method based on the limit state function is used in this work to conduct the remaining life prediction and reliability assessment [29]. The method takes into account the uncertainty in the operating pressure and the uncertainties associated with the burst pressure.

In this work, the limit state function is defined as the difference between the maximum allowable pressure of the corroded component, P_{corr}, and the operating pressure (P_{op}):

$$Z(t) = P_{corr}(t) - P_{op}. \tag{4.9}$$

Operating pressure, P_{op}, can be characterized by a Gumbel distribution as in the CSA Z662-07 [25] recommendation and P_{corr} is estimated using Equation (4.8).

It is assumed that a component can work safely while $Z > 0$ ($P_{corr} > P_{op}$), and that a failure would occur if $Z \leq 0$ ($P_{corr} \leq P_{op}$). Therefore, the probability of failure can be equated with the probability that the failure pressure is equal to or lower than the operating pressure [30]. Then, the failure probability of corroded equipment can be expressed as:

$$P_f = probability\ (Z \leq 0) = \phi(-\beta) \tag{4.10}$$

where ϕ is the standardized normal distribution function and β is the reliability index. The reliability index β can be estimated from load and resistance variables using the First Order Second Moment (FOSM) reliability method and the limit state Equation (4.9):

$$\beta(t) = \frac{\mu_{P_{bdc}(t)} - \mu_{P_{op}}}{\sqrt{\sigma^2_{P_{bdc}(t)} + \sigma^2_{P_{op}}}}. \tag{4.11}$$

Note that the calculation of failure probability above is conducted under the assumption that individual pits are mutually independent. Although FOSM cannot take into account the probability distribution tail behaviour, it is used in this work because of its simple practical implementation.

4.2.2.3. Step 2.3: Remaining Life Estimation

Pit growth over time results in increased pit depth, which consequently increases the failure probability due to reduced allowable working pressure of the affected component. Table 4.1 summarizes three criteria that have been frequently used in the literature to estimate the remaining life of defective components.

Table 4.1. Remaining life criteria

Criterion	Description	Related works
Maximum allowable operating pressure	Maximum allowable operating pressure of the corroded equipment is estimated using a pressure resistance model	• API 579-1/ASME FFS-1 [31], uses the intersection of the maximum allowable pressure curve and the threshold value, which is operating pressure, to estimate the remaining life
Defect size	Defect size and the intact thickness of the equipment is used for decision-making	• Ossai [32] uses the time when the corroded wall thickness is in the range of 45% to 85% of the original wall thickness • API 510, Pressure Vessel Inspection Code [33], API 570, Piping Inspection Code [34], and API 653, Storage Tank Inspection Standard [35], use the time when remaining thickness below the pit is less than one half the required thickness. • DNV-F101 [28] uses the time until a defect reaches the acceptable measured defect depth curve by measuring corrosion rate mean with regard to burst limit state • Considering the effect of inspection accuracy for defect measurement and corrosion rate, DNV-F101 [28] uses the time until the first defect reaches the allowable defect size curve
Failure probability	Based on limit state analysis and FOSM reliability method	• Hasan et al. [24] and Shekari et al. [13], use the intersection time of predicted failure probability of 0.5 and the component failure probability • DNV-F101 [28] uses the time before the annual probability of failure exceeds the annual target failure probability

Application of any of the criteria in Table 4.1 could result in a different estimated remaining life. To address this challenge, in contrast to existing methods that usually use one of the criteria given in Table 4.1, this work uses all three criteria to estimate the residual life of corroded equipment. Then, the remaining life is considered as the minimum of estimated remaining life values using these criteria.

Inspection codes such as API 510 [33], API 570 [34], and API 653 [35], do not accept scatter pits during inspections if the remaining thickness below the pit is less than one-half of the required thickness. Consequently, using the defect size criterion in Table 4.1, this work considers the failure time as the time when the maximum pit depth curve (the expected value of Equation 4.5) intersects half of the component thickness. For the failure probability (the third criterion in Table 4.1), the minimum value of reliability index, β, in Equation (4.11) is assumed to be zero (it can be negative, but this is logically incorrect), which corresponds to a highest failure probability of 0.5 for the limit state analysis [24]. Therefore, the threshold value of the failure probability can be considered as 0.5. Any other threshold value can be selected based on the criticality of the operation and the input of expert knowledge.

Having selected the remaining life as the minimum of the remaining life values estimated from all three criteria, the maximum interval until the next inspection time is recommended to be half of the remaining life [36]. An appropriate inspection technique is recommended within this time interval to identify pitting corrosion [37].

4.2.3. Step 3: Bayesian Updating

4.2.3.1: Step 3.1. Developing a Standard MPD Distribution

The last step of the methodology applies Bayesian analysis to update the probability density function (PDF) of maximum pit depth (Equation 4.6), estimated in Step 1, using inspection data. However, the predicted prior distribution for maximum pit depth for each year is an empirical distribution, which cannot be directly used in Bayesian analysis due to its structural restrictions. To address this challenge, before implementing the Bayesian updating, a standard distribution is fitted to the predicted MPD distribution for the year that the inspection has been conducted. Then, using the adjusted Anderson-Darling (A-D) statistic, a goodness-of-fit test is performed and the best fit is selected as the one with the smallest A-D statistic. The best fitted distribution is considered as the revised prior MPD distribution.

4.2.3.2. Step 3.2: Likelihood Distribution

After each inspection, new data for maximum pit depth become available. This data is used in this step to estimate the likelihood probabilities of deteriorating components to update the prior distribution of maximum pit depth. The inspection data are subject to inspection measurement errors. The actual readings of pit depth from the inspection tool are subjected to measurement errors and hence, the measured pit depths are different from the actual pit depth. In this study, to address this concern, the measurement errors are assumed to be independent and modeled by Gaussian distribution with zero mean and known variance σ_E^2, where the standard deviation σ_E equals 0.05 [18]. Assuming that all of the pits are detected, a goodness-of-fit test using the probability plot and Anderson–Darling (A-D) test is then used to select the best distribution for inspection data.

For conciseness, this work only considers updating the MPD model parameters using pit depth inspection data. A similar approach can also be applied to update the parameters of the average pit density (APD) model using pit density inspection data.

4.2.3.3. Step 3.3: Posterior MPD Distribution

Using the prior distribution and likelihood distribution estimated in the previous steps, the posterior MPD distribution can be estimated using Bayes' rule [17]:

$$f''_{MPD}(MPD|MPD_0) = \frac{L(MPD_0|MPD)f'_{MPD}(MPD)}{f_{MPD_0}(MPD_0)} \tag{4.12}$$

where the denominator is known as the normalizing factor, $L(MPD_0|MPD)$ is likelihood, f'_{MPD} is the prior distribution, and f''_{MPD} is the posterior distribution. The posterior probability is the likelihood that a variable will be in a particular state, given the values of the input variables, the conditional probabilities and an associated set of rules governing how the probabilities are combined [17].

The traditional Bayesian updating approach, which assumes conjugate prior and likelihood distributions, is frequently used in many diverse applications, as the model is not highly data intensive. As conjugate priors lead to analytical solutions for the posterior distribution, this provides much computational ease and flexibility. However, because conjugate pairs are often unable to capture the realistic behaviour of the parameters [18], use of a traditional Bayesian approach (conjugate-likelihood pair) introduces significant errors. In this work, by applying the Markov process, the developed MPD prior distribution was observed to follow Type 1 Extreme Value distribution (Gumbel) [11]. Also, the likelihood distribution estimated in Step 2 follows one of the following distributions: Weibull, Lognormal or Type 1 Extreme Value distributions. As these prior and likelihood distributions are not conjugate pairs for application of traditional Bayesian analysis, an analytical close form solution of these distributions is not possible. Alternatively, methods based on numerical simulation should be used [38]. In this study, the Markov Chain Monte Carlo (MCMC) and Metropolis–Hasting (M–H) algorithm [39] are used to estimate posterior distribution for maximum pit depth.

The MCMC simulation is a technique to sequentially generate random samples from a complicated distribution (in this case, the posterior distribution) by constructing a Markov chain that converges to become the target distribution. The commonly used sampling algorithm in MCMC simulation is the Metropolis–Hasting (M–H) algorithm. The M-H algorithm is a rejection-sampling algorithm used to generate a sequence of samples following a probability distribution that is difficult to sample directly. More details about the MCMC and M-H methods can be found in [38]. In this work, a code is developed using MATLAB software [40] to implement the MCMC simulation and the M-H sampling algorithm in order to estimate the posterior MPD distribution for the assessment year.

4.2.3.4: Step 3.4: Updating Markov Transition Rate

In Step 3.3, only the MPD distribution of the current year of assessment has been updated. However, apart from the current year, the MPD distribution should be updated for future years to revise the remaining life evaluation. For this purpose, the proposed cumulative distribution function for MPD distribution based on the Markov process (Equation 4.5) is fitted to the posterior MPD distribution obtained in Step 3.3. For simplicity, only the parameter χ of the Markov transition rate is updated. Then, a search procedure based on the least squares method is applied to find the parameter χ of the fitted MPD distribution based on the Markov process (Equation 4.5). The new χ *can* be used to update the MPD distribution for the coming years.

Once the MPD distribution is updated, as shown in Figure 4.1, Step 2 should be repeated to estimate both the new maximum allowable pressure and the revised remaining life of the component. The entire procedure must be repeated after each new inspection is performed to update the MPD distribution using Bayesian analysis.

4.3. Case Study

The inspection data of maximum pit depth obtained from an offshore production facility operating in the North Sea, taken from Thodi et al. [41], is used to test the presented model. The data used is obtained from a straight piping section of the gas condensate (GC) system flow lines. The selected pipe has a nominal outside diameter of 180 mm, an operating pressure of 14 MPa, a length of 15 m and a nominal wall thickness of 7.13 mm, with a specified minimum tensile strength (SMTS) of 510 MPa. The first inspections are conducted after six years of the piping's installation on 11 pre-defined inspection locations on the selected pipe. The maximum pit depth in these 11 areas is found to be in the range of 0.4 mm to 1.2 mm.

The description of model parameters and their estimated values used in this case study are provided in Tables 4.2 and 4.3. The initial model parameters for maximum pit depth are estimated using expert knowledge, which is standard for a new installation.

Table 4.2. Parameters used for pitting evaluation of piping case study

Symbol	Description	Estimated Value
n	Number of Markovian states. The thickness is divided into n layers to develop the Markov model.	300
A	Parameter for pit density in Equation (4.1)	18.3
η	Parameter for pit density in Equation (4.1)	0.06
ψ	Parameter for pit density in Equation (4.1)	0
w	Parameter for pit density in Equation (4.1)	1
χ	Parameter in transited states equation of Markov process	2.80
ω	Parameter in transited states equation of Markov process	0.09

Table 4.3. Probabilistic models of the basic design and operational variables of the pipe [24,42]

	Tensile strength	Thickness	Diameter	Operating Pressure	Length
Distribution Type	Normal	Normal	Normal	Gumbel	1520 mm
Mean	510 (N/mm^2)	Nominal thickness (7.12 mm)	Nominal diameter (300 mm)	1.05 P_{op} (14 bar)	-
Coefficient of Variation	0.01	0.03	0.01	0.03	-

4.3.1. Prior Maximum Pit Depth Distribution

The proposed model based on the Markov process in Equation (4.5) is used to estimate the CDF of maximum depth at year 6 when the first inspection is performed. All figures and estimations in the following sections are determined for 10,000 simulation runs. Using the A–D statistics, the goodness-of-fit test has been conducted and the Type I Extreme Value (EV) distribution is selected as the best fit as it has the smallest A–D statistic. The empirical PDF for MPD distribution obtained from Equation (4.6) and the fitted EV distribution are shown in Figure 4.2. As can be seen in Type I Figure 4.2, the maximum pit depth modeled using the Markov process closely follows EV distribution, which matches the observations from experimental studies that found the extreme value theorem distributions to be the best fit for experimental data; see for example [43].

Although some studies [44,45] argue that the Type I EV distribution is not suitable to describe the distribution of pitting corrosion maxima in different materials and environments due to the dependency of maximum pit depth, most of the authors have considered the pits to be independent, making the assumption that this condition is satisfied at least approximately [46]. However, even with some dependence between pit depths, for example due to the interaction between growing pits, the Type I EV distribution is justified to describe the pit depth extreme values [46].

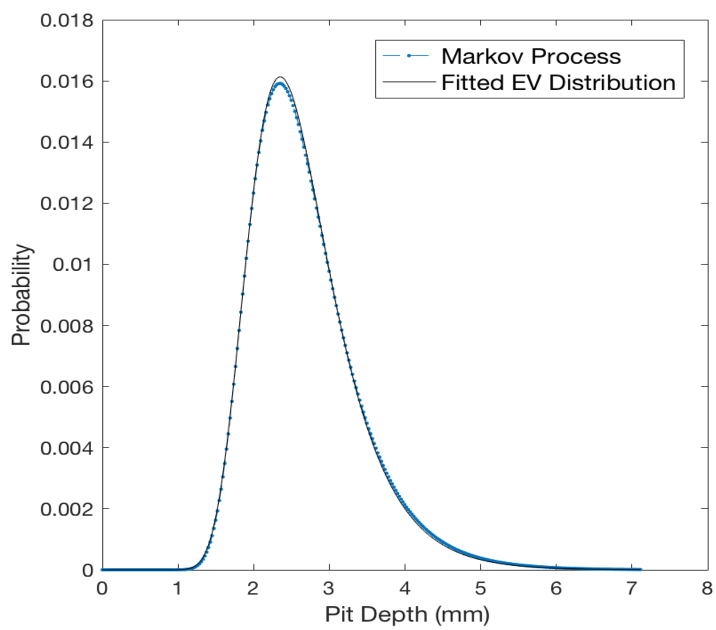

Figure 4.2. Prior maximum pit depth distribution at year 6 (first inspection)

4.3.2. Likelihood Function

To estimate likelihood distribution, first, random samples of measurement errors are generated using a normal distribution with zero mean and the standard deviation of 0.05 mm. The resulting error distribution is added to the maximum pit depth dataset found during inspections to account for the potential uncertainty associated with inspection measurement. The new inspection dataset is tested with frequently used probability distribution models such as Normal, Lognormal, 3 Parameter-Lognormal, Weibull, 3 Parameter-Weibull, Exponential, 2 Parameter-Exponential and Extreme Value distributions. The goodness-of-fit test is performed using the A–D statistics and the best fit is reported as the one with the smallest A–D statistic. Type I EV distribution with local and shape parameters 19.37 and 12.77 was selected as the best fit for the MPD inspection data. The fitted distribution is shown in Figure 4.3. In this figure, the maximum pit depth data are shown using the Markov states number. The thickness of each Markov state can be obtained as τ/n, where n represents the number of states and τ is the thickness of the component.

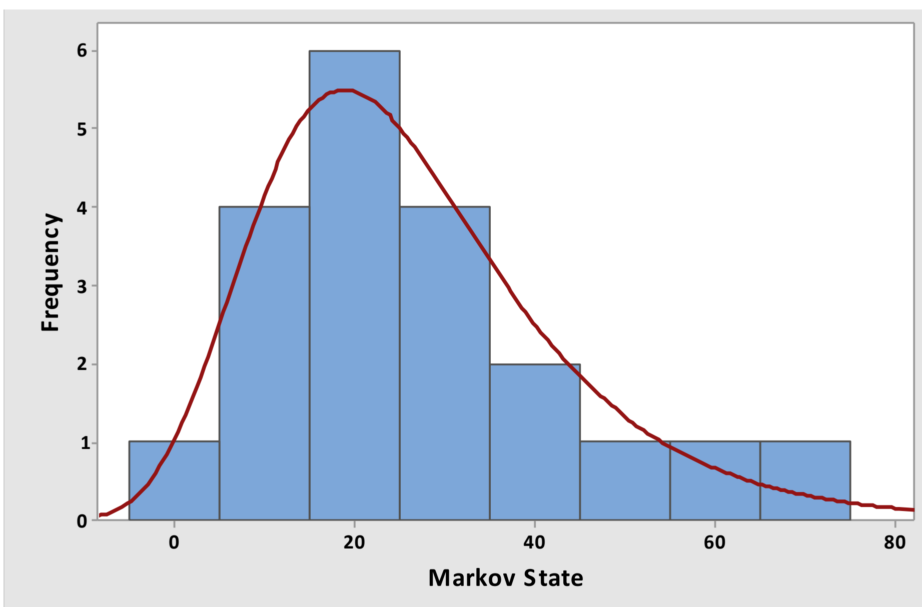

Figure 4.3. Extreme value distribution with local and shape parameters 19.37 and 12.77 for likelihood function of maximum pit depth inspection data

4.3.3. Posterior Distribution

Since the prior-likelihood combinations are non-conjugate pairs, the simulation-based Metropolis-Hastings (M-H) algorithm is used to estimate the posterior models. Using a MATLAB code and the prior and likelihood parameters determined from previous steps, the M-H algorithm has been used to simulate the posterior samples and estimate their parameters. The posterior estimation based on the M-H algorithm converges to the results with around 10,000 samples [38].

Based on the result of the A-D test for posterior data estimated from MCMC, Type I EV distribution with local and shape parameters 89.86 and 33.23 is found to be the best fitted distribution. The prior-posterior analysis results obtained using the M-H algorithm for maximum pit depth of the case study are summarized in Table 4.4, and are shown graphically in Figure 4.4. These results show that the MPD values obtained from inspection data were lower than expected, as the posterior MPD distribution has shifted to the left. This shift of the MPD distribution to the left indicates that the prediction of the prior MPD distribution has been conservative.

Table 4.4. Prior and posterior distributions for the Maximum Pit Depth (MPD)

Variable	Distribution Type	Scale parameter	Location parameter
Prior MPD	Extreme Value	21.73	100.8
Posterior MPD	Extreme Value	33.23	89.86

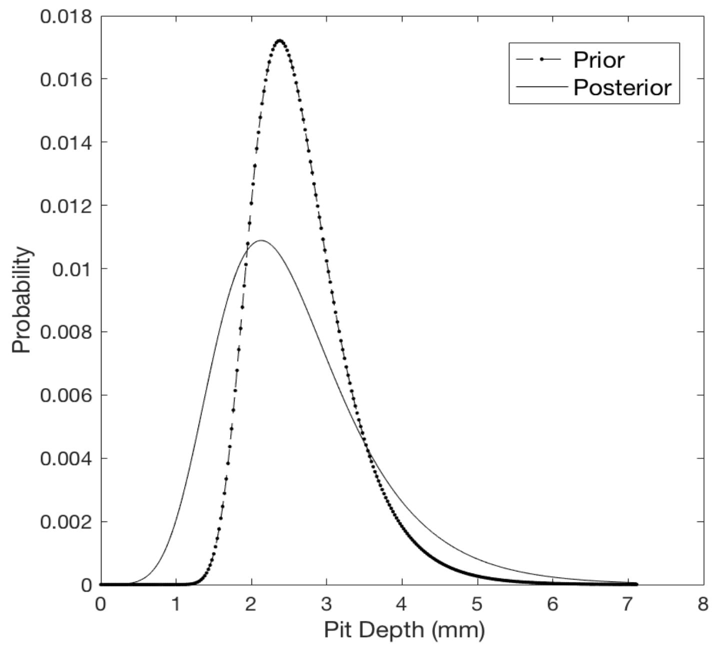

Figure 4.4. Prior and posterior maximum pit depth distributions for year 6 (first inspection)

Figure 4.5 demonstrates the effect of incorporating inspection data using the proposed Bayesian method on the initially estimated maximum pit depth values using the Markov model. This figure also illustrates the time-variant nature of the maximum pit depth model. As shown Figure 4.5, the distribution of MPD values shifts toward the deeper pits values over time. However, this shift happens at a lower rate after updating the initial predictions using the inspection data, indicating relatively less severe pit behaviour for this case study compared to the initial expectations based on expert knowledge. A shift with higher rate may also occur if the inspection results show a more aggressive pit growth rate compared to the initial predictions. This illustrates the significance of the proposed method to revise the Markov model predictions using the inspection results.

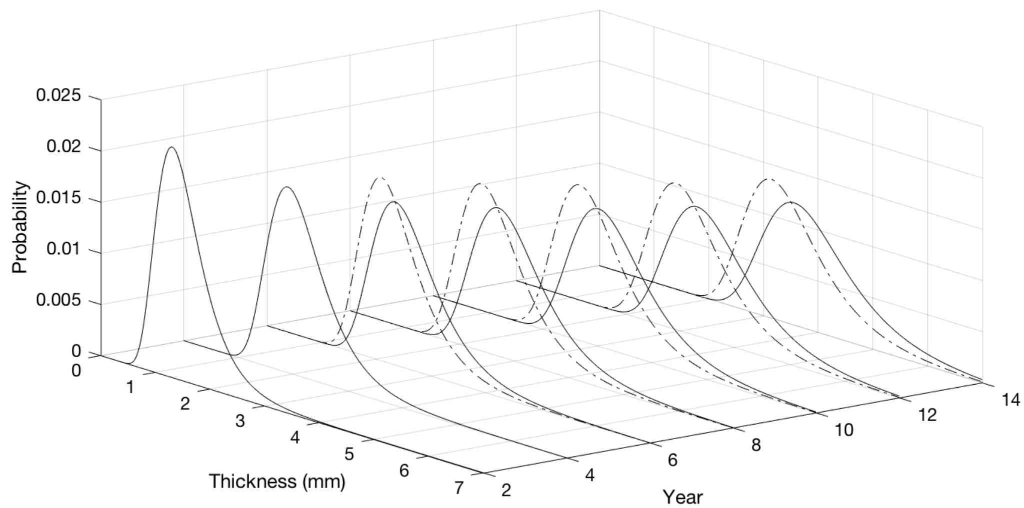

Figure 4.5. Prior and posterior distributions of maximum pit depth over time

The box plots for predicted prior and posterior MPD distributions are shown in Figure 4.6 to represent their distributional characteristics. As can be seen in Figure 4.6, pits are generated immediately after the commissioning of the piping system and continue to grow. In these plots, each box represents 50% of estimated MPD values for the corresponding year. The median of the values is shown by the line that divides the box into two parts. The upper and lower whiskers represent MPD values outside the middle 50%. The plots also show the minimum, maximum and outlier values. These plots help to study the distributional characteristics and the level of uncertainty of the data; the smaller the boxes, the lower the amount of uncertainty. The curve passing through the box plots represents the mean MPD values.

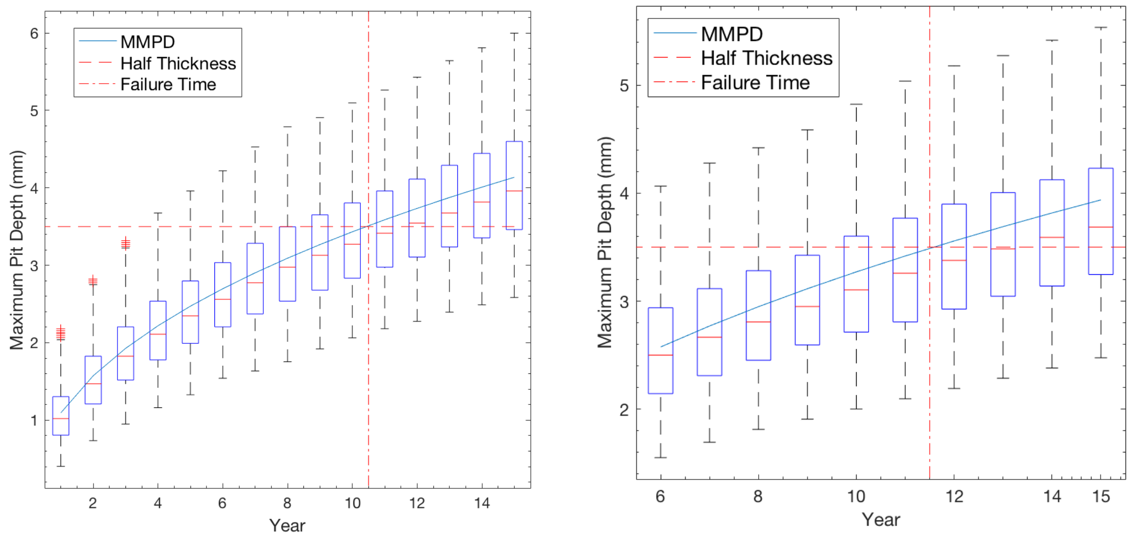

Figure 4.6. Box plots of maximum pit depth values: (left panel) prior distributions, (right panel) posterior distributions. Posterior MPDs in the right panel are shown for year 6 and later, as the first inspection is performed at year 6.

4.3.4. Maximum Allowable Pressure

Figure 4.7 shows the box-and-whisker plots for maximum allowable pressure for the defective pipe (P_{corr}) using both prior and posterior MPD distributions. Figure 4.7(a) represents the P_{corr} predictions over time determined at installation time using Equation (4.8) and the prior MPD distribution from Figure 4.2. After estimation of the posterior MPD distribution in year 6 and application of the least squares method, the updated parameter χ of the Markov transition rate is changed from 2.80 to 2.76. Then, using updated MPD distribution with new χ, P_{corr} values are updated and presented in Figure 4.7(b). As can be seen, the estimated P_{corr} using the initial mean of prior MPD distribution, denoted by MMPD, are lower than the updated MMPD. Figure 4.7 demonstrates that as pits grow over time, due to reduction in material strength, the maximum allowable pressure of the defective pipe decreases accordingly.

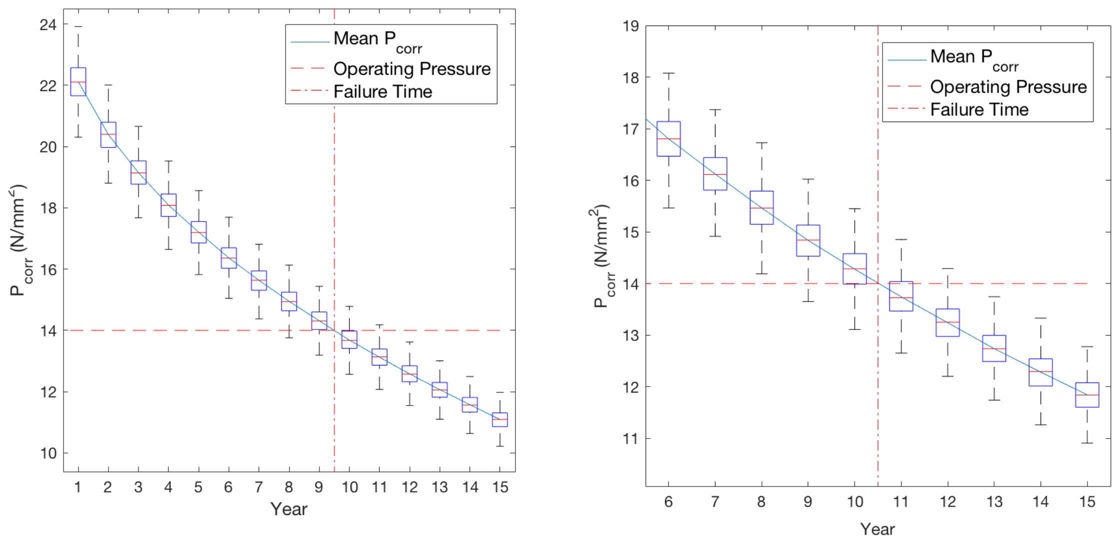

Figure 4.7. Box plots of maximum allowable pressure (Pcorr) for the defective pipe over time: (left panel) using prior MPD distribution, (right panel) using posterior MPD distribution. Posterior Pcorr values in the right panel are shown for year 6 and later, as the first inspection is performed at year 6.

As shown in Figure 4.7, the allowable pressure of the defected pipe decreases with an increased exposure period due to metal loss and the consequent degradation of material strength. This, in turn, reduces the capacity of the piping system to resist the effects of internal fluid pressure. Moreover, as shown in Figure 4.7, the relationship between time and decreased allowable pressure is found to be slightly nonlinear. It is also shown in Figure 4.7 that after updating the MPD distribution, the allowable pressure falls below the nominal operating pressure of 14 MPa only after an exposure period of about 10.5 years. If a longer operational period is required, it will be necessary to repair or remove the damaged section of the pipe or to reduce the operating fluid pressure.

4.3.5. Probability of Failure

The estimated prior and posterior P_{corr} distributions in Figure 4.7 are plugged into Equation (4.11) to obtain reliability index values for different exposure times. Then, the estimated reliability index values, $\beta(t)$, are used in Equation (4.10) to obtain probability of failure curves over time and the results are shown in Figure 4.8. Figure 4.8 shows the increase in the probability of failure (POF) of the defective component as pits grow and P_{corr} decreases over time. In both POF curves in Figure 4.8, pits start to form at almost the same time, as in this case only the MPD model is updated and the pit initiation model parameters are considered constant. However, the rate of increase in the updated POF curve, determined using posterior MPD distribution, is higher due to the conservative estimation of the Markov model parameters at the installation time. These results show the importance of integrating Bayesian updating with the Markov model to facilitate the incorporation of inspection data in remaining life calculations.

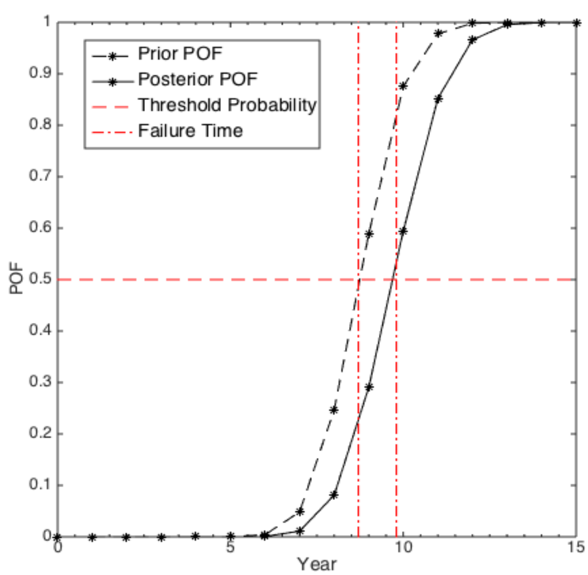

Figure 4.8. Probability of failure (POF) of the defected pipe over time

4.3.6. Remaining Life Evaluation

For this case study, three criteria discussed in Section 4.2.3 are used to estimate the remaining life of the piping section affected by pitting corrosion and the results are shown in Table 4.5. As discussed in Section 4.2.3, the remaining life of the pipe under analysis in this case study can be considered as the minimum of the remaining life values based on each of the three criteria. Accordingly, from Table 4.5, the remaining life of the pipe using prior and posterior distributions is determined as 8.8 and 9.9 years, accordingly.

Table 4.5. Estimated remaining life values for the piping case study using different criteria

		Estimated Life (Years)	
Criteria	**Related Figure**	**Using Prior Distribution**	**Using Posterior Distribution**
Defect size	Figure 4.6	10.3	11.3
P_{corr}	Figure 4.7	9.5	10.5
Probability of failure	Figure 4.8	8.8	9.9

In Figure 4.8, the mean value of the pit depth ranges from 0.0 to 4.2 mm over a period of 15 years; however, the updated maximum pit depth will reach 3.9 mm in year 15. Consequently, the failure time estimated based on maximum allowable pressure and probability of failure changed from 9.5 years to 10.5 years and from 8.8 years to 9.9 years, respectively. The increase in the estimated remaining life using the posterior distributions is due to the reduction in the conservatism of the estimations after incorporation of inspection results. This indicates that the combination of the environment and the material used was less susceptible to pitting corrosion than the initial experts' expectation. These results highlight the importance of updating the parameters of the Markov model for reliable estimation of allowable pressure and the remaining life. The proposed integration of Bayesian updating with the Markov model satisfies this need by revising and improving the model predictions over time as inspection results from the system become available.

In this study, only the mean value of MPD distribution is used for estimation of the failure probability. Alternatively, other statistics such as 95% of MPD distribution can be used to obtain more conservative results. Thus, one of the advantages of developing the probability distribution of the maximum pit depth is the ability to investigate the uncertainty involved in the model outputs [13].

4.3.7. Sensitivity Analysis

An important part of the proposed model to predict pit behaviours and probability of failure (POF) is to use expert knowledge for the estimation of Markov model parameters, in particular the Markov transition rate parameters. Expert knowledge is defined as what qualified decision makers know because of their technical practices, training, and experience. It can be the best source of information when empirical data are scarce or unavailable; for example, in new installations with no operational and inspection histories [47]. However, the use of expert knowledge adds to the uncertainty of the estimated model outputs. This section describes two sensitivity analyses to investigate the significance of the uncertainty associated with using expert knowledge in the proposed method.

In the first sensitivity analysis, for year 6 (first inspection), 11 experiments were conducted using the Markov transition rate $\chi = 2.8$ as the base value (taken from Table

4.2) and then changing the χ in the range of -20% to +20% to estimate the corresponding prior MPD distributions. For each experiment, the inspection data from Section 4.3.1 were used to carry out the Bayesian updating to estimate the posterior MPD distributions. Then, for each experiment, the mean MPD (MMPD) values from both prior and posterior distributions were estimated and the results are shown in Figure 4.9. As can be seen in Figure 4.9, for 10,000 Monte Carlo simulation runs, changes in χ in the range of -20% to +20% have resulted in approximately a -28% and +39% change in estimated prior MMPD values, and about a -31% and +34% change in estimated posterior MMPD values, respectively. These results indicate that the impact of change in χ follows the same relatively linear change in both prior and posterior MMPDs.

Another sensitivity anaylsis is conducted to investigate the sensitivity of the POF values to changes in χ. For this purpose, 11 experiments were conducted by changing χ in the range of -20% to +20% and investigating the effect on estimated probability values. All experiments were conducted for 10,000 simulations runs and the results are shown in Figure 4.9. As can be seen from Figure 4.9, in general, the negative change in χ results in an underestimation of POF and positive changes in χ leads to the overestimation of POF. Also, prior and posterior POF values approach zero rapidly for negative changes in χ values. The reason for these low probability values is that the sensitivity analysis has been conducted for year 6, when the pits are still not very deep. Moreover, negative changes in χ represent lower transition rates between Markovian states, indicating a lower pit growth rate. On the other hand, positive changes in χ represent higher Markovian transition rates and higher pit growth rates, which will result in a rapid increase in POF.

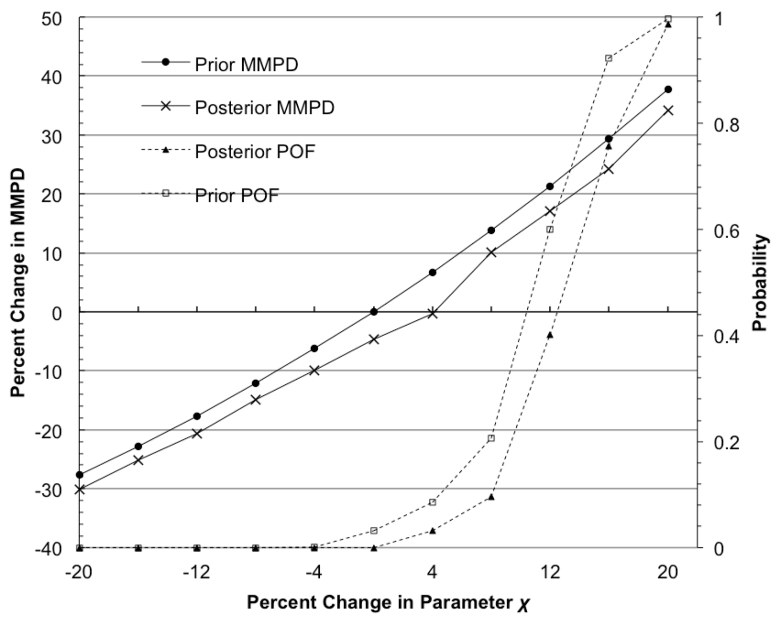

Figure 4. 9. Sensitivity analysis: the effect of change in the Markov transition rate (χ) on MMPD and probability values for year 6 (first inspection)

4.3.8. Discussion

As was shown in the sensitivity analysis section, the potential error in estimating the initial model parameters due to the uncertainty associated with expert knowledge estimates can result an in inaccurate prediction of pit depth and POF values, which is not surprising. This fact justifies the fundamental objective of this work to use inspection results to update initial predictions by integrating the Markov model with Bayesian analysis. The incorporation of inspection results in the reduction of uncertainties associated with model estimates by revising the Markov model parameters. The application of data from similar operations can be used to reduce the uncertainty associated with initial model parameters using expert knowledge. In the absence of data from similar operations, accelerated laboratory and field tests, such as those suggested by

Caines et al. [48], can be used to collect data for similar metal and operational conditions. The collected data can be used to calibrate the Markov model and estimate the model parameters. Then, the methodology proposed in this work can be used to improve these estimates using the inspection data over time.

The proposed updating procedure can be repeated when the next inspection is performed and new data become available. By conducting more inspections and repeating the procedure over time, the revised model becomes more representative of a real-world situation. Using the information from the updated failure probability values, a more reliable decision can be made regarding the next course of action, such as run, repair, rerate, or replace the damaged component.

To keep the paper concise, Bayesian updating is only applied to revise the Markov model parameters. This is not a limitation of the proposed methodology, as a similar updating mechanism can be easily applied to revise the APD model parameters using the pit density inspection data. Moreover, in this study, the uncertainty of inspection data is considered by using a probability distribution (likelihood function) and a measurement error distribution for inspection data. To further investigate the inspection uncertainty, future studies can also incorporate the effect of inspection data sample size and the probability of detection of pits.

In this work, the maximum pit depth and the number of pits are assumed to be independent. The potential dependency between these pit characteristics and other potential dependencies, such as material-environmental conditions, cannot be captured using the proposed model due to the inherent limitations of the Bayesian approach. These limitations can be addressed in future works by using the concept of the Copula Bayesian Network proposed by Elidan [49] and Hashemi et al. [50].

4.4. Conclusions

The prediction of the life of assets susceptible to pitting corrosion is important to ensure timely implementation of inspection activities to avoid catastrophic failures. In this paper, a methodology is developed to update a time dependent, predictive maximum pit depth model by using a non-homogenous Markov process. The model enables the prediction of the remaining life of assets affected by pitting corrosion. This is an important requirement for new installations with scarce data, particularly for critical services in remote areas such as offshore operations. The methodology further incorporates the inspection data in the remaining life analysis by using the Markov Chain Monte Carlo and Metropolis–Hasting algorithm to carry out Bayesian updating to revise the prior distribution of maximum pit depth. Using the least squares method, the proposed methodology estimates the updated parameter of the Markov process to revise the predicted distributions of maximum pit depth, failure pressure, failure probability and the remaining life of the asset. Although some of the models used in this work are from the literature, this work provides a probabilistic framework for modelling and incorporating inspection data to culminate results in an effective remaining life analysis.

The application of the proposed method is illustrated using a piping case study with real corrosion inspection data. The results of the Bayesian updating showed that the time dependent MPD distribution as well as the remaining life estimations were overestimated using expert knowledge. These results highlighted the fact that the incorporation of inspection data using Bayesian analysis to revise the Markov model parameters can provide a more realistic prediction of pit behaviour and failure time. A sensitivity analysis is conducted to investigate the effect of uncertainty of expert knowledge on the estimation of the prior Markov transition parameter. Overall, the case study results showed the importance of integrating Bayesian updating with the Markov process to address the uncertainty in the initial model parameter estimates and to revise these estimates using inspection results.

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5. ECONOMIC RISK ANALYSIS OF PITTING CORROSION IN PROCESS FACILITIES[4]

Preface

A version of this manuscript has been accepted for publication in the International Journal of Pressure Vessels and Piping. I am the primary author of this paper. Along with the co-authors, Faisal Khan and Salim Ahmed, I developed the conceptual model. I conducted the literature review and proposed a model for the overall economic impacts of pitting corrosion. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback. The co-author Faisal Khan helped in developing and testing the concepts/models, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Salim Ahmed contributed through support in development, testing and improvement of the models. Salim Ahmed also assisted in reviewing and revising the manuscript.

Abstract

This paper presents a predictive probabilistic model to estimate the overall economic impacts of pitting corrosion by considering both the corrosion costs and significant losses that may occur if failures occur because of pitting corrosion. The major loss categories are considered as business loss and accidental loss. Models are proposed to estimate the elements in each loss category. Corrosion prevention, monitoring, maintenance and

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management (CPM3) costs are considered as the main categories of corrosion costs and the probabilistic models are proposed to estimate these costs. The Monte Carlo (MC) method is used to integrate the loss and cost models and also to address the uncertainties in these models. The effect of inflation on loss values and the mitigating impact of CPM3 costs are also taken into consideration in the developed models. The application of the proposed risk model is demonstrated using a piping case study. As highlighted in the case study, the developed models help to assess corrosion economic risk, which is used for corrosion prevention and control's decision-making.

5.1. Introduction

Corrosion is not only an engineering issue but also an economic problem. A study supported by NACE International estimated the global cost of corrosion to be US$2.5 trillion in 2013, which is equivalent to 3.4% of the global Gross Domestic Product (GDP) [1]. Corrosion can be a life-limiting cause of deterioration by general corrosion, pitting, and environmentally assisted cracking to plant equipment which in turn can lead to loss of containment of hydrocarbon fluids and other process fluids [2]. However, several studies, such as ASM [3], Kruger [4] and NACE [1] concluded that between 15 and 35% from the loss of corrosion could be saved by the application of existing technology to prevent and control corrosion. Therefore, it is vitally important that risk practitioners and engineering managers be aware of the overall economic impact of corrosion by taking into account the potential corrosion consequences as well as the positive effect of corrosion management.

Different approaches are needed to investigate the probabilistic aspects of each specific corrosion mechanism. The focus of this work is to develop a risk-based economic impact analysis approach for pitting corrosion. Pitting corrosion is a localized metal loss that can be characterized by a pit diameter on the order of the plate thickness or less, and a pit depth that is less than the plate thickness [5]. If growing pits remain undetected, the damaged equipment may experience leakage once the pits transform into holes, breaking through the equipment shell. Moreover, the reduced strength of the pressurized equipment suffering from pitting corrosion can cause equipment failure, leading to the release of material and energy and environmental pollution. Furthermore, the interrupted operation due to equipment failure causes loss of production and affects company profit [5]. Thus, consequence analysis is to be integrated into pitting risk assessment to identify and evaluate such outcomes.

Traditional consequence assessment techniques usually involve a variety of mathematical models, such as source and dispersion models that predict the release rate of hazardous materials, fire and explosion models, impact intensity models and toxic gas models [6–11]. In these models, the consequences are usually considered as a function of affected areas. The following challenges were identified for corrosion consequence analysis using the traditional approaches:

i. Ignoring the uncertainty associated with loss estimations when using deterministic values for consequence assessment.

ii. Not considering the mitigating effect of corrosion prevention, monitoring, and management on estimated losses.

iii. Not considering the time value of money when estimating future losses based on the current dollar value.

The purpose of this work is to develop models for overall economic impact analysis of pitting corrosion, while addressing the issues identified above. As will be discussed in Section 5.2, the overall loss is considered as the summation of accidental losses due to loss of containment and subsequent business losses. One major contribution of this work is to consider business loss as a function of time, which is usually ignored in most traditional consequence analysis literature [6–11].

The second major contribution of this work is the consideration of uncertainty in the proposed loss models through development of probability distributions for the input parameters. For this purpose, the uncertain input parameters of each loss model are identified. Then, the distribution of each is proposed by identifying uncertain parameters based on expert knowledge, operational history and related literature.

As will be discussed later in this paper, the investment in CPM3 strategies can substantially reduce failure losses. Furthermore, reduction in failure frequency is equally important, as it not only reduces costs and losses but also positively affects market share and company morale and reputation [12]. Therefore, it is of critical importance to model both corrosion losses and costs considering the remediating measures for corrosion. Another important contribution of this work is to address this challenge through the application of the CPM3 adjustment factor.

One of the major shortcomings of traditional corrosion consequence analysis methods is using constant (today's) dollar values for loss and risk estimation, ignoring the effect of inflation. This work applies engineering economics rules to incorporate the effect of inflation when projecting estimated loss into the future.

The organization of this paper is as follows: Section 5.2 describes the differences between failure costs and failure losses and the application of the Program Evaluation Review Technique (PERT) distribution to capture expert knowledge. Section 5.3 reviews the consequence analysis techniques and proposes the methodologies to estimate accidental and business losses. The practical application of the proposed methodology is demonstrated using a case study in Section 5.4, followed by concluding remarks.

5.2. Preliminaries

5.2.1. Corrosion Costs vs. Corrosion Losses

It is advisable that corrosion losses be presented in monetary values to facilitate better financial planning and control. Such economic impact analysis also provides a performance assessment tool to identify and evaluate corrosion cost saving opportunities. Accordingly, corrosion costs and corrosion losses are defined in this work as:

- Corrosion cost is the cost of all efforts that prevent, control, or mitigate corrosion losses;
- Corrosion loss is financial loss caused by failures due to corrosion

The classification above is used in this work to discriminate between corrosion costs and corrosion losses. Intuitively, corrosion costs are the sum of all costs that would disappear if there were no corrosion problems. In other words, the informative difference between "corrosion cost" and "corrosion loss" is that the former adds value, while the latter reduces value.

5.2.2. Elements of Corrosion Losses and Corrosion Costs

In order to develop the corrosion economic consequence analysis model, the first steps are to classify the corrosion costs and losses and to identify the elements of each class. The classification of corrosion induced failure losses is straightforward. There is a general agreement in the literature to classify these losses as [6–8,11,13,14]:

i. Accidental losses: The loss due to release of hazardous fluids from pressurized processing equipment and subsequent consequences for people, properties and the environment [15].
ii. Business losses: business loss occurs when an organization fails to generate enough revenue to cover the expenses associated with the process operation [14]. The two most common causes for process systems to incur business loss are: (i) process shutdown due to the activation of safety systems; and (ii) process downtime after an incident. The causes of business loss often have a severe impact on the organization in terms of business disruption and the services provided to clients, which eventually affects reputation.

In contrast to corrosion losses, there have been different classifications of corrosion costs in the literature. Corrosion costs vary in relative significance from industry to industry; some are readily recognized and others are less recognizable. The main basis used in this study to classify and identify the elements of corrosion costs is the study published by the

U.S. Congress directed the National Bureau of Standards (NBS) in 1978 [16] . This study was, and still remains, probably the most comprehensive investigation of the full extent of corrosion on the economy of a nation [4] and has been used in different corrosion literature to investigate corrosion costs [17]. Accordingly, the corrosion costs are classified in this work as follows, with the definitions adopted from the BS 6143 Part 2 [12]:

i. Prevention costs: The cost of any action taken to install, operate, improve and maintain corrosion prevention activities.

ii. Monitoring costs: The cost of monitoring, evaluating, and assessing the system to control corrosion.

iii. Maintenance costs: The cost incurred to keep equipment in good working order to function under stated conditions.

iv. Management costs: The cost of any management actions taken to investigate, reduce, and transfer the corrosion risk.

Table 5.1 summarizes the elements of corrosion costs and potential losses. Capital and design costs and associated costs are excluded in this classification as the scope of this work covers the operational expenses during the useful life of the asset.

Table 5.1. Elements of corrosion losses and corrosion costs

Type of Economic Impact	Classification	Examples
Corrosion Costs	Prevention costs	• Coatings • Inhibitors • Cathodic protection
	Monitoring costs	• Corrosion monitoring (corrosion coupons and probes) • Corrosion tests • Inspection
	Maintenance costs	• Maintenance and repair • Replacement of equipment • Redundant equipment
	Management costs	• Training • Quality assurance • Corrosion control planning • Safety and integrity management systems • Administration • Insurance
Corrosion Losses	Accidental Losses	• Human health loss • Asset loss • Environmental cleanup cost
	Business Losses	• Business interruption loss • Reputational loss

5.2.3. Application of PERT Distribution to Capture Expert Knowledge

The monetary quantification of corrosion costs is a challenging task due to scarce and unreliable data, particularly for new installations with no operational and business performance histories. In such cases expert knowledge is often regarded as the best or only source of information. However, the application of expert knowledge to estimate unavailable data is usually criticized in the literature due to obvious shortcomings such as potential inconsistency and uncertainty. The potential inconsistency in using expert knowledge can be significantly reduced using techniques such as the use of multiple, diverse experts and the inclusion of pretesting, training, and validation stages [5,18]. Also, the potential uncertainty of any quantified variable using expert knowledge can be incorporated into the estimation process using the technique known as Program Evaluation Review Technique (PERT) distribution.

PERT distribution is a special case of Beta distribution (Equation 5.1) that uses three expert-estimated parameters: minimum, most likely (mode), and maximum values to convert these three discrete values into a continuous cost distribution. For this purpose, as shown in Equations 5.2 and 5.3, the PERT distribution uses these three discrete values of expert estimates to generate the distribution shape parameter [19]. PERT distribution has also been used recently to estimate business losses due to abnormal situations in process facilities [14]. PERT distribution is used in this work for the estimation of corrosion costs and their effectiveness in remediating corrosion losses. As PERT distribution is used in different sections of this paper, the method is explained here to avoid repetition.

Using the PERT distribution, the expert is asked to estimate three values (minimum, most likely and maximum) for the selected variable (in this work, corrosion costs and shape parameter of adjustment factors) [14]. Then, a set of modified PERT distributions is plotted using Equation (5.1) and the expert is asked to select the shape that fits his/her opinion most accurately:

$$f(x) = \frac{\left(x - x_{\min}\right)^{v-1}\left(x_{\max} - x\right)^{w-1}}{B\left(v_{PERT}, w_{PERT}\right)\left(x_{\max} - x_{\min}\right)^{v+w-1}} \tag{5.1}$$

where x is any of the elements and $B(v, w)$ is a Beta function with parameters of the Beta distribution as:

$$v_{PERT} = 1 + \gamma_{PERT} \left(\frac{x_{\text{mode}} - x_{\min}}{x_{\max} - x_{\min}} \right) \tag{5.2}$$

and

$$w_{PERT} = 1 + \gamma_{PERT} \left(\frac{x_{\max} - x_{\text{mode}}}{x_{\max} - x_{\min}} \right). \tag{5.3}$$

In standard PERT distribution, the default value of 4 can be used for γ_{PERT} [19]. A higher or lower value of γ_{PERT} can be used for the cases where the desired distribution should be more peaked or flatter around the mode, respectively [14].

5.3. Methodology

Figure 5.1 shows the proposed framework to estimate the economic consequences of corrosion. The proposed methodology starts with estimation of losses due to release of hazardous fluids and subsequent consequences on the business performance of the system, people, assets and the environment. Probability distributions are used to take into consideration the effect of stochastic factors contributing to the uncertainty in each loss category. Having estimated the overall loss distribution, and to provide a more realistic loss estimation, the mitigating effects of corrosion prevention, monitoring, maintenance and management factors are considered to adjust the estimated corrosion induced failure probability. A mathematical model is also proposed to consider the effect of inflation on overall loss value. The details of each step of the loss assessment methodology are provided below:

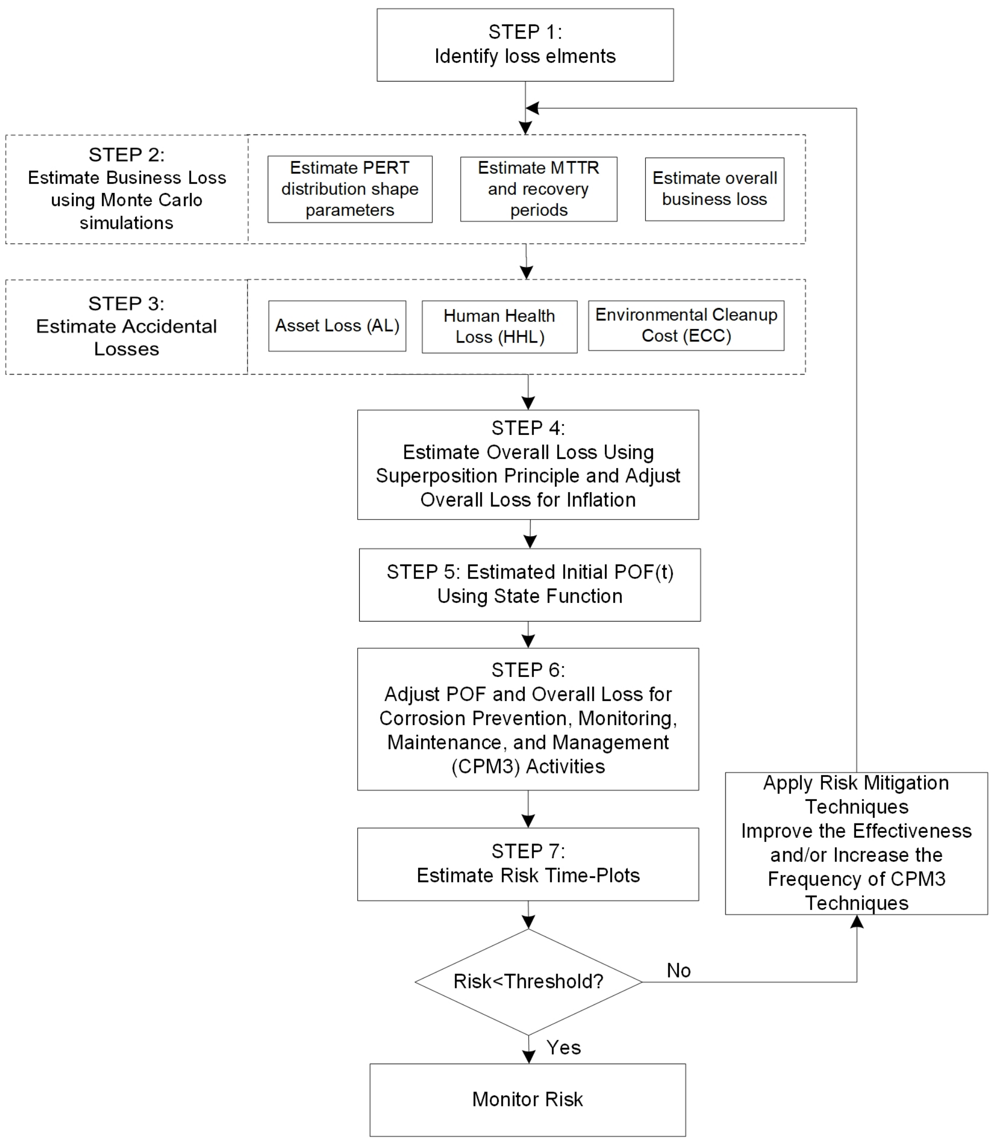

Figure 5.1. Methodology for risk-based economic impacts analysis of pitting corrosion

5.3.1. Step 1. Identification of Loss Elements

Table 5.2 shows the main elements of accidental and business losses in this work. The methodology to estimate each of the identified elements is provided in the following sections. Reputational loss is another element of the business loss due to damaged organization's trustworthiness in the marketplace after a major incident [14]. To keep the work concise, the reputational loss is not included within the scope of this work.

Table 5.2. Loss categories due to pitting corrosion

Loss Category	Loss type	Remarks
Accidental Loss	Asset loss (AL)	Loss of physical assets, such as damage to property and loss of equipment due to failure
	Human health loss (HHL)	The loss due to the fatalities/injuries and the costs associated with fatality and/or injury
	Environmental cleanup cost (ECC)	Costs of removing, containing, and/or disposing of hazardous waste from property, or material and/or property that consists of hazardous waste during permanent or temporary closure or shutdown of associated equipment
Business Loss	Business loss due to lost production (BL_{dt})	Business loss during process downtime. This loss can be determined as the expected gross revenues from sales of the product over a period of time by projecting the past 12 to 24 months of the company's sales forward, minus expected changes in inventory values, material use and transportation costs [14]
	Business loss over the recovery period (BL_{rp})	Business loss due to lost market share after the business is restored. This loss is determined by comparing the organization's business performance in the past 12 to 24 months before process downtime with the performance over the recovery period

5.3.2. Step 2. Estimation of Business Loss

Business loss is associated with the interruption in production and subsequent financial consequences when a loss of containment occurs. The main elements of business loss are the losses due to plant downtime and lost market shares after an accident occurs. In most existing methodologies [6,8,11,15], the profit loss is calculated based on production hours lost during process downtime multiplied by the production cost per hour. This approach does not consider the cost elements required to repair and restore the damaged unit or the uncertainty associated with them. Moreover, this approach relies on the assumption that once the production from a damaged unit is restored after an accident, the unit will have the same business performance as before the accident. However, in reality, the business might need a period of time to recover, especially after long downtimes, due to lost market share, return of the personnel, and potential failures after the commissioning of repaired/new equipment.

To address these shortcomings, the PERT distribution technique, adopted from project management literature [19] is used in this work to model the business loss.

5.3.2.1. Step 2.1. Estimation of downtime and recovery time

Downtime ($\Delta\tau_{dt}$) is the time period between accident occurrence and the production restart time. When a component fails, it enters into a repair process, which itself includes several subtasks. Therefore, the estimation of the downtime requires the consideration of all major subtasks:

i. Access time, defined as the amount of time required to gain access to the failed component.
ii. Troubleshooting time, which is the amount of time required to determine the cause of failure.
iii. Repair or replacement time, defined as the actual hands-on time to complete the restoration process.

iv. Verification time, which is required to validate the restoration to ensure that the unit has been returned to an operational condition.

Supply and maintenance delays can also significantly affect the downtime. If all the needed replacement parts are readily available and the necessary maintenance resources and facilities are immediately available upon failure, then supply and maintenance delays can be considered as zero [20].

The downtime reflects the maintainability of equipment and is usually measured using the mean time to repair (MTTR). MTTR is considered a random variable and is modeled in this work using an exponential distribution assuming a constant repair rate. However, for the case of non-constant repair rates, distributions with a time-dependent hazard function, such as Weibull and lognormal, can be used [20].

The recovery period ($\Delta\tau_{rp}$) is defined in this work as the time span that an organization would take from the production restart to the restoration of business income to the same position it had before the failure occurred. Recovery period is also considered to follow an exponential distribution. When information is lacking, Hashemi *et al*. [14] recommended the use of $\Delta\tau_{rp} = 0.5\times\Delta\tau_{dt}$ as a starting value. This value can be revised later based on expert knowledge and failure history.

5.3.2.2. Step 2.2. Overall business loss

In almost all traditional loss models, business loss (BL) is a linear function of time [14]. The reason for this assumption is that the production loss rate is considered constant (time independent). However, it is more realistic to consider BL as a nonlinear function of time. Compared to a linear model, a nonlinear BL model penalizes the system for consistent business loss because companies face a reduced market share due to interrupted operations. In addition to elements such as loss of production, this reduction in operational output may include laying off employees, selling equipment or assets and closing underperforming business facilities, losing market share especially for long-term downtimes.

To address these challenges, Equation (5.4) is proposed to consider nonlinear cases of business loss as a function of time:

$$BL = BL_{dt} + BL_{rp} \tag{5.4.a}$$

where

$$BL_{dt} = BL_{dt}^{PERT} \cdot \{(1 - exp[-MTTR^2/(2B_1)^2] + B_2 \cdot MTTR^{B_3})\} \tag{5.4.b}$$

$$BL_{rp} = BL_{rp}^{PERT} \cdot \left\{\left(1 - exp\left[\left(-\Delta\tau_{rp}\right)^2/(2B_1')^2\right] + B_2' \cdot \left(\Delta\tau_{rp}\right)^{B_3'}\right)\right\} \tag{5.4.c}$$

where BL_{dt}^{PERT} and BL_{rp}^{PERT} are business losses during downtime and recovery periods estimated from PERT distribution, $MTTR$ is the mean time to repair and $\Delta\tau_{rp}$ is the mean value of the recovery period. B_i and B_i' are parameters that are chosen in a way to best reflect business loss from historical data. This equation can address both linear and non-linear behaviours for business loss in downtime and recovery periods. For example, if B_1 is set to be 0 and B_3 to 1, the business loss and downtown period will have a linear relationship. On the other hand, the business loss in the downtime period follows an exponential distribution if B_2 is zero. Having estimated the distribution of different elements in 4.a, Monte Carlo simulation is used to model the distribution of overall BL.

5.3.3. Step 3. Estimation of Accidental Loss Elements

As shown in Table 5.2, human health loss, asset loss and environmental cleanup loss are three main elements of accidental loss. These consequences are caused by loss of containment and their values are usually estimated as a function of the affected area and are expressed in financial terms. In this work, the impact (damage) area is calculated based on the level I consequence analysis outlined in API RP 581 [6], as it provides a standardized and reproducible methodology for application in process plants. However, users may apply different source and dispersion models to determine impact areas [9]. Based on the API RP 581 methodology, impact areas from events such as pool fires, flash fires, fireballs, jet fires and vapour cloud explosions are quantified based on the effects of thermal radiation and overpressure on surrounding equipment and personnel. The event tree technique is then utilized to assess the probability of each of the various event outcomes and to provide a mechanism for probability-weighting the consequences of loss of containment. Having estimated the impact areas, the elements of accidental loss are calculated, as discussed in the following sections.

5.3.3.1. Step 3.1. Asset Loss

The asset loss can be calculated as multiplication of the cost of damage to the component, as well as to other components and buildings in the vicinity of the failure, damage area and assets' density ($/area) [9,11]. To reduce the complexity and required input data, a constant value of the process unit replacement cost is used to compute the total damage cost to other assets based on the damage area. Beside the value of the components, the installation cost of the component in the damaged area is another important factor that needs to be taken into consideration. For this purpose, the Lang factor is used, which is defined as the ratio of the total cost of installing a process in a plant to the cost of its major technical components [21]. Therefore, asset loss (*AL*) can be calculated as:

$$AL = \left(1 + f_L\right) \cdot a_d \cdot C_u \tag{5.5}$$

where f_L is the Lang factor, C_u is the process unit replacement cost ($/unit area) and a_d is the damage area. Equation (5.5) has two terms: the first part estimates the component(s) cost and the second term estimates the total replacement cost using the Lang factor. The mean value of the Lang factor varies from plant to plant; however, a mean value of 3.7 can be used as a reasonabe estimate [21]. In this study, a normal distribution with mean μ_{FL} = 3.7 and standard deviation σ_{FL} = 1 is considered for the Lang factor to take into account the associated uncertainty. To recognize the uncertainty associated with estimating unit cost (C_u), the PERT distribution approach described in Section 2.1 is used to assign a distribution to C_u, given an estimated empirical mean and variance. Having estimated the distribution of different parameters in Equation (5.5), the MC simulation method is used to estimate the distribution of asset loss.

5.3.3.2. Step 3.2. Human Health Loss

Another consequence to consider when a corrosion failure occurs is the potential injury and fatality losses, collectively referred to as human health loss (*HHL*) in this work. For a given scenario, *HHL* is calculated in terms of the number of fatalities/injuries and the costs associated with fatality and/or injury [8,9]:

$$HHL = a_d \cdot d_p \times C_{hh} \tag{5.6}$$

where a_d is the damage area; d_p is the population density (people/area); and C_{hh} is the unit human health (fatality/injury) loss. The concept of the value of statistical life (VSL) can be used as a basis to estimate C_{hh}. The VSL is the value that individuals place on a marginal change in their likelihood of death [22]. Although VSL is very different from the value of an actual immeasurable human life, when looking at risk/reward trade-offs that people make with regard to their health, economists often consider the VSL in financial decision-making. The estimation of VSL and the cost of injuries should be based on the unique situations of the facility as this depends in several facility/country-specific factors [23]. However, when lacking such information, the VSL data in a study by Bellavance *et al.* [23] and the ratio between cost of fatality versus moderate and slight injuries reported by [24] can be used as the starting values. Finally, the MC simulation is integrated with Equation (5.6) to simulate the distribution of the human health loss.

5.3.3.3. Step 3.3. Environmental Cleanup Cost

Environmental consequences as a result of loss of containment can be significant and should be added to other costs including fines and other penalties. Adopted from API RP 581, the environmental cleanup cost (ECC) due to hydrocarbon spill is calculated as [6]:

$$ECC = \frac{C_{ec} \cdot m\left(1 - f_e\right)}{\rho_l} \tag{5.7}$$

where f_e is the estimated fraction of material to evaporate as a function of the normal boiling point and can be determined from a table or an empirical equation in API RP 581 [6]. m is the discharge mass of the released fluid, ρ_l is the liquid density at storage or normal operating conditions, and C_{ec} is the environmental clean-up cost (including fines, penalties, and other applicable costs) in \$/barrel (bbl). The distributions of the m and C_{ec} are to be determined from operational history and applicable environmental regulations. Then, the Monte Carlo simulation is conducted with Equation (5.7) to obtain the C_{ec} distribution. Applicable regulatory legislator as well as related literature along with expert knowledge can be used to estimate the distribution of C_{ec}. For example, DNV-RP-

G101 [25] provides some guidelines to estimate a base value for ECC for offshore platform oil spills.

5.3.4. Step 4. Overall Loss Estimation and Effect of Inflation

In order to estimate the overall risk of failure due to pitting corrosion, the overall loss should be determined first by aggregating individual loss elements. The overall loss is estimated by the superposition principle as the summation of the business loss and accidental loss elements, estimated from previous steps. The application of the superposition principles is based on the independency assumption among losses. Therefore, overall loss can be determined as:

$$OL_0 = BL + HHL + AL + ECC \tag{5.8}$$

Related consequence analysis literature such as API RP 581 [6], CCPS [11] and DNV-RP-G101 [25] also considers independent losses for overall loss calculation due to easier practical applications. This assumption can be relaxed by considering the potential dependency among losses and the application of copula-based loss aggregation methods, such as the one proposed by Hashemi et al. [26].

The overall loss estimation is Equation (5.8) is based on a constant dollar value assumption. However, prices of goods, services, shares, equipment and components bought and sold by firms, as well as factors such as the value of environmental damage fines and penalties, change over time. Consequently, the assumptions made for loss estimation change and adjustments should be made accordingly for projected loss values. Most existing corrosion consequence analysis approaches only estimate the constant (today's) dollar value of the losses in coming years and the effect of inflation is not considered in the estimation. However, to ensure more accurate estimation of losses in the future due to corrosion failures, actual dollar value should be used. Actual dollar is expressed in the monetary units at the time the cash flows occur.

Inflation is an important concept in any economic analysis because the purchasing power of money rarely stays constant. Because of inflation, a unit of currency in one period of time is not equivalent to the same unit at another time. Economic analysis requires that comparisons be made on an equivalent basis. Thus, it is important to incorporate the effect of inflation in analysis of the losses. For this purpose, for each year, the inflation rate is applied to the overall loss determined from Equation (5.9) to consider the effect of actual dollar value for the estimated loss.

Converting the estimated today's dollars into actual dollars in year *t* relative to a base year (current year of assessment) is performed using Equation (5.9):

$$OL'(t,f) = OL_0.(1+f)^t \tag{5.9}$$

where:

- OL': actual dollars in year *t* relative to the base year;
- OL_0: today's dollars estimated from Equation (5.8) equivalent to OL';
- *f*: the inflation rate per year, assumed to be constant from year 0 to year *N*.

5.3.5. Step 5. Estimation of Initial POF

The probability of failure is estimated using limit state function analysis. For this purpose, Maximum Pit Depth (MPD) is considered as the critical characteristic of pitting corrosion. Then, a time-dependent MPD model [5], proposed earlier, is integrated with the maximum allowable operating pressure model in DNV-RP-F101 [27] as follows:

$$P_{corr}(t) = \gamma_m \frac{2\tau f_u (1-\gamma_d (\frac{MPD(t)}{\tau})^*}{(D-\tau)\left(1-\frac{\gamma_d (\frac{MPD(t)}{\tau})^*}{Q}\right)} \tag{5.10}$$

where τ is the component thickness (*mm)* and P_{corr} (t) is the maximum allowable pressure (N/m^2) as a function of time for a component susceptible to pitting corrosion, $Q=\sqrt{1+0.31\left(l/\sqrt{D\tau}\right)^2}$ and $\left(MPD(t)/\tau\right)^*=\left(MPD(t)/\tau\right)+\varepsilon_d StD\left[MPD(t)/\tau\right]$. *MPD (t)* is the maximum pit depth (*mm*)**;** D is the outside diameter of the pipe (*mm*); l is the length of the pitted area (*mm*); f_u is the ultimate tensile strength (N/m^2) ; γ_m is the partial safety factor for longitudinal corrosion model prediction; γ_d is the partial safety factor for pit depth; ε_d is a factor for defining a fractile value for the pit depth; and $StD[MPD/\tau]$ is the standard deviation of the random variable (MPD/τ). The values of γ_d, γ_m, and ε_d are provided in DNV RP-F101 [27].

To estimate MPD, the methodology in [5,28] is adopted in this work. In this methodology, the non-homogenous Markov process is used to estimate the MPD. The probability of a deepest pit in a state less than or equal to state i, at time t, can be estimated using the expression:

$$\theta_H\ (i, t|\chi, \omega) = \prod_{k=1}^{m} \{1 - [1 - \exp\ (-\rho(t - t_k)]^i\} \quad i = 1, \ldots, n \tag{5.11}$$

where t is the time of assessment (year), t_k is the initiation time of pits (year), n is the total number of states in the Markov chain, m is the average pit density (APD) at time of assessment and $\rho(t\text{-}t_k)$ is the number of transited states of a pit that grows in a short time interval (t_k, t).

$$APD(t) = \frac{A}{\psi}\left[1 - e^{-\psi t}\right] + wt^{\eta} \tag{5.12}$$

t_k is the pit initiation time. By assuming that all pits initiate in order at times t_1, t_2, ..., t_m, the initiation time t_k (year) for each pit , k = 1, 2, ..., m, can be estimated by calculating the inverse of the pit density [29,30]:

$$t_k = APD^{-1}(k), k = 1, 2, \ldots, m \tag{5.13}$$

Finally, probability of failure (POF) due to corrosion is calculated as follows:

$$POF_0 = \phi(-\beta) = 1 - \phi(\beta) \tag{5.14}$$

where ϕ is the normal cumulative distribution function and β is the reliability index, to be determined as:

$$\beta = \frac{\mu_{P_{corr}} - \mu_{P_{op}}}{\sqrt{\sigma^2_{P_{corr}} - \sigma^2_{P_{op}}}} \tag{5.15}$$

where $\mu_{P_{corr}}$ and $\mu_{P_{op}}$ are the average of P_{corr} and the operating pressure, and σ_{Pcorr} and σ_{Pcorr} are the standard deviation of P_{corr} and operating pressure distribution, respectively. P_{corr} is determined using Equation (5.10). Equation (5.15) is developed using the limit state function, where P_{corr} and P_{op} are load and resistance variables. The estimation of POF is dependent on the precision of the independent variable of the limit state function [6]. The extent of corrosion damage to estimate the limit state variables may have considerable uncertainty, especially when damage is into the future.

5.3.6. Step 6. Application of CPM3 Adjustment Factors

As discussed earlier, Corrosion Prevention, Monitoring, Maintenance and Management (CPM3) costs are incurred by an organization to prevent potential losses to people, property and the environment. The CPM3 costs have a mitigating effect on potential corrosion losses. As stated in BS 6143-2 [12], an increased awareness of the cost to the organization due to corrosion leads first to an increase in control costs. Then, as corrosion monitoring and control identify areas of improvement, more is spent on corrosion prevention compared to mitigation. Finally, as preventive actions take effect, both the frequencies of failures due to corrosion and the consequent losses reduce [12].

Other than insurance, that has a direct mitigating impact on overall loss by transferring part of the residual risk to a third party, the quantification of the mitigating impact of other corrosion cost elements is not straightforward. Spending more on prevention, monitoring, maintenance and management does not necessarily reduce the overall loss. In fact, the effectiveness and the frequency of these measures, which are also a function of cost, indicate their mitigating performance. Therefore, adjustment factors are used in this work to take into account the effectiveness of corrosion costs in reducing either the probability or severity of corrosion losses.

5.3.6.1. Step 6.1. Effect on Corrosion Loss Severities

Insurance coverage is a corrosion management strategy that can directly affect the severity of the overall loss by transferring a part of the residual risk to an insurer as follows:

$$OL = OL' - IR \tag{5.16}$$

where *OL'* is the overall loss ($) estimated from Equation (5.9) and *IR* denotes insurance recovery ($). Thus, by knowing the amount of potential *IR*, the adjusted overall loss can be estimated using Equation (5.16) by incorporating the mitigating effect of insurance. The estimation of insurance recovery is not within the scope of this work.

5.3.6.2. Step 6.2. Effect on Corrosion Loss Probabilities

The effectiveness of CPM3 techniques directly affects the probability of corrosion losses. Industry best practices and standards consider the effect of corrosion inspection and maintenance effectiveness using effectiveness factors. For instance, API RP 581 [6], categorizes effectiveness factors as "A" through "E", with an "A" category providing the most effective program and "E" representing an ineffective or missing program. In the API 581 approach, the effectiveness values are point-based, ignoring the associated uncertainty. To address this challenge, a methodology for estimation of CPM3 adjustment factors is presented in this section considering uncertainty.

In this work, the adjusted POF is determined by applying the adjustment factors as follows:

$$POF(t) = AF_{CPM3} \times POF_0(t) \tag{5.17}$$

where $POF_0(t)$ is the original POF estimated using Equation (5.14), ignoring the mitigating impact of CPM3 actions. In Equation (5.17), AF_{CPM3} denotes the CPM3 adjustments factor. It considers the overall mitigating impact of all CPM3 costs and their influence on the mechanical integrity of the component attacked by corrosion. AF_{CPM3} is defined as:

$$AF_{CPM3} = 1 - exp\left(\frac{-t^2}{(t_{design}/\alpha_{AF}^2)}\right) \tag{5.18}$$

where t is time, t_{design} is the design life of the equipment, and α_{AF} is the shape factor. The value of AF_{CPM3} varies between 0 and 1, where the value of 1 shows the ineffectiveness, or lack of, the associated CPM3 element and values closer to 0 show more effectiveness to reduce the POF. The consideration of the impact of design life in AF_{CPM3} is required as its value directly affects the selection and implementation of CPM3 actions over the asset life cycle.

The shape factor α_{AF} can have values between 0 to 10, where the value of 0 represents fully effective CPM3 (i.e., a corrosion proof system). As the value of α_{AF} approaches 10, the adjusted POF curve becomes closer to the original POF, representing ineffective CPM3 actions. The exact estimation of the α_{AF} value is not an easy task, as different factors could affect the value of the shape factor, including:

- The effectiveness of selected methods for detecting/mitigating pitting corrosion. This is also referred to as probability of detection (POD) in the literature.
- The frequency of selected CPM3 methods.
- The operator/management skill in implementing the selected CPM3 methods.
- The existence of proper procedures and auditing system to ensure compliance with procedures.

Moreover, if the selected CPM3 actions are not appropriate for detecting and mitigating pitting corrosion, higher CPM3 costs do not necessarily mean a lower probability of pitting corrosion failure. However, higher investments in proper CPM3 actions directly affect the POF due to pitting corrosion. The estimated CPM3 costs are important parameters to be considered when estimating α_{AF}. Therefore, as discussed in Section 5.2.3, the application of PERT distribution is proposed in this work to estimate the cost associated with CPM3 strategies.

Quantifying the individual effect of all aforementioned factors on α_{AF} using a separate model is cumbersome due to the lack of reliable data for CPM3 effectiveness, cost data, operator skill, and management performance. Furthermore, the uncertainty associated with estimating the effectiveness of CPM3 measures should be taken into consideration. Therefore, the use of expert knowledge, along with the PERT distribution, is a better approach to estimate the value of the CPM3 adjustment factor based on the estimated cost and other contributing factors mentioned above. Thus, the PERT distribution explained in Section 5.2.3 is used to estimate α_{AF}. The aforementioned guidelines for α_{AF} estimation, along with the maintenance, operation and management histories should be used to assign minimum, most likely and maximum α_{AF} values. Having estimated the PERT distribution for α_{AF}, Monte Carlo simulations are used to obtain a distribution for AF_{CPM3} using Equation (5.18).

5.3.7. Step 7. Risk Calculation

The overall risk is calculated using the Monte Carlo Simulation method to take samples from the overall adjusted loss and adjusted probability distributions and then calculating the risk for each pair of realized probability and loss values using this equation:

$$R(t) = POF(t) \times OL(t) \tag{5.19}$$

where *POF*(*t*) and *OL (t)* distributions are estimated from Equations (5.17) and (5.16), respectively. To evaluate the equipment using the estimated risk, an acceptable risk level (in dollars) can be defined. When the risk at a time t exceeds the acceptable level, risk mitigation actions must be carried out to prevent the occurrence of an accident or mitigate its consequence.

5.4. Case Study

5.4.1. Case Study Overview

The practical application of the proposed risk-based economic impact analysis of pitting corrosion is demonstrated using a case study. The pipeline under study is newly installed on an offshore oil rig and the inspections confirmed that it was free from fabrication damage at the time of installation. However, based on experiences from similar offshore facilities, pitting corrosion can occur anywhere in the production environment, including in downhole tubulars, topside equipment and pipelines. The system is susceptible to internal pitting corrosion due to favorable conditions and the presence of process contaminants such as CO_2 and H_2S. The pipe specifications include: outside diameter of 200 millimeter (mm), thickness of 7.036 mm, length of 1.5 m, tensile strength of 410 N/mm^2 and operating pressure of 15 MPa.

Undetected pitting corrosion can result in loss of containment, entailing potential fire, explosion and extensive damage to topside equipment with the subsequent production shutdown. Due to the remoteness of operations and difficulties in scheduling regular inspections, the application of the proposed risk-based pitting evaluation model can help operators to estimate the risk of pitting corrosion. The estimated risk can be used for different decision-making purposes such as prioritization of inspection and maintenance activities. For this purpose, the proposed methodology in Figure 5.1 to estimate pitting corrosion risk is applied. In the following sections, first, the estimated elements of business and accidental losses are estimated to assess the overall loss. Then, the calculated overall loss is adjusted considering the inflation rate. The probability of failure is calculated and adjusted using the CPM3 adjustment factor. Finally, risk is calculated as the product of probability and consequences of failure due to pitting corrosion.

5.4.2. Estimation of Business Loss

The proposed PERT methodology is applied to estimate business loss elements. Table 5.3 shows the following information, which is used to estimate overall business loss due to pitting corrosion:

- Minimum, mode and maximum values for each loss element. These conservative values are estimated using expert knowledge from similar processes and can be updated as more reliable information becomes available.
- Parameters of PERT distributions, i.e. v_i^{PERT} and w_i^{PERT}, calculated using Equations (5.2) and (5.3) based on minimum, mode and maximum loss values.
- Parameters of Equation (5.4), which are selected for illustration purposes to represent the non-linear relationship between the business loss and time.

The recovery period and MTTR are considered as random variables and are modeled using exponential distributions assuming a constant repair rate. Based on the previous experiences and performance history of the repair and maintenance team, the mean of MTTR is considered as 90 days. Accordingly, the mean of the recovery period is considered as half of the MTTR, to represent the time required for the business to be restored after a failure. Parameters of Equation (5.4) in Table 5.3 and other parameter values can be adjusted over time as more information becomes available by comparing the organization's business performance in the past 12 to 24 months. Finally, Equation (5.4.a) and Monte Carlo simulations with $J = 10^6$ iterations are used to estimate the overall business loss. The mean, standard deviation, 50% percentile (P50) and 99.9% percentile (P99.9) of the estimated overall business loss are shown in Table 5.3.

Table 5. 3. Business interruption loss elements for the case study

Loss Element	Description	Minimum ($/day)	Mode ($/day)	Maximum ($/day)	PERT Parameters		Parameters of Equation 5.4		
					v^{PERT}	w^{PERT}	***B1***	***B2***	***B3***
BL_{dt}	Profit loss due to production loss over process downtime	375×10^3	575×10^3	875×10^3	2.6	3.4	0	1.08	1.01
BL_{rt}	Profit loss over recovery period	125×10^3	192×10^3	292×10^3	2.6	3.4	0	0.5	0.6

5.4.3. Estimation of Accidental Loss Elements

5.4.3.1. Damage Area Estimation

To determine accidental losses, the first step is to estimate the component damage and/or personnel injury. For this purpose, API RP 581 [6] methodology is used for consequence area modeling. In API RP 581, for different discrete hole size scenarios (small, medium, large and rupture), release rates are calculated based on the phase and properties of the fluid, such as flow rate, type of fluid, initial phase, total mass, equipment volume and percentage of liquid volume. The release rates are then used in closed form equations to determine the consequence areas for component damage and personnel injury [6]. For illustration purposes, the impact areas are considered to follow Lognormal distributions as it can model positive real values of potentially skewed and asymmetric distributions with possible extreme values. A mean of 260 ft^2 and standard deviation of 210 ft^2 for the Lognormal distribution of component damage area, and a mean of 1310 ft^2 and standard deviation of 625 ft^2 for the Lognormal distribution of personnel injury consequence area are used. However, these numbers and associated distributions should be calculated using approaches such as API RP 581 [6] methodology for the process under study. To keep the work concise, no environmental cleanup loss is assumed for this case study, by assuming that the released hydrocarbon will readily evaporate.

5.4.3.2. Asset Loss Modeling

Equation (5.5) is used to estimate the asset loss, which includes the replacement cost for the pipe and the total damage cost to other assets located within the estimated component damage radius. The process unit replacement cost (C_u) is considered to follow a Normal distribution with mean of \$24,000/ft^2 and standard deviation of \$1,600/ft^2, determined from the project design information and construction contract. Then, Equation (5.5) is used to determine the overall asset loss by applying Monte Carlo simulations with $J = 10^6$ iterations. Table 5.4 shows the statistical information of the asset loss distribution.

5.4.3.3. Human Health Loss Modeling

Equation (5.6) is used to model the human health loss, which requires the estimation of population density, personnel injury area and the value of statistical life (VSL). The population density is estimated using the PERT distribution of the number of people on board with a minimum of 60, maximum of 120 and a mode of 100 people during operations and considering a uniform distribution of personnel over the rig unit area of 18,000 ft^2. The VSL is significantly influenced by the country of origin of the study, year, and other sources of the risk variables [23]. For the purpose of this case study, the VSL is considered to follow a lognormal distribution with a mean of $8,420,568 and variance of $7,890,597, taken from a study by Bellavance *et al.* [23]. The use of lognormal distribution helps to consider potential extreme observations in rare major events due to its ability to have fat tails. It is assumed that all people in the personnel injury consequence area (Section 5.4.3.1) will be fatally injured. The human health loss is then estimated using Equation (5.6) by applying MC simulations with $J = 10^6$ iterations and the results are shown in Table 5.4.

5.4.4. Overall Loss Estimation

Table 5.4 summarizes the results of loss evaluations for this case study. The P50 (50^{th} percentile) and P99.9 (99.9^{th} percentile) for each loss element are also provided in Table 5.4, which helps to communicate the uncertainty associated with each estimated loss. From Table 5.4, the expected *BL* value contributes approximately 41% of the overall expected loss. This is not a surprising observation as the production unit will typically experience several days of downtime due to loss of containment. Finally, the overall loss is estimated as the summation of all loss elements and the results are shown in Table 5.4. Figure 5.2 shows the distribution of the overall loss for this case study with a mean value of 151 million dollars. The application of probability distributions to model losses is one of the advantages of the proposed methodology, compared to the point-based deterministic approaches in traditional consequence modeling models such as API RP 581 [6] and CCPS [11]. The estimated overall loss distribution is integrated later with failure probability distribution to obtain the risk distribution.

Table 5.4. The value of estimated loss elements for the case study (all losses are reported in USD million)

Loss	Mean	Standard Deviation	P50	P99.9	Percentage (Mean/Total Loss)
BL	61.8	62.9	41.6	467.5	40.9
AL	29.4	6.6	29.2	51.0	19.5
HHL	59.8	55.9	43.2	494.7	39.6
Overall	151.0	84.2	130.2	632.9	--

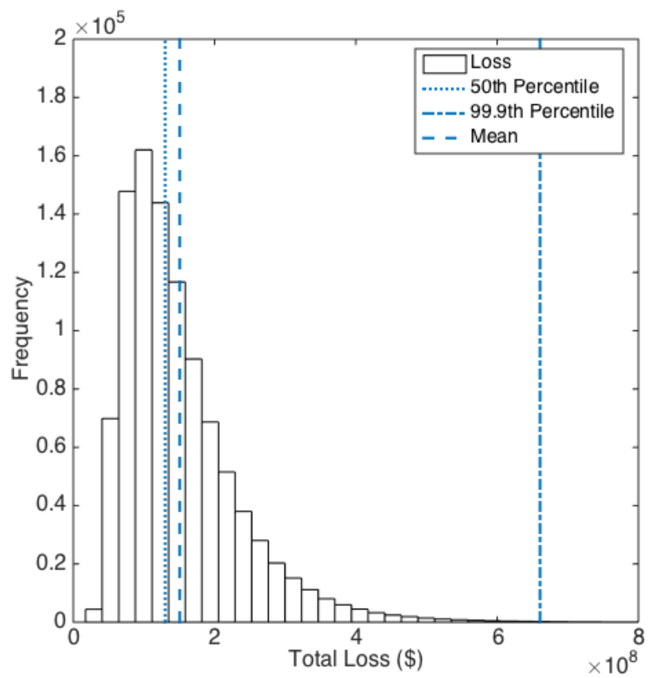

Figure 5.2. Overall loss for the case study

5.4.5. Probability Estimation

5.4.5.1. Initial Probability Estimation

As discussed in Step 5 of the presented methodology, the state function approach in Shekari et al. [5] is used to calculate the probability of failure (POF). The first step is to estimate the maximum pit depth (MPD) change over time. As shown in Figure 5.3, MPD is considered as a function of time and is modelled using Equation (5.11). Then, the P_{corr} distribution is estimated using Equation (5.11) and is plugged into Equation (5.15) to obtain reliability index values for different exposure times. Finally, the estimated reliability index values, $\beta(t)$, are used in Equation (5.14) to obtain the initial POF time plot and the result is shown in

Figure 5.4. As can be seen in Figure 5.4, the POF is negligible until year two. However, as pits grow, the POF increases sharply after the second year due to the reduction in material strength and maximum allowable operating pressure. As will be discussed later in Section 5.4.7, the developed POF curve is used to estimate overall risk over time.

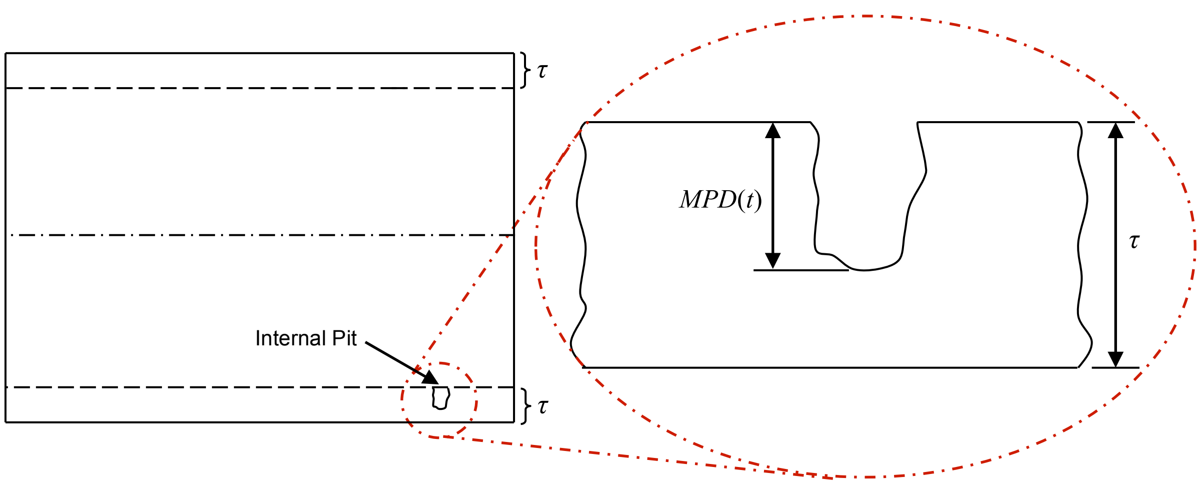

Figure 5.3. Internal pit growth over time for the pipe case study

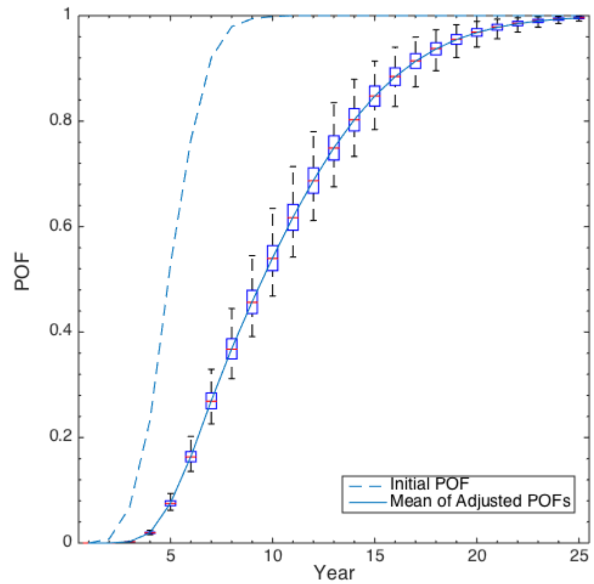

Figure 5.4. Initial and adjusted probability of failure (POF) curves due to pitting corrosion for the case study. The box plots represent the minimum, first quartile, median, third quartile, and maximum values of adjusted POF over time.

5.4.5.2. Adjusted Probability Curve

The initial POF curve in Figure 5.4 did not take into account the mitigating impact of existing Corrosion Prevention, Monitoring, Maintenance and Management (CPM3) measures. The proposed approach in Step 6.2 is used in this section to adjust the estimated initial POF by incorporating the effective CPM3. For this purpose, the expert is asked to estimate minimum, most-likely, and maximum shape factor values of the adjustment factor (α_{AF}) based on the guidelines provided in Step 6.2 and the plant-specific information such as type, effectiveness, and frequency of CPM3 actions, operators' skill, management effectiveness and compliance with procedures. Table 5.5 shows the selected α_{AF} values and the calculated PERT distribution parameters for the CPM3 adjustment factor (AF_{CPM3}). The distribution parameters of α_{AF} are calculated using Equations (5.2) and (5.3). Conservative values are used in Table 5.5 as starting values, which are inevitable for new installations and for cases without proper operational history. However, these values can be revised over time as more information becomes available from the system.

Using Equation (5.17), the initial POF is adjusted by incorporating the estimated adjustment factor distribution and the results are shown in Figure 5.4. The representation of the POF adjustment factor using a probability distribution aids to capture the uncertainty associated with CPM3 strategies and their impact on adjusted POF. The minimum, first quartile, median, third quartile, and maximum values of the adjusted POF are shown in Figure 5.4 using box plots. The solid line in Figure 5.4 shows the mean values of POF over time. These box plots help practitioners to consider the potential POF uncertainty for inspection, maintenance and management planning. From Figure 5.4, it can be seen that the adjusted POF values start to increase at a lower rate compared to initial POF values, considering the mitigating impact of CPM3 actions to prevent, detect and correct pitting damage. Consequently, there is a significant decrease in estimated POF values compared to the initial POF where the impact of CPM3 methods was ignored. For instance, as shown in Figure 5.4, in year 4 the failure probability is decreased from 0.23 to 0.019 by incorporating the impact of CPM3 methods. The advantages of the proposed approach to quantify the mitigating impact of CPM3 strategies are discussed further in the next section.

5.4.6. Risk Calculation

The estimated overall loss in Step 6.1 and adjusted POF in Step 6.2 are combined using Equation (5.19) to determine the risk versus time profile. For simplicity, inflation is considered to be a constant value of 2% throughout the system life cycle and its impact on loss is determined using Equation (5.9). The estimated overall risk as a function of time is shown in Figure 5.5. Since risk is the combination of probability and loss, the estimated risk is negligible for the first three years, as the POF is negligible (see Figure 5.4). As POF starts to increase due to the pits' growth, so does the risk. The solid line in Figure 5.5 shows the increase in mean risk values and the box plots represent the variability in estimated risk over time due to uncertainty associated with POF and loss estimations. The increasing boxplot sizes over time in Figure 5.5 represent an increasing trend of the uncertainty of risk predictions over time. In other words, as the time interval between the assessment time (current time) and the intended prediction time (future time) increases, so does the uncertainty of pit behaviour (depth) and risk predictions, unless inspection data becomes available to update the model predictions. This increasing trend of uncertainty over time shows the importance of conducting periodic inspections to validate and update model predictions and decrease the associated uncertainties. The integration of the proposed pitting corrosion economic impact analysis model with a Bayesian analysis is a subject for future research by authors to address this need.

The proposed probabilistic pitting risk assessment provides a significant improvement compared to the methods used in traditional corrosion risk assessment literature (such as API 581 [6], DNV-RP-C302 [31], Thodi *et al.* [7]) where risk is simply shown using a risk matrix or a simple curve. Application of the developed risk time plot in Figure 5.5

aids to make risk-informed decisions while considering the uncertainty associated with both POF and loss estimates. As will be discussed in the next section, by assigning a threshold risk value, the developed risk plot can be used for remaining life evaluation and risk-based inspection and maintenance planning.

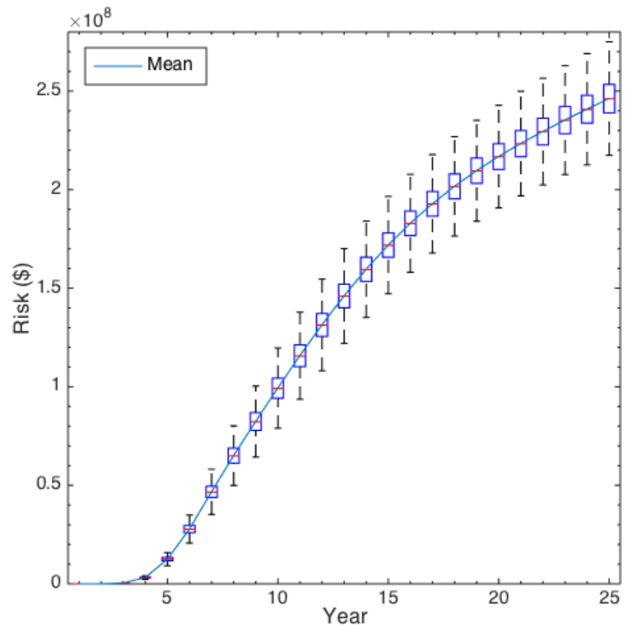

Figure 5.5. Box plot of risk of pitting corrosion over time for the case study

5.4.7. Sensitivity Analysis

A sensitivity analysis is conducted to investigate the impact of each loss category on estimated risk. For this purpose, 11 experiments are conducted by changing the values of each loss category in Table 4 in the range of -25% to +25% to estimate the corresponding change in overall risk in years 15. As can be seen in Figure 5.6, for 10,000 Mote Carlo simulation runs, changes in both business and human health losses in the range of -25% to +25% have resulted in approximately the same amount of changes in the range of -

10% to +10% in estimated risk values. The similar trend in risk chnages for these two loss catgeories is because of the close values of their means and standrad variations (see Table 5.4). However, the same amount of changes in asst loss values have resluts in only a change in the range of -5% to +5% in estimated risk values. This is not a suprising obseravtion as the mean value of asset loss is almost half of the mean values of business and human health lossees. Similar senesitivity analysis was conducted for year 10, which resulted in almost the same results. Another obseravtion from Figure 5.6 is the linear change in risk values due to the change in the amount of each loss category. This linear relationship is due to the linear relationship between risk and loss in Equation 5.19. The sensisticity analysis of the effects of loss categories is a case-specific problem and should be repeated if the assumptions for estimation of losses change.

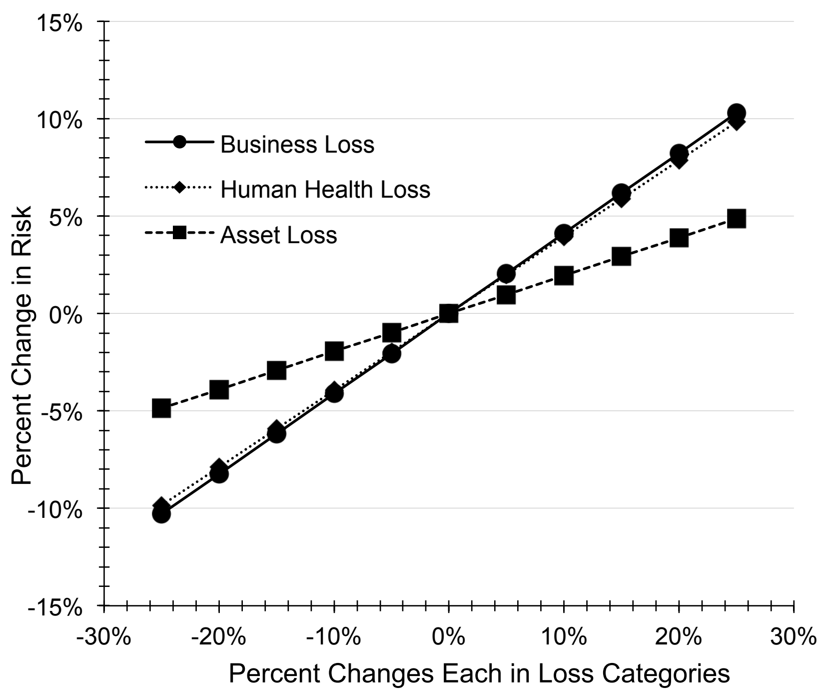

Figure 5.6. Sensitivity analysis of the effect of loss categories on estimated risk for year 15

5.4.8. Discussions

One of the primary applications of the proposed methodology is risk-based remaining life evaluation of components affected by pitting corrosion. For instance, by defining a threshold risk for the system, the intersection of the risk profile and threshold risk value can be used as a criterion to make inspection, repair, rerating, or replacement decisions. As shown in Figure 5.5, for instance, considering the threshold risk as 120 million United States dollars (USD) for this case study, the risk exceeds the threshold value after 11.2 years. Alternatively, other criteria such as remaining intact thickness or POF can be used for remaining life evaluation [32]. However, use of the proposed risk-based approach in remaining life evaluation helps to consider both POF and loss in decision-making.

To facilitate a better investigation of the importance of considering inflation as well as Corrosion Prevention, Monitoring, Maintenance and Management (CPM3) adjustment factors (AF_{CPM3}) in overall risk estimation, the proposed model is applied to two different scenarios and the results are compared with the estimated remaining life values from Figure 5.5. The considered scenarios are:

- Base Scenario: Base case scenario is taken from the previous section (Figure 5.5) where the effects of both inflation and AF_{CPM3} are considered.
- Scenario 1: The effects of both AF_{CPM3} and inflation are ignored.
- Scenario 2: Only the effect of AF_{CPM3} is considered (0% inflation).

Table 5.5 shows the information for all scenarios. CPM3 costs are also shown in Table 5.5 to facilitate cost-benefit analysis by comparing the amount of change in the remaining life with the investment in CPM3 methods. Similar CPM3 costs are considered for both

Base Scenario and Scenario 2; only the effect of inflation is ignored in Scenario 2. The CPM3 costs are reported in dollars per day in Table 5.5, as offshore platforms are usually rented by operators and maintenance costs are reported as an average value per unit of time. In Scenario 1, it is assumed that the only existing corrosion protection is the initial design and material selection and no CPM3 action is considered after putting the platform into service. Although this is an unrealistic scenario, the purpose here is to show how the proposed methodology can be used for cost-benefit analysis of investing in CPM3 strategies.

Using the assumptions in Table 5.5, the overall risk due to pitting corrosion is estimated for each scenario and the time plot' mean values are shown in Figure 5.7. The developed risk time plots are then used to estimate the remaining life of the pipe and the results are shown in Table 5.5.

Table 5.5. Different scenarios for remaining life evaluation of the pipe case study

Scenario	Inflation	CPM3 Costs (thousands $/day)					α_{AF} (AF shape parameter)					Remaining Life (Years)	% Change in Rem. Life (compared to Scenario 1)
		Min	Mode	Max	v_{cost}^{PERT}	w_{cost}^{PERT}	Min	Mode	Max	v_{α}^{PERT}	w_{α}^{PERT}		
Base	2%	13	15	18	2.6	3.4	3	3.3	3.8	2.5	3.5	11.2	90%
1	0%	0	0	0	0	0	NA	NA	NA	NA	NA	6.1	NA
2	0%	13	15	18	2.6	3.4	3	3.3	3.8	2.5	3.5	14	137%

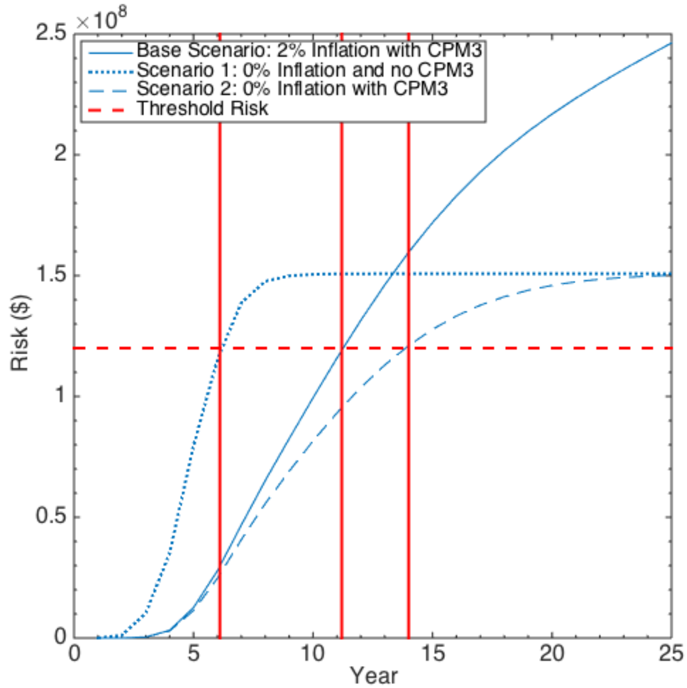

Figure 5.7. Mean values of risk of pitting corrosion over time for different scenarios of the case study

As can be seen from Figure 5.7, compared to Scenario 1 with no CPM3 action and 0% inflation, the risk is decreased significantly in the base scenario and also shifted to the right. The reason is that the application of CPM3 strategies decreases the rate of pitting corrosion by detecting, preventing, monitoring, and/or repairing the pitting damage. From Table 5.5, investing in CPM3 strategies with a mode value of USD 5.475 million/year (estimated from Table 5.5 as the product of 365 days and CPM3 cost of $15,000 per day) has resulted in a 90% increase in the estimated life in the Base Scenario compared to Scenario 1 (considering the threshold risk of USD 120 million). This helps the risk practitioners to investigate the effect of investment in CPM3 strategies and the resulting reduction in the risk. For example, with the current assumptions in Table 5.5, the risk in Scenario 1 exceeds the threshold value after 6.1 years. However, an annual investment of

USD 5.475 million (estimated from Table 5.5) in CPM3 has resulted in 75.7% reduction in risk in year 6.1 from USD 120 million in Scenario 1 to USD 29 million in the base scenario.

On the other hand, as can be seen in Figure 5.7, ignoring the effect of inflation in Scenario 2 has resulted in under-estimation of the risk and a 25% increase in the estimated remaining life compared to the base scenario. The risk in both Scenarios 1 and 2 approaches a maximum value of USD 151 million over time, which is estimated based on the worst-case failure scenario and maximum credible loss of USD 151 million (from Figure 5.2). However, the risk in the base scenario keeps increasing over time due to the consideration of the effect of inflation and the increases in the dollar value of the loss if the failure happens in the future. These results show the importance of taking into account the effects of both inflation and CPM3 strategies in overall economic impact analysis of corrosion, which are usually ignored in traditional corrosion loss modeling methods. Moreover, the estimated risk time plots can be used for cost-benefit analysis of plant upgrade programs and decision-making about investments to improve the effectiveness of CPM3 techniques.

5.5. Conclusions

Evaluating the pit growth rate of assets is not enough to ensure their safe operation. Instead, both probabilities and consequences of failure due to pitting should be considered to enable a risk-informed decision-making process for evaluating deteriorating assets. In this study, a risk-based approach is proposed for overall economic impact analysis of pitting corrosion. The proposed model estimates the business loss and accidental losses due to pitting corrosion failure. By modelling the maximum pit depth growth and using the state function approach, the initial probability of failure is estimated. The mitigating impact of corrosion prevention, monitoring, maintenance and management (CPM3) is recognized by modeling the cost of CPM3 strategies and the application of the adjustment factor based on the effectiveness of corrosion remediation techniques and their associated costs. The consideration of CPM3 costs affects the probability of failure and the severity of failure losses. To ensure more accurate prediction of risk in the future due to corrosion failures, the actual dollar value is used by incorporating inflation in the proposed loss model. Compared to traditional methods, such as API RP 581, that only consider the impact of inspection effectiveness and management factors using point-based adjustment factors, the proposed method provides a mechanism to (ii) consider the impact of all corrosion prevention, monitoring, maintenance and management factors, (ii) capture the uncertainty associated with effectiveness and costs of CPM3 strategies, and (iii) conduct a risk based cost-benefit analysis by considering the overall cost of CPM3.

The proposed models are applied to an offshore piping case study. In the case study, losses are classified into two categories: business loss and accidental loss. The consideration of the CPM3 adjustment factor has resulted in an increase in the estimated remaining life because of the mitigating effect of corrosion control measures. Also, the results of the case study highlight the fact that ignoring inflation can significantly cause underestimation of overall loss. The integration of the Bayesian approach with the proposed loss models can be a subject for future research to update the estimated risk dynamically based on new information from the system.

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6. DYNAMIC RISK MANAGEMENT OF ASSETS SUSCEPTIBLE TO PITTING CORROSION[5]

Preface

A version of this manuscript has been submitted to the Corrosion Science journal. I am the primary author of this paper. Along with the co-authors, Faisal Khan and Salim Ahmed, I developed the conceptual model and subsequently translated this to the numerical model. I conducted the literature review and proposed a new technique to develop a dynamic risk framework. I carried out most of the data collection and the comparison of risk models. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' feedback. The co-author Faisal Khan helped in developing and testing the concepts/models, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Salim Ahmed contributed through support in the development, testing and improvement of the models. Salim Ahmed also assisted in reviewing and revising the manuscript.

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Abstract

This paper presents a methodology to assess and dynamically update the risk of pressurized components affected by pitting corrosion. The proposed dynamic risk management framework considers the time-dependent growth of pits and uses the non-homogenous Markov process to model the maximum pit depth. The developed maximum pit depth model is incorporated into a limit state function to model probabilities of affected components. Economic consequences are estimated considering both business and accidental losses due to failure of the affected component. Finally, risk is estimated by integrating the probability of failure and associated consequences. The estimated risk is updated using Bayesian analysis as new inspection data become available and the economic condition of the process evolves. This paper also evaluates different risk management strategies including prevention, control and mitigation measures to make effective decisions related to localized corrosion. The application of the proposed method is demonstrated using an offshore piping system.

6.1. Introduction

Insulation of offshore assets is required to conserve energy and ensure safe, reliable and cost-effective operations. Corrosion Under Insulation (CUI) occurs in the operating temperature range for most offshore applications and has been reported to attack different types of carbon steel and stainless steel [1]. The presence of external insulation can lead to corrosion which is much more severe than would be expected if the equipment was uncoated [2]. Pitting corrosion is one of the most dangerous forms of CUI and requires specific consideration of insulated equipment due to the technical difficulties of pit detection and prevention. Pitting corrosion is a localized form of corrosion that occurs when one area of a metal surface becomes anodic with respect to the rest of the surface. It can also occur when highly localized changes in the corrodent in contact with the metal cause an accelerated localized attack [3], [6].

Several studies have been conducted to investigate pit behaviour and the proposed models for pitting corrosion. These models are used in a variety of methods to predict failures, optimize maintenance and inspection schedules and aid in material selection [4]–[11]. Pit models are also used in risk assessment to predict a failure by providing a framework for remaining life evaluation and risk-informed decision-making [12]. The importance of using risk-based methods to schedule inspection and maintenance activities is now recognized by the industry as ensuring safety while prioritizing limited resources. Numerous quantitative, semi-quantitative, and qualitative models have been developed to help engineers make risk-based decisions about damaged equipment, such as [12]–[17]. Most corrosion risk assessment methods, such as those discussed in [12]–[17], have the common shortcoming of being static. However, pitting corrosion is a complex process and pit behaviour changes over time due to different causes including, but not limited to, operational changes, feed variability, uncertainty in expert knowledge estimates and changes in asset conditions due to maintenance activities [18], [19]. Hence, it is essential to use a dynamic risk assessment approach which considers prior knowledge of the pitting corrosion process along with inspection data and new information from the system in order to calibrate the model over time [20].

Bayes' rule and Bayesian analysis have gained popularity in the dynamic risk assessment literature as a promising tool, suitable to cope with complex and uncertain situations [21]. For the case of corrosion, Farias and Netto [22] applied the Bayesian method to predict the corrosion distribution combined with a nonlinear corrosion evaluation model [23]. Zhang et al. [24] and Qin et al. [25] developed models for corrosion defects' depth and updated have been model parameters using the Bayesian framework. However, none of these methods are developed specifically to model pit characteristics, such as the maximum pit depth, which is essential for remaining life evaluation of components affected by pitting corrosion. In the context of pitting corrosion, for instance, Mao [26] presented a probabilistic model that considers the uncertainties of in-service inspection. Mao's model utilized a Markov Chain Monte Carlo (MCMC) simulation and a Bayesian method for estimating the model parameters [26]. Mokhtar et al. [27] used a Bayesian methodology to update corrosion model parameters according to the evolution of environmental conditions. Bhandari et al. [20] presented a probabilistic model for predicting the long-term pitting corrosion depth of steel structures in a marine environment using Bayesian analysis. In a study by Kasaie et al. [23], the experimental results were used to develop a pitting corrosion evaluation method by combining extreme value analysis and Bayesian inference analysis [23].

One of the important advantages of Bayesian analysis is its ability to use inspection data to update the prior belief about the pit's behaviour. For instance, Straub [9] used new inspection data (pit depth measurements) to estimate the likelihood probabilities of deteriorating components to update the prior distribution of the model predictions for maximum pit depth (MPD). The traditional Bayesian updating approach assumes conjugate prior and likelihood distributions. Conjugate priors provide computational ease and flexibility that facilitate the development of analytical solutions for the posterior distribution. As conjugate pairs are often unable to capture the realistic behaviour of the parameters [26], use of the traditional Bayesian approach (conjugate-likelihood pair) may introduce significant potentially uncertainty. To address this limitation, the Markov Chain Monte Carlo (MCMC) and Metropolis–Hasting (or M–H) algorithm [28] are used to estimate posterior distribution for non-conjugate distributions.

Most available models update pit characteristics, such as pit depth, as a function of time. The pit behaviour leads to the failure probability, which is an element of a risk assessment framework. Dundulis et al. [29] presented a method to estimate and update failure probability using new inspection data. In their study, they developed an overall framework based on statistical data analysis and the Bayesian method. Qin et al. [25] presented time-dependent failure probability of the corroding pipeline by considering the measurement errors associated with inline inspection tools using the Bayesian updating. Maleki and Xin [30] proposed a quantitative method to revise the risk calculated in the Risk-Based Inspection (RBI) scheduling. Their proposed approach estimates unconditional probability of failure, which is modified using a Bayesian updating method, allowing the conditional probability to represent a new failure likelihood to be utilized in RBI planning [30]. In Mokhtar et al. [27], the Bayesian updating on the basis of the Metropolis - Hastings algorithm is used to update the failure probability of the whole system using observed data. More recently, a hybrid model is developed by the authors [31] for pitting evaluation, integrating the Markov process with Bayesian analysis to provide a dynamic probabilistic framework, overcoming the major limitation of the Markov process. This model is further improved in the current work by using probability distributions for Markov model parameters to address the uncertainty associated with estimating these parameters.

Despite several efforts in dynamic corrosion risk assessment such as [21], [32]–[36], to the best of authors' knowledge, there is no model developed specifically for dynamic risk assessment of pitting corrosion. The existing efforts in the field of pitting corrosion dynamic evaluation are limited to updating pit behaviours [20], [23]–[26] or failure probability [25], [27], [29]–[31]. This review of pitting corrosion literature identifies two major research gaps: (i) there is a need to develop a dynamic risk assessment model that can update pit behaviour and failure probability and use this information to update risk of failure, and (ii) a risk-based pitting corrosion management system is required to integrate corrosion prevention, control and monitoring measures with the risk assessment model to support successful implementation of the dynamic risk management framework for pitting corrosion. A risk-based corrosion management approach ensures appropriate resources and procedures are allocated, with specific tasks and actions to prevent and manage pitting corrosion.

The purpose of this work is to address the two identified knowledge gaps by making two main contributions. The first contribution is to improve and integrate a dynamic failure probability estimation model previously proposed by the authors [31] with a loss estimation methodology to develop a dynamic risk assessment framework. The proposed model uses inspection data to update the distribution of Markov model parameters. The dynamic probability estimation model is then integrated with an economic impact analysis model to dynamically estimate the risk of pitting corrosion and to determine the remaining life of the asset susceptible to pitting corrosion. The second contribution of this work is to propose a dynamic pitting corrosion management framework. The proposed pitting corrosion management framework provides a mechanism to support decision-making about the selection and implementation of corrosion management strategies. The practical application of the proposed model is demonstrated using an offshore piping system case study.

6.2. Methodology

The proposed dynamic risk management methodology for pitting corrosion is shown in Figure 6.1. It consists of two major parts: (i) initial risk assessment and (ii) dynamic risk management of pitting corrosion. The first column in Figure 6.1 shows different steps of the proposed methodology; the other four columns categorize different steps in four major phases of corrosion risk management, which are (i) initial pit modeling, (ii) risk assessment, (iii) evaluation of corrosion management measures and (iv) data collection and model updating. The purpose of this categorization is to relate each step of the methodology to different phases of the Plan-Do-Check-Adjust corrosion management steps (described later) to ensure adequate allocation of resources to support the implementation of each step.

The proposed initial pitting corrosion risk assessment consists of six steps. Figure 6.1 shows the references to the previous works by authors developing methodologies for each of these six steps. The main contribution of this work for the initial risk assessment part of the methodology is to recognize the uncertainty of the Markov model parameters in Step 1 of the methodology by considering a probability distribution for these parameters, rather than point-estimate values, as in Shekari et al. [31]. As shown in Figure 6.1, the second part of the methodology includes the adoption of the Plan-Do-Check-Adjust (PDCA) risk management strategy proposed by Khan et al. [37] and its integration with the proposed pitting corrosion risk assessment model, which is another main contribution of this work. The details of each step of the methodology are described in the following sections.

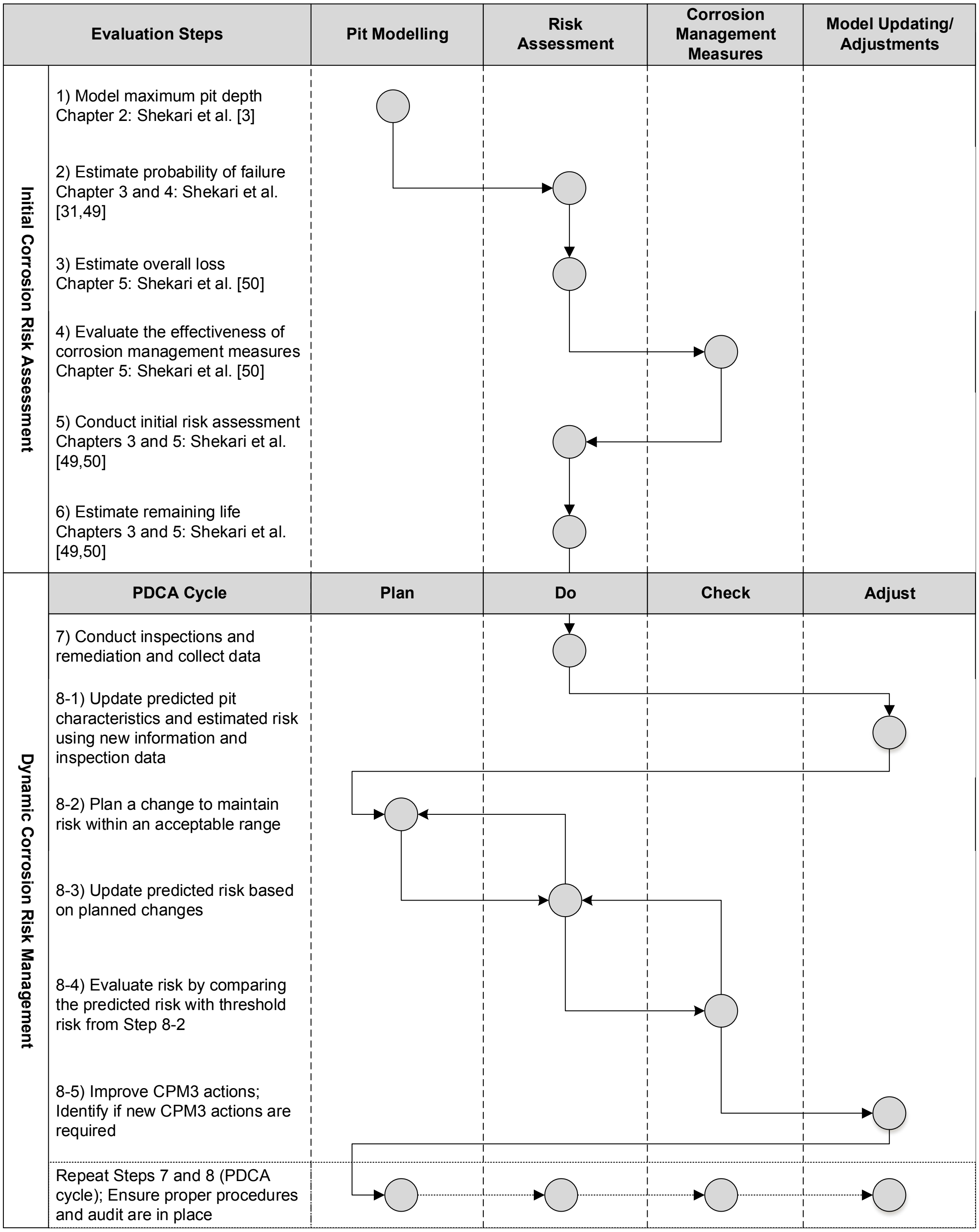

Figure 6.1. Dynamic risk management methodology for pitting corrosion

6.2.1. Step 1: Maximum Pit Depth (MPD)

The deepest pits are a major concern for causing system failure [26]. Markov process [38] and Extreme Value Theory [39] are the two primary approaches which are used in the literature to model maximum pit depth. In an earlier study, Shekari et al. [3] conducted a comprehensive review of these maximum pit depth models and concluded that the Markov process is a preferred method for MPD modelling, as it can address the structural limitations of models based on the Extreme Value Theorem, such as being static and time-independent [3]. The authors also studied the important factors that should be considered in modeling MPD in insulated equipment and adopted a model based on the time dependent non-homogenous Markov process (for simplicity, henceforth it is referred to as the Markov process) to model MPD under insulation [3].

The MPD model based on the Markov process proposed by Shekari et al. [3] is adopted in this work to model MPD in an insulated asset. For this purpose, the pit density should be estimated first. There are different studies to model pit density (pit per unit area) such as [40]–[43]. To address both linear and non-linear behaviours of pit initiation, the following model is used to estimate average pit density:

$$APD(t) = \frac{A}{\psi}\left[1 - e^{-\psi t}\right] + wt^{\eta} \tag{6.1}$$

where A, Ψ, w, and η are the parameters [42], [43]. The relationship between APD and time is then used to estimate the pit initiation times by assuming all pits occur in order at times t_1, t_2, …, t_m. Based on this assumption, using t_k to represent pit birth times and considering that APD at time t is m, the pit initiation time can be determined by solving this equation:

$$t_k = APD^{-1}(k), k = 1, 2, \ldots, m. \quad (6.2)$$

Then, the Markov process is used to model MPD by discretizing the material thickness to non-overlapping intervals Δd, which correspond to the n possible Markov states i (i = 1, ..., n). For example, a pit in state i has a depth between (i-1) × Δd and i × Δd. Then, the probability that the deepest pit is in a state less than or equal to state i, at time t, can be estimated using the expression:

$$\theta_H (i, t|\chi, \omega) = \prod_{k=1}^{m=APD}\{1 - [1 - \exp(-\rho(t - t_k)]^i\}, \quad i = 1, \ldots, n, \quad (6.3)$$

where n is the total number of states in the Markov chain, t_k is the pit initiation time, and m is average pit density. The variable $\rho(t)$ is the number of transited states by a pit and is assumed to be a power function [44] with parameters X and ω:

$$\rho(t) = \chi(t - t_k)^{\omega}. \quad (6.4)$$

In the original model proposed by Shekari et al. [3], point-based estimates based on literature and expert knowledge were used for the model parameters χ and ω, ignoring the potential uncertainty associated with these parameters. To address this shortcoming, this work uses probability distributions for both parameters to capture the associated uncertainty.

As mentioned above, $\rho(t)$ is the number of transited states by a pit and is controlled by two parameters, χ and ω. The parameter ω varies between 0 and 1 to allow for both linear and nonlinear pit transition behaviour and is assumed to follow a Normal distribution. The parameter χ is assumed to follow a Weibull distribution, allowing for flexible representation of different pit transition behaviours [27]:

$$F_\chi(x) = 1 - \exp\left(-\left(\frac{x}{w_2}\right)^{w_1}\right), \tag{6.5}$$

where $F_\chi(x)$ is the cumulative distribution function of the parameter χ, and w_1 and w_2 are respectively the shape and scale parameters of the Weibull distribution. The parameters of the χ and ω distributions can be determined from a set of maximum pit depth inspection data from the system under study, or similar operations, by the use of the least square method or by any other statistical model [27], [45], [46].

6.2.2. Step 2: Failure Probability

The common method in the literature to estimate the probability of failure of defected equipment is to use burst pressure and operating pressure in the limit state equation. Standards and codes such as AMSE B31G [47] and DNV F-101 [48] give different failure pressure models for this purpose. Some guidelines to choose the best model based on different factors such as component type, age and type of service are provided in [11].

Shekari et al. [49] used failure pressure models and proposed a methodology for the probability of failure of equipment affected by pitting corrosion.

The model presented by Shekari et al. [49] is used in this work to estimate the probability of failure of pitting damage, as it provides a mechanism to incorporate the uncertainty associated with predicted pit growth. To determine maximum allowable pressure for a defected component (P_{corr}), the time-dependent MPD model from Step 1 is integrated with the maximum allowable pressure model in DNV-RP-F101 [48]. For this purpose, the effective thickness is determined after subtracting the MPD from the original equipment thickness. To simplify the model, an idealized rectangle is considered as the equivalent of the defect profile related to pitting [49]. Thus, the P_{corr} for a component with pitting corrosion can be determined as follows:

$$P_{corr}(t) = \gamma_m * \left(2\tau f_u (1 - \gamma_d (\frac{MPD(t)}{\tau})^* \Big/ (D - \tau) \left(1 - \frac{\gamma_d (\frac{MPD(t)}{\tau})^*}{Q}\right)\right), \quad (6.6)$$

where:

- τ is the component thickness (*mm*)
- $P_{corr}(t)$ is the maximum allowable pressure (N/m^2) as a function of time for a component susceptible to pitting corrosion
- $Q = \sqrt{1 + 0.31\left(1/\sqrt{D\tau}\right)^2}$
- $(MPD(t)/\tau)^* = (MPD(t)/\tau) + \varepsilon_d StD[MPD(t)/\tau]$
- *MPD*(*t*) is the maximum pit depth (*mm*)

- D is the outside diameter (mm)
- l is the length of the pitted area (mm)
- f_u is the ultimate tensile strength (N/m^2)
- γ_m and γ_d are partial safety factors for longitudinal corrosion model prediction and pit depth
- ε_d is a factor for defining a fractile value for the pit depth based on the accuracy of the inspection method
- $StD[MPD/\tau]$ is the standard deviation of the random variable (MPD/τ)

The values of γ_d, γ_m, and ε_d are provided in DNV RP-F101 [48]. Using the distribution of MPD from Step 1, Monte Carlo simulations then obtain the distribution of P_{corr} for a specific time t using Equation (6.6).

Based on the limit state analysis and the First-Order Second-Moment (FOSM) reliability method, the reliability index, β, as a function of time can be determined by Equation (6.7) using load (operating pressure, P_{op}) and resistance (P_{corr}) variables. Probability distributions are used for P_{corr} and P_{op} to treat the uncertainty associated with them. Equation (6.6) provides the probability distribution for P_{corr}. The probability distribution of P_{op} can be determined from process operational information. Then, $\beta(t)$ is determined as:

$$\beta(t) = \frac{\mu_{P_{corr}(t)} - \mu_{P_{op}}}{\sqrt{\sigma^2_{P_{corr}}(t) - \sigma^2_{P_{op}}}} \tag{6.7}$$

where μ_{Pcorr} and μ_{Pop} are the mean and σ_{Pcorr} and σ_{Pop} are the standard deviation of P_{corr} and P_{op} distributions, respectively. Once the reliability index, β, is calculated, the probability of failure (POF) as a function of time is calculated as:

$$POF_0(t) = \emptyset[-\beta(t)] = 1 - \emptyset[\beta(t)] \tag{6.8}$$

where $\phi(\cdot)$ is the normal cumulative distribution function. Equation (6.8) determines the POF as a function of time, since MPD, used to obtain $P_{corr}(t)$ in Equation (6.6), is a function of time.

Equation (6.7) is applicable for the linear limit state function assuming normally distributed variables [27]. If any, or both, of these conditions is not satisfied, the application of Equation (6.7) causes an error in estimation. The size of the error will depend on the degree of nonlinearity and on the amount of mismatch between the normal and real distribution function [27]. For such cases, an iterative algorithm can be used instead of Equation (6.7) to solve the problem, such as the one proposed in [27]. However, the change in the method of reliability index computation will not affect the rest of the methodology in this work for calculating POF.

6.2.3. Step 3: Loss Modeling

In an earlier work by the authors, Shekari et al. [50] conducted a comprehensive review of corrosion consequence analysis methodologies such as [51]–[56] and identified three main shortcomings with most of the existing approaches: (i) use of point-based estimates for consequence assessment, (ii) ignoring the time value of money, and (iii) not considering the mitigating effects of corrosion management measures. In this study, the economic impact analysis model for pitting corrosion proposed by Shekari et al. [50] is used, as it can address the identified limitations. In this model, two main categories of loss are considered: (i) business loss, and (ii) accidental losses including asset loss (AL), human health loss (HHL), and environmental clean-up cost (ECC). Table 6.1 illustrates the models used to estimate these loss elements, recognizing the uncertainty associated with estimation of each loss element. An interested reader may refer to Shekari et al. [50] for the detailed procedure to estimate each

Table 6.1. Models to estimate corrosion loss elements [50]

Loss Element	Model
Business loss (BL)	$BL = BL_{dt} + BL_{rp}$ (6.9.a) $BL_{dt} = BL_{dt}^{PERT} \cdot \{(1 - exp[-MTTR^2/(2B_1)^2] + B_2 \cdot MTTR^{B_3})\}$ (6.9.b) $BL_{rp} = BL_{rp}^{PERT} \cdot \left\{\left(1 - exp\left[\left(-\Delta\tau_{rp}\right)^2/(2B_1')^2\right] + B_2' \cdot \left(\Delta\tau_{rp}\right)^{B_3'}\right)\right\}$ (6.9.c) • BL_{dt}^{PERT} and BL_{rp}^{PERT} are business losses during downtime and recovery periods estimated from PERT distribution by having minimum, most likely, and maximum loss values, estimated using expert knowledge • $MTTR$ is the mean time to repair • $\Delta\tau_{rp}$ is the mean value of the recovery period that can be modelled using exponential distribution • B_i and B_i' are parameters that are chosen in a way to best reflect business loss from historical data
Asset loss (AL)	$AL = \left(1 + f_L\right) \cdot a_d \cdot C_u$ (6.10) • f_L is the Lang factor, and is considered to follow a normal distribution with mean μ_{f_L} = 3.7 and standard deviation σ_{f_L} = 1 • C_u is the process unit replacement cost ($/unit area), estimated using PERT distribution, given an estimated empirical mean and variance [50] • a_d is the damage area, calculated based on the level I consequence analysis outlined in API RP 581 [56]
Human health loss (HHL)	$HHL = a_d \cdot d_p \cdot C_{hh}$ (6.11) • a_d is the damage area [56] • d_p is the population density (people/area)

Loss Element	Model
	• C_{hh} is the unit human health (fatality/injury) loss, estimated using the reported values of statistical life (VSL) [57]
Environmental cleanup cost (ECC)	$ECC = \frac{C_{ec} \cdot m_{dm} \cdot (1-f_e)}{\rho_l}$ (6.12) • f_e is the estimated fraction of material evaporating as a function of the normal boiling point [56] • m_{dm} is the discharge mass of the released fluid • ρ_l is the liquid density at storage or normal operating conditions • C_{ec} is the environmental clean-up cost (including fines, penalties, and other applicable costs) in \$/barrel (bbl). The distributions of the m_{dm} and C_{ec} are to be determined based on the information from operational history and applicable environmental regulations.

Assuming independence between losses and constant dollar values, the summation of the business loss (Equation (6.9.a)) and accidental loss elements (Equations (6.10) to (6.12) in Table 6.1) is used to estimate the overall loss:

$$OL_0(t) = BL + HHL + AL + ECC. \tag{6.13}$$

To consider the effect of inflation on estimated loss, Equation (6.14) is used to convert the estimated today's dollars into actual dollars in year t relative to a base year (current year of assessment):

$$OL'(t) = OL_0 . (1 + f)^t \tag{6.14}$$

where OL' is overall loss in actual monetary value (for example, in dollars) in year t relative to the base year, OL_0 is the overall loss based on today's monetary value, estimated from Equation (6.13) and f is the inflation rate per year, assumed to be constant from year 0 to year t. The estimated overall loss is a function of time as (i) business loss in Equation (6.9.a) is a function of the duration of downtime and recovery periods, and (ii) the value of predicted loss in the future is adjusted based on the inflation rate.

6.2.4. Step 4: Impact of Corrosion Management Measures

Corrosion Prevention, Monitoring, Maintenance and Management (CPM3) costs are incurred by an organization to prevent potential damage to people, property and the environment. Shekari et al. [50] proposed the application of CPM3 adjustment factors to take into account the effectiveness of corrosion management measures in reducing either the probability or severity of corrosion losses.

6.2.4.1. Step 4.1. Effect on Corrosion Loss Probabilities

The effectiveness of CPM3 techniques directly affects the probability of corrosion losses. The adjusted POF is determined by applying the adjustment factors as follows:

$$POF(t) = AF_{CPM3} \times POF_0(t) \tag{6.15}$$

where $POF_0(t)$ is the original POF estimated using Equation (6.8) and AF_{CPM3} denotes the CPM3 adjustments factor, which considers the overall mitigating impact of all CPM3 costs and their influence on the mechanical integrity of the component attacked by pitting corrosion and is estimated by:

$$AF_{CPM3} = 1 - exp\left(\frac{-t^2}{2\left(t_{design}/\alpha_{AF}\right)^2}\right) \tag{6.16}$$

where t is time, t_{design} is the design life of the equipment, and α_{AF} is the shape factor, which can have values between 0 to 10, where 10 represents ineffective CPM3 actions. For $\alpha_{AF} \to 0$, the second term in Equation (6.16) approaches 1 and AF_{CPM3} approaches 0, representing fully effective CPM3. The Program Evaluation Review Technique (PERT) distribution using expert estimates of minimum, most-likely, and maximum shape factor values (α_{AF}) is then used to recognize the uncertainty associated with estimating α_{AF} values. Finally, the estimated PERT distribution of α_{AF} and Monte Carlo simulations are used to estimate the distribution of AF_{CPM3} [50].

6.2.4.2. Step 4.2. Effect on Corrosion Loss Severities

Insurance is a corrosion management strategy that has a direct mitigating impact on overall loss by transferring part of the residual risk to a third party as follows:

$$OL(t) = OL'(t) - IR, \tag{6.17}$$

where *OL'* is the overall loss ($) estimated from Equation (6.14) and *IR* denotes insurance recovery ($). Estimation of insurance recovery is not within the scope of this work.

6.2.5. Step 5: Risk Calculation

The product of overall adjusted loss and adjusted probability distributions are used to estimate the overall risk using Monte Carlo simulations:

$$R(t) = POF(t) \times OL(t), \tag{6.18}$$

where *POF*(*t*) and *OL*(*t*) distributions are estimated from Equations (6.15) and (6.17), respectively.

6.2.6. Step 6: Remaining Life Estimation

Shekari et al. [31] reviewed three criteria that have been frequently used in the literature to estimate the remaining life of defected components. These criteria include maximum allowable working pressure, defect size and failure probability. Then, the remaining life is considered as the minimum of estimated remaining life values using these criteria. However, the application of these criteria as a decision-making factor for remaining life evaluations does not take into account the consequences of failures due to pitting corrosion. To address this shortcoming, the risk of failure due to pitting corrosion can be used as the decision criterion for remaining life evaluation [50]. Thus, the calculated risk of failure in the previous section and its intersection with a threshold risk value is used in this work to determine the remaining life of the asset susceptible to pitting corrosion. This approach provides a risk-informed framework to consider both the probability and the consequences of failure for remaining life estimation. An inspection, repair, or replacement is required before the remaining life is calculated in order to maintain the risk of failure below the threshold value.

6.2.7. Step 7: Inspection, Remediation, Data Collection

Deterioration processes, such as pitting corrosion, commence from day one of the equipment's service [58]. Thus, in order to ensure that the condition of the assets remains in compliance with the safety requirements throughout their operational life, a certain number of inspections, condition monitoring and maintenance is required throughout the asset service life [58]. Thus, once the remaining life is estimated, the proposed methodology continues with detailed pitting inspection, repair and maintenance of the corroded component and data collection to update and validate the model outputs. Discussion of proper inspection and remediation methods for pitting corrosion is not in the scope of this work. API 571 [1] provides general guidelines for important factors and potential inspection techniques for different damage mechanisms, including pitting corrosion. More detailed guidelines for inspection and repair of different components can be found in API 510 [59] for pressure vessels, API 570 [60] for piping systems, API 653 [61] for storage tanks, and CSA Z662 [62] and DNV-RP-F101 [48] for pipelines.

6.2.8. Step 8: Pitting Corrosion Management

The integration of the proposed pitting risk assessment model with a corrosion management system is required to develop a detailed picture of asset condition over time, re-assess the asset integrity using new information, and to revise inspection and maintenance strategies based on the latest asset conditions. To achieve this purpose, a structured corrosion management system is proposed in Figure 6.2 to monitor and record the performance of corrosion management (CPM3) measures and to feed the information into the risk management model. The result is a robust risk-informed decision-making process to promote continuous improvement of corrosion management processes.

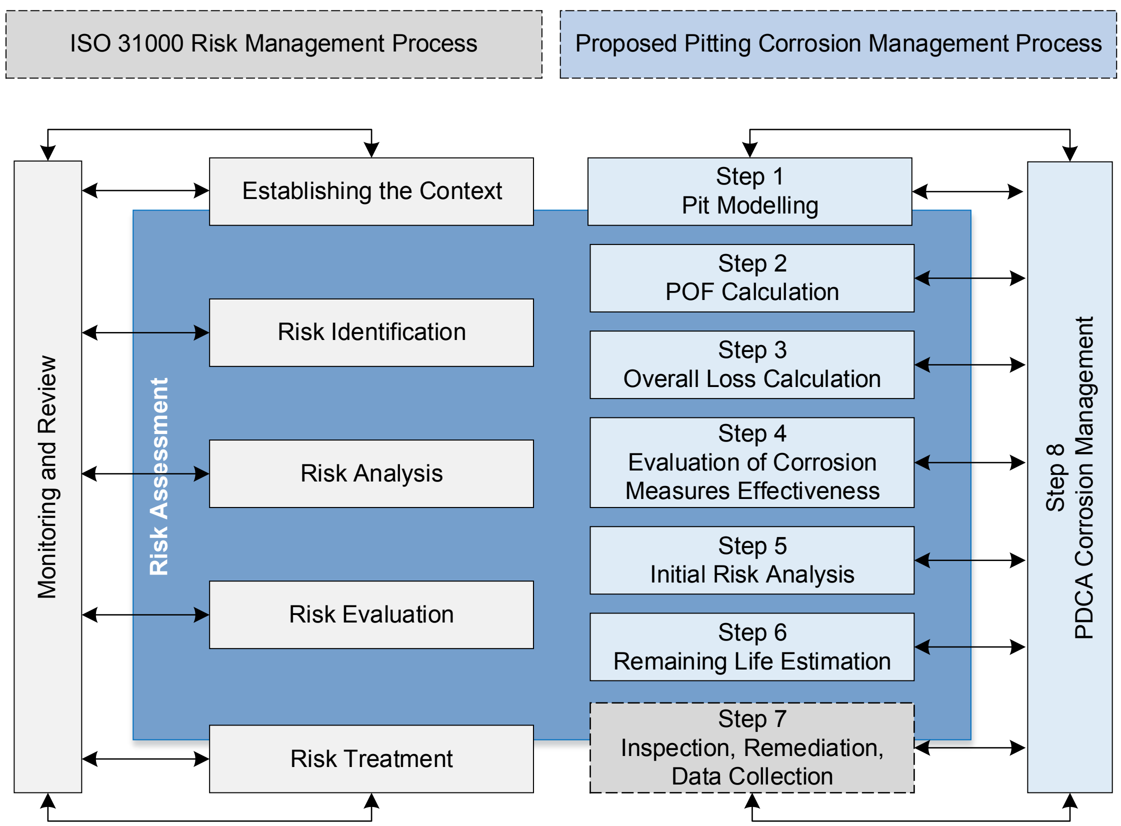

Figure 6.2. Relationship of ISO 31000 risk management principle and the proposed risk-based pitting corrosion management approach; adopted from ISO 31000 [63] and DNV-RP-C302 [58]

The left side of Figure 6.2 shows the six-step procedure proposed by ISO 31000 [63] to conduct an effective risk management process. The right side of Figure 6.2 shows the proposed steps for conducting pitting corrosion risk management. As shown in Figure 6.2, the information from Steps 1 to 7 of the initial risk assessment process should be fed to Step 8 to conduct a risk-based corrosion management. The required sub-activities of the corrosion management process are illustrated in the lower panel of Figure 6.1 (the overall methodology) and are explained in the following sections.

6.2.8.1. Step 8.1. Bayesian Updating

The first step of the proposed corrosion management process is to update the model predictions based on new inspection data. Estimated probability of failure can change over time due to changing pit behaviour. The predicted pit behaviour is a function of Markov model parameters in Equation (6.4), which are originally determined from prior information. However, due to complex pit behaviour and changing external conditions, the pitting corrosion may evolve differently from the predictions. For this reason, the Markov model parameters have to be updated when new information becomes available. The Bayesian method is one of the most appropriate and popular methods used for this purpose [27]. The Bayesian approach incorporates new information from a system in a probabilistic framework, in order to update the prior state of knowledge. For this purpose, Bayes' theorem is used here to determine the posterior distribution of the Markov model parameters through the expression:

$$\pi(\theta|x_{ob}) = \frac{L(x_{ob}|\theta)\pi(\theta)}{\int L(\theta|x_{ob})\pi(\theta)d\theta} \tag{6.19}$$

where:

- θ is a vector of Markov model parameters
- x_{ob} is a set of observations (inspection data)
- $\pi(\theta)$ is the prior distribution of θ
- $L(\theta|x)$ is the likelihood function of the observation x given the unknown parameter θ
- $\pi(\theta|x_{ob})$ is the posterior distribution of θ

In an earlier study by the authors [31], a hybrid model is developed for pitting evaluation by integrating the Markov process with Bayesian analysis to provide a dynamic probabilistic framework, overcoming the major limitation of the Markov process, which is the lack of adoption of new data to update model parameters. However, the model in [31] has two limitations: (i) point-based values are used for Markov model parameters, ignoring the uncertainty associated with estimating these parameters, and (ii) only one parameter is updated, for simplicity. This study aims to address these limitations by considering a probability distribution for both parameters and updating both parameters using inspection data.

The purpose of Bayesian updating in this section is to use the maximum pit depth (*MPD**) determined from inspection data at the corresponding time *t* to obtain the posterior distribution of θ, which is a vector of the Markov model parameters (i.e.

$\theta \equiv \{\chi, \omega\}$). However, the Bayes' rule cannot be used in this form in Equation (6.19) due to the difficulty of analytical integration of the denominator (the normalizing factor). To address this challenge, the Markov Chain Monte Carlo (MCMC) and Metropolis - Hastings (M-H) algorithm are used in the literature [27], [64] for general corrosion.

The M-H algorithm was originally developed by Metropolis et al. [65] and generalized later by Hastings [66] with the purpose of generating a sequence of samples following a probability distribution that is difficult to sample directly. The M-H algorithm is used in this work to overcome the computational difficulties of the normalizing factor by using the same sequence used in MCMC simulation to compute an integral [31], [64].

The M-H algorithm in this work is adopted from the work by [27]. The proposed algorithm starts from the initial distributions of Markov model parameters $\theta^{(0)} \equiv \{\chi^{(0)}, \omega^{(0)}\}$. As described earlier in the Markov modeling section, the initial parameters ω and χ are assumed to follow Normal and Weibull distributions, respectively, and can be obtained from a sample of maximum pit depth data or information from similar operations. Then, the generated candidate is compared against an acceptance criterion using a proposal distribution. If the generated candidate is accepted, it is used to generate the next candidate; otherwise, another candidate is sampled from the previous state.

Once the parameters of the Markov model transition rate are updated using the M-H algorithm, the MPD distribution is also updated using Equation (6.3). Then, other steps of the pitting risk assessment methodology should be repeated to estimate both the new maximum allowable pressure and risk to revise the remaining life of the component. The entire procedure must be repeated after a new inspection is performed to update the MPD distribution using Bayesian analysis.

6.2.8.2. Steps 8.2 to 8.5 Corrosion Management's PDCA

As discussed above, a fundamental principle of corrosion risk management is iteration [58] to:

i. Ensure control and continuous monitoring of the corrosion threat
ii. Analyze the performance of corrosion management strategies
iii. Analyze lessons learned
iv. Detect changes in estimated risk
v. Revise inspection and maintenance strategies

To achieve these objectives, the integration of the Plan-Do-Check-Adjust (PDCA) management method with the proposed risk assessment approach is proposed, adopted from the process safety dynamic risk management framework in Khan et al. [37]. Figure 6.1 shows how the proposed PDCA management cycle integrates with the ISO 31000 Risk Management Process and Figure 6.2 highlights the required steps of the proposed PDCA corrosion risk management methodology. As shown in Figure 6.1, once the parameters of the pitting model are updated using inspection data, the proposed PDCA corrosion management cycle continues as follows:

i. Step 8.2: Based on lessons learned during the operation and inspection of the asset as well as the feedback from the risk updating step, plan a change, or revise an initial change plan, to ensure all controls are effective to maintain the asset risk within an acceptable range. This step also involves setting or revising the threshold risk based on the corporate overall risk policy and culture.

ii. Step 8.3: Update predicted risk based on planned changes in Step 8.2 by following Steps 2 to 6.

iii. Step 8.4: Test the planned change by comparing the updated predicted risk with the planned risk and evaluating the effectiveness of the planned CPM3 actions.

iv. Step 8.5: If the planned reduction in risk is not achieved, repeat Steps 8.2 to 8.4 by improving the effectiveness of existing CPM3 actions or identifying and applying new corrosion management strategies.

Table 6.2 shows examples of different CPM3 strategies. More discussions on risk-cost-trade off analysis to support corrosion management decision making are provided later in the case study.

Table 6.2. Examples of CPM3 strategies

CPM3 Elements	Examples
Prevention	• Coatings • Inhibitors • Cathodic protection
Monitoring	• Corrosion monitoring (coupons and probes) • Corrosion tests • Inspection
Maintenance	• Maintenance and repair • Replacement of equipment • Redundant equipment
Management	• Training • Quality assurance • Corrosion control planning • Safety and integrity management systems • Administration • Insurance

The information transfer between PDCA phases of the proposed methodology in Figure

6.1 is shown using loops, because the evaluation of different scenarios of corrosion management actions may be required by repeating these steps to ensure the selection of an adequate and cost-effective scenario without compromising the safety of the system. Once the change in corrosion management measures is decided and implemented, the PDCA cycle is repeated by collecting new information and inspection data and updating the estimated risk. More details about the development of different corrosion management scenarios and the evaluation of their mitigating impact on overall pitting corrosion risk and cost are described in an earlier work by the authors [50].

6.3. Application of the Proposed Framework

The inspection data obtained from an offshore production facility operating in the North Sea (Figure 6.3) has been used to test and validate the proposed dynamic risk-based pitting evaluation model. The data is obtained for a gas condensate system. The system came into service in 1995. The first inspection was conducted in 1997 due to proven susceptibility of similar systems to pitting corrosion, followed by another inspection in 2001. For illustration purposes, the inspection data of a 6-inch flowline of the gas export system is used, as more data for pitting corrosion was available for this pipe section. The selected pipe has an operating pressure of 16 MPa, a length of 20 m and a nominal wall thickness of 7.113 mm, with a specified minimum tensile strength (SMTS) of 75 ksi. The Maximum Pit Depth (MPD) from each inspection year's dataset for this pipe section was extracted to test the model. The MPD values for 1997 and 2001 inspection years were respectively 0.4 mm and 1.2 mm. The dataset [2,0.4] is used to update the model predictions and the dataset [6,1.2] is used to validate the model predictions, where the first and second number in each dataset show the time since installation and the observed MPD value.

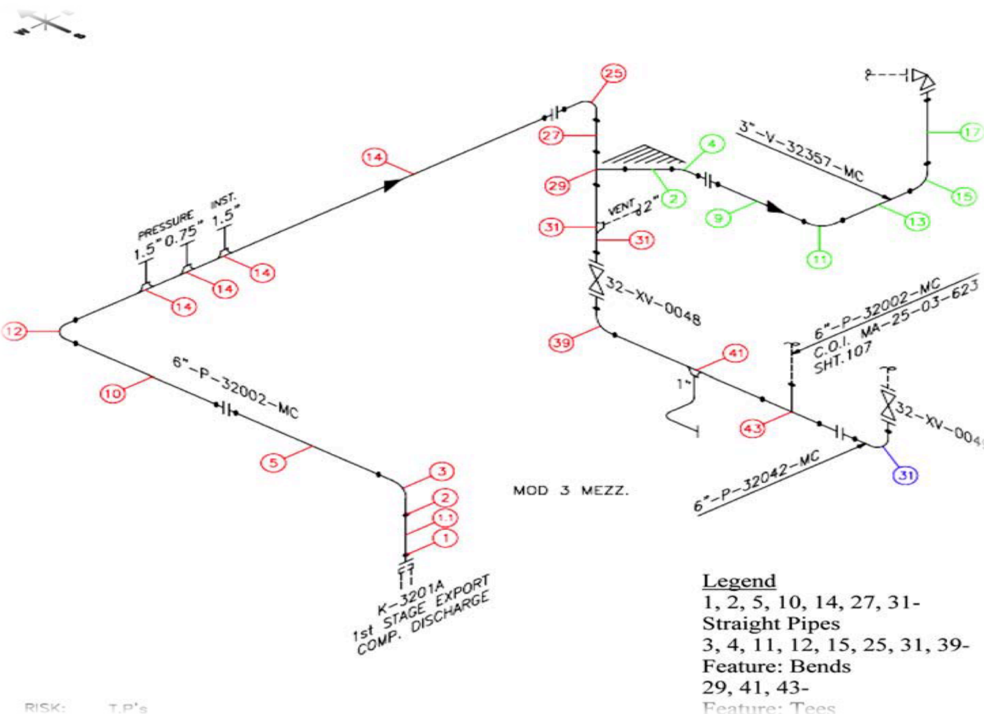

Figure 6.3. Piping isometric sketch of the offshore production facility case study

6.3.1. Maximum Pit Depth (MPD) Modeling

6.3.1.1. Initial MPD Model

The proposed pit depth model based on the Markov process in Equations (6.3) and (6.4) is used to estimate the distribution of MPD in different years. For this purpose, the distribution of the parameters of the Markov process transition rate in Equation (6.3) should be estimated first. This can be challenging for a new installation with a lack of prior inspection data. For new installations, the prior distribution of Markov parameters can be estimated using a set of maximum pit depth inspection data from similar operations, using least square method or by any other statistical model such as those in [67], [68] . Otherwise, expert knowledge estimates should be used as starting values, which can be updated as new information from the system becomes available. For the system under study in this work, an inspection of a similar offshore platform in the North Sea after 7 years of operation showed that the maximum pit depth of a pipe with similar specifications was 1.5 mm. Thus, a search procedure based on the least squares methods [27] and the dataset [7,1.5] was used to estimate prior Markov model parameters. Figure 6.4 shows the inspection data point and the mean values of prior MPD distributions over time. The estimated prior Markov model parameters are shown in Table 6.3.

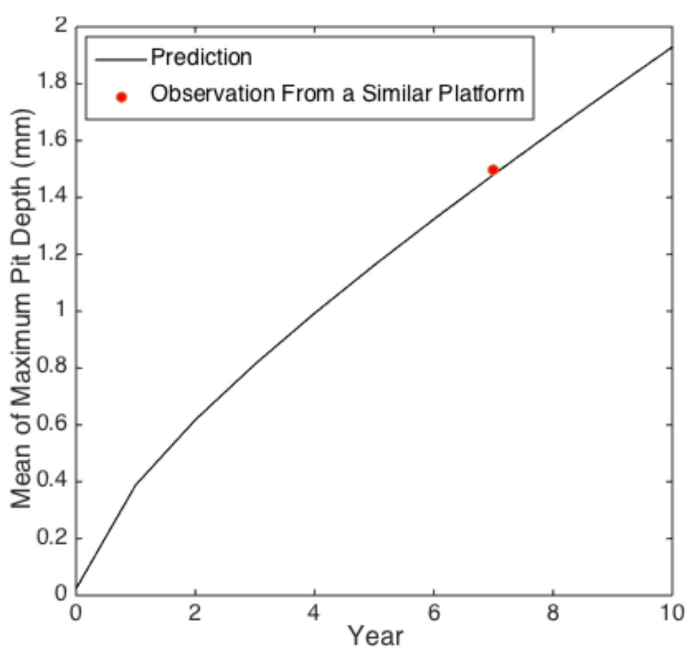

Figure 6.4. Initial MPD model, trained using sample inspection data from a similar offshore production facility

Table 6.3. Distribution parameters of Markov model parameters

	χ (Weibull Distribution)[a]		ω (Normal Distribution)	
Distribution	w_1	w_2	μ_ω	σ_ω
Prior	8.20	1.98	0.20	0.04
Posterior	11.94	1.91	0.19	0.05

[a] w_1 and w_2 are the shape and the scale parameters of the Weibull distribution. μ_ω and σ_ω are mean and standard deviation of each parameter.

6.3.1.2. Updating and Validating MPD Model

From the inspection data, the MPD value in 1997 (2 years after the installation date) is 0.4 mm. However, as shown in Figure 6.4, the predicted MPD value in year 2 using the Markov model is 0.65 mm. To calibrate the model for more accurate MPD predictions, the inspection data in 1997 and the proposed Bayesian analysis based on the M-H sampling algorithm are used to update the model prediction by revising the distributions of prior Markov model parameters. The MCMC simulation and the M-H sampling algorithm described in Step 7 are implemented using 10^5 iterations in order to estimate the posterior MPD distribution for each assessment year. The updated MPD values are shown in Figure 6.5.

Although the updating mechanism enables incorporation of inspection data, the revised predictions should be validated to ensure improvements in model predictions after updating. For this purpose, the inspection data for 2001 (year 6) is used to evaluate and validate the revised predictions of the model. As shown in Figure 6.5, the revised model prediction of MPD value at year 6 is 1.3 mm. These results in Figure 6.5 show the efficiency of the proposed updating algorithm, as the initial model prediction at year 2 was 62.5% higher than the actual inspection observation (0.65 mm model prediction compared to the real observation of 0.4 mm) compared to only 8% over estimation at year 6 (1.3 mm model prediction compared to the real observation of 1.2 mm) using the updated model. The relatively higher overestimation value of initial model prediction is justifiable from a practical point of view as higher level of conservatism is desirable when no information is available for a new installation. However, the results in Figure 6.5 show that the level of conservatism in model predictions has decreased significantly after model updating using the first inspection data. Obviously, as more inspection data becomes available over the asset service, the accuracy of the model predictions improves by repeating the updating procedure.

For this case study, the inspection data at year 2 has shown that the actual pit growth rate has been lower that the expected values. Therefore, the updating mechanism using the inspection data has shifted the model prediction curve downward, as shown in Figure 6.5, to avoid over estimation. Another scenario is also considered to test the ability of the updating algorithm to revise the predictions in cases where the aggressiveness of the pitting corrosion has been higher than the initial prediction. For this purpose, it is assumed that at year 2 the inspection data has obtained the value of MPD as 0.9 mm. The updated model result for this scenario is also shown in Figure 6.5, showing that the revised curve has shifted upward to calibrate the model. Overall, Figure 6.5 shows the ability of the proposed updating algorithm to adjust model predictions with the changing aggressiveness of the environment (i.e. the prior parameters are overestimated or underestimated).

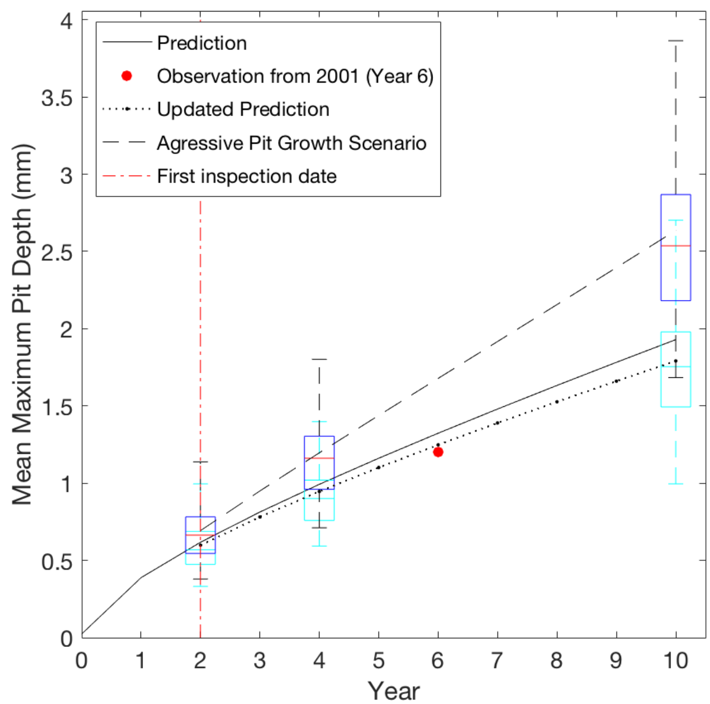

Figure 6.5. Revised MPD model based on real inspection data. The revised model prediction is validated by comparing the model prediction with real inspection data at year 6.

Figure 6.5 also shows boxplots to represent the variability in MPD predictions. For clarity, only the boxplots for selected years are shown. These boxplots represent the minimum, first quartile, median, third quartile and maximum values of estimated MPD over time. Two important characteristics can be observed from the boxplots in Figure 6.5. Firstly, the size of the boxplots in each year is relatively bigger for the aggressive pit growth scenario compared to the initial prediction scenario. This observation can be attributed to the larger mismatch between the model prediction (prior information) and the actual MPD (observations) obtained from inspection in year 2 for the aggressive pit growth scenario, resulting in higher values of standard deviation. The second observation from Figure 6.5 is that the size of the boxplots increases over time, due to higher uncertainty associated with MPD predictions as the time interval between the inspection date and the intended prediction time in the future increases. As will be discussed later, this shows the importance of repeating the model updating using periodic inspections to decrease the model prediction's uncertainty.

6.3.2. Risk Calculation

To estimate the risk of failure due to pitting corrosion, first the probability of failure (POF) of the defected pipe over time is calculated using Equations (6.6) to (6.8). For this purpose, both the initial and revised MPD distributions over time in the previous steps are used in the burst pressure model, Equation (6.6). Then, Monte Carlo simulations with 10^5 iterations are performed to estimate POF values using Equation 8. Then, Equation (6.15) is used to take into account the mitigating impact of existing Corrosion Prevention, Monitoring, Maintenance and Management (CPM3) measures and adjust the initial POF value. For this purpose, the expert is asked to estimate minimum, most likely and maximum shape factor values of the adjustment factor (α_{AF}) based on the guidelines provided in Shekari et al. [50] and the plant-specific information such as type, effectiveness, and frequency of CPM3 actions, operators' skill, management effectiveness and compliance with procedures. Then, the PERT distribution technique described in Step 4.1 by Shekari et al. [50] along with Monte Carlo simulations with 10^5 iterations are used to estimate the adjusted values of both the initial and updated POF value using Equation (6.15). The results of the adjusted POF values are shown in Figure 6.6. The results in Figure 6.6 show a shift to the left in the POF curve and a reduction in conservatism of the POF estimation after updating the prior POF using inspection data. The proposed POF estimation method allows both updating of POF based on inspection data and adjustment of estimated POF based on the effectiveness of CPM3 actions.

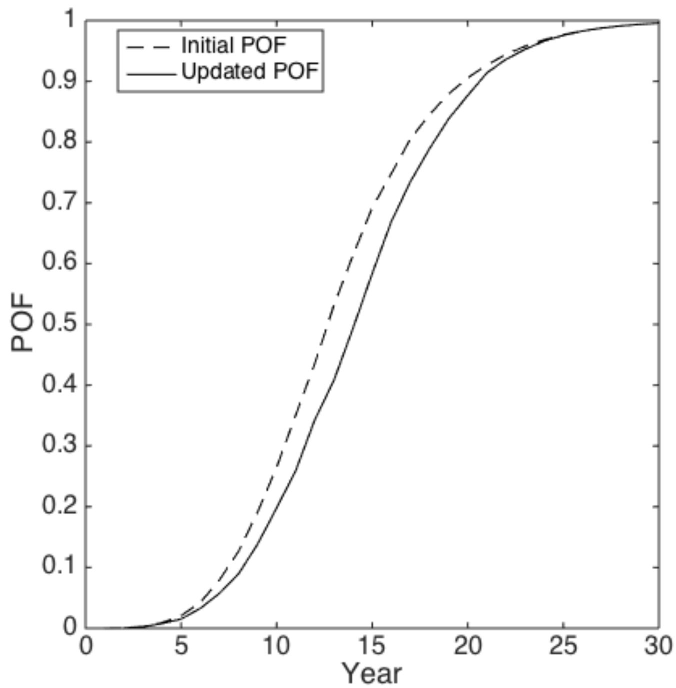

Figure 6.6. Adjusted values of initial and updated POF values

Since loss data for the current case study were not available, the loss estimation values from an earlier case study on an offshore platform were used for illustrative purposes [50]. Table 6.4 summarizes the results of loss evaluations for this case study. The P50 (50th percentile) and P99.9 (99.9th percentile) for each loss element are also provided in Table 6.4, which help to communicate the uncertainty associated with each estimated loss. Table 6.4 also shows the estimated overall loss, estimated as the summation of all loss elements. Figure 6.7 shows the distribution of the overall loss for this case study, with a mean value of 151 million USD.

Table 6.4. The value of assumed loss elements for the case study (all losses are reported in million USD)

Loss	Mean	Standard Deviation	P50	P99.9	Percentage (Mean/Total Loss)
BL	61.8	62.9	41.6	467.5	40.9
AL	29.4	6.6	29.2	51.0	19.5
HHL	59.8	55.9	43.2	494.7	39.6
Overall	151.0	84.2	130.2	632.9	--

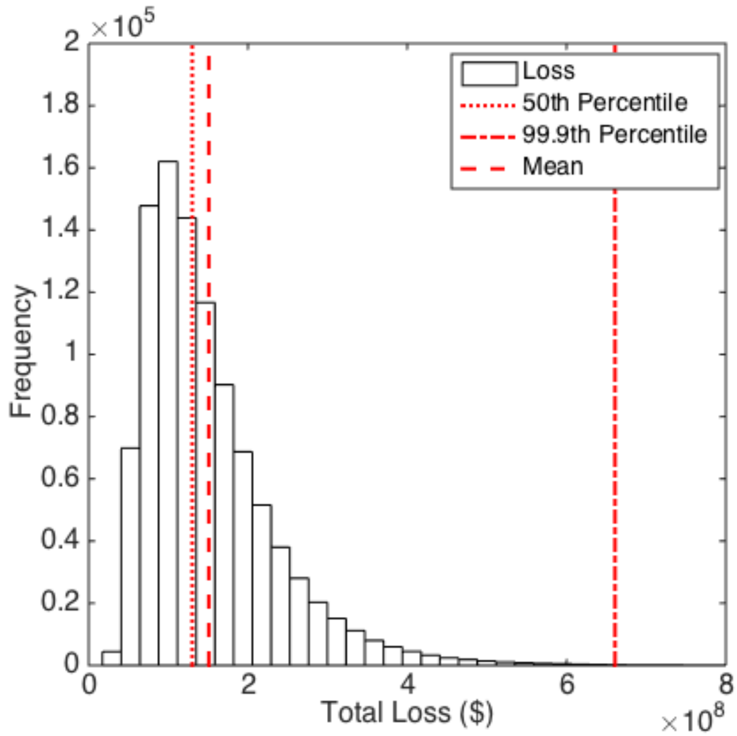

Figure 6.7. Overall loss distribution

Equation (6.18) is used to combine the overall loss distribution and failure probability distribution to obtain the risk distribution for each corresponding time. A constant inflation rate of 2% is considered for simplicity and its impact on loss is determined using Equation (6.14). Figure 6.8 shows the estimated risk profiles using both initial and updated POF values. The solid line in Figure 6.8 shows the increase in mean risk values and the boxplots represent the variability in estimated risk over time due to uncertainty associated with POF and loss estimations. As shown in Figure 6.8, the updated risk profile starts to increase at a lower rate compared to initial risk, as the inspection results in 1997 have shown a less aggressive pit growth compared to the initial expected pit behaviour. The boxplots in Figure 6.8 represent the uncertainty of risk predictions, which shows an increasing trend over time (larger boxplot sizes over time). For clarity, only the boxplots for the updated risk profile for the enhanced CPM3 scenario (explained in the Corrosion Management Decision Making Section) are shown for every five years. Intuitively, the level of uncertainty of future predictions increases over time due to uncertainty in pitting corrosion behaviour affecting the parameters in the future, unless inspection data becomes available to update the model predictions. This increasing trend in risk estimation uncertainty over time shows the importance of conducting periodic inspections to validate and update model predictions.

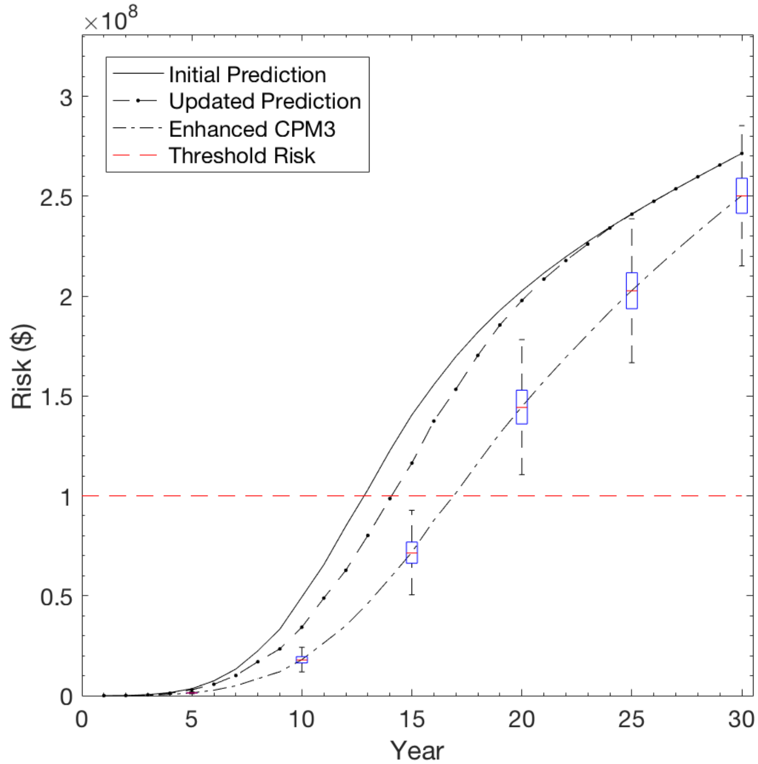

Figure 6.8. Estimated initial and updated risk profiles

6.3.3. Remaining Life Evaluation

As shown in Figure 6.8, the remaining life of the pipe section is estimated as the intersection of the threshold risk values and risk profiles. For illustrative purposes, the threshold risk value for this case study is considered as 100 million dollars. Estimation of threshold risk value is organization-specific and so is determined by asset decision-makers based on the organizations' risk acceptance and the criticality of the operation. Using the threshold risk value, the remaining life of the pipe is estimated as 12.2 and 13.1 years using initial and updated risk profiles. This means that the next inspection and maintenance turnaround for this pipe section should be performed well before these estimated remaining life values to maintain the risk of failure due to pitting corrosion at lower values. Based on the American Petroleum Institute's (API) piping, storage tank and pressure vessel inspection codes [25–27], inspection should be conducted, at maximum, half of the estimated component-remaining-life. This recommendation can be used as a starting point and can be revised based on the criticality of the operation and available resources. As shown earlier in this case study, the inspection data was used to revise model predictions. Such periodic inspections are critical to only to update the predicted MPDs, but also to validate the model outputs.

6.3.4. Corrosion Management Decision Making

The effectiveness of corrosion mitigation measures and CPM3 actions plays an important role in the integrity and risk of failure of the asset. Both initial and updated risk curves in Figure 6.8 are determined based on the initial estimates of the effectiveness of CPM3 actions. Another important advantage of the proposed risk-based pitting evaluation model is providing a risk-based tool to conduct a cost-benefit analysis of enhancing corrosion management strategies. To demonstrate this feature of the model, another scenario is shown in Figure 6.8, where the effectiveness of CPM3 strategies is improved after the inspection in year 2. Consequently, the risk profile of this scenario is shifted to the right, resulting in the remaining life extension, compared to the original updated risk profile.

Shekari et al. [50] proposed a methodology based on the PERT distribution technique to estimate the associated cost of each CPM3 strategy. The estimated cost of each CPM3 strategy combined with the risk-based remaining life evaluation in this work provides a risk-based cost-benefit analysis framework. For instance, let C_A denote the annual cost associated with the original CPM3 strategies and C_B show the annual cost associated with the enhanced CPM3 scenario in Figure 6.8. Then, the remaining life of the pipe can be increased by 26% from 13.1 years for the case of the original CPM3 strategy to 16.5 years for the enhanced CPM3 scenario by investing $\left(C_B - C_A\right)$ dollars on CPM3 actions to further decrease the rate of pitting corrosion by improving the methods used for detecting, preventing, monitoring, and/or repairing the pitting damage. Compared to traditional corrosion risk assessment literature (such as API 581 [56], DNV-RP-C302 [58], Thodi et al. [12]) where risk is simply shown using a risk matrix or a simple curve, the proposed methodology provides an effective risk-based approach to quantify and compare the value of different investment portfolios of asset integrity management strategies while addressing the uncertainty associated with risk estimation.

It should be noted that the proposed methodology only estimates the risk of failure due to pitting corrosion. The estimation of risk due to other damage mechanisms and the aggregation of all estimated risks are required to provide a more accurate picture of the overall asset integrity due to different failure mechanisms. The scope of the proposed risk-based pitting corrosion management can be expanded to apply to other corrosion mechanisms by changing the corrosion model in Step 1 of the methodology.

6.4. Conclusions

This paper provides a risk-based management approach for pitting corrosion. The application of the Markov process allows time-dependent modeling of pit depth. On the other hand, the application of Bayesian analysis provides a mechanism to dynamically update the prior distributions of the Markov model for pitting corrosion, which finally results in updating the probability of failure. The Markov Chain Monte Carlo and Metropolis - Hastings algorithm which have been adapted for pitting corrosion provide flexibility to adapt to the observed data using a non-conjugate distribution with the consideration of the prior distributions of the time dependent Markov model parameters. The application of the proposed dynamic risk management framework ensures continuous improvement of the corrosion management process based on the performance and effectiveness of corrosion prevention, maintenance, monitoring and management actions.

The case study results show the effectiveness of the proposed dynamic risk estimation approach where the failure probability and risk of failure of a pipe due to pitting corrosion are updated from observed inspection data for both increased and decreased aggressiveness of the corrosion environment. The case study also shows the advantage of the proposed risk-based pitting corrosion management model used as a time-dependent metric to measure and monitor the performance and effectiveness of corrosion mitigation strategies. This model can help engineers to use both cost and risk to make decisions for inspection and maintenance planning and improve safety performance of systems susceptible to pitting corrosion. The application of the dynamic risk management framework to the case study established its effectiveness for the risk-informed decision-making process by constantly monitoring, evaluating and improving the corrosion management performance.

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7. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

7.1. Summary

This thesis proposes new methodologies and models to conduct dynamic risk evaluation and management of pitting corrosion. These methodologies and models provide a comprehensive tool to predict and monitor pitting corrosion progress, make operational decisions based on both probability and consequences of failure due to pitting corrosion, and evaluate the performance of corrosion management strategies.

The proposed methodology models pit density using the non-homogenous Poisson process and induction time for pit initiation is simulated as the realization of a Weibull process. The non-homogenous Markov process is then used to estimate maximum pit depth in order to describe the propagation of pit depths throughout a discretized set of states. The burst pressure capacity of the defected component is calculated by adopting the maximum allowable pressure models and using the estimated maximum pit depths. The burst pressure and operating pressure are then used to develop the limit state equation. Using the First Order Second Moment (FOSM) method, the reliability index is then calculated, which is finally used to determine the probability of failure.

A predicative Fitness-for-Service (FFS) approach is also proposed in this work that uses multiple time-dependent decision criteria including remaining intact thickness, probability of failure, burst pressure and risk of failure to make operational decisions and predict the remaining life of the defected asset. To update the probability of failure and the remaining life of the pitted components, Bayesian updating is used. The Markov

Chain Monte Carlo (MCMC) simulation in conjunction with the Metropolis–Hastings (M–H) algorithm are employed to carry out the Bayesian updating. This overcomes the restrictive assumptions of conjugate prior and likelihood distributions in traditional Bayesian updating methods.

This thesis also presents a predictive probabilistic model to estimate the overall economic impacts of pitting corrosion by considering both the corrosion costs and significant losses that may occur if failures occur because of pitting corrosion. Corrosion prevention, monitoring, maintenance and management (CPM3) costs are considered as the main categories of corrosion costs and probabilistic models are proposed to estimate these costs. The effect of inflation on loss values and the mitigating impact of CPM3 costs are also taken into consideration in the developed models. Finally, a structured corrosion management system is proposed by adoption of the Plan-Do-Check-Adjust (PDCA) risk management strategy to monitor the performance of corrosion management measures (CPM3 actions) and to feed the information into the risk management model. The result is a robust risk-informed decision-making process for susceptible assets to promote continuous improvement of corrosion management processes by constantly monitoring, evaluating and improving the corrosion management performance. The application of the proposed models and methodologies is demonstrated using different case studies.

7.2. Conclusions

7.2.1. Pit Characteristics: Initiation Time, Density and Maximum Depth

As discussed in this thesis, pit generation, pit density and maximum pit depth are three important characteristics of pitting damage that should be taken into consideration. Since pits under insulation occur non-uniformly in time with variable generation rates, it was concluded that the non-homogeneous Poisson process is a preferred method to model pit generation. To model the average pit density, a multi-variable model with a combination of linear and exponential modes is used to ensure flexibility to model complex pit behaviour. It is also concluded that the non-homogeneous Markov process is an adequate method to model the dynamic nature of maximum pit depth under insulation over time, as the parameters and transition rate of the Markov model provide flexibility for capturing a combination of important factors for pitting corrosion. The case study results in Chapters 2 and 3 highlight the ability of these proposed approaches to track and predict pit characteristics in insulated assets, which are difficult to inspect in real life problems, especially for the case of offshore facilities.

7.2.2. Stochastic Pit Behaviours: The Importance of Probabilistic Approaches

Pitting corrosion behaviour changes over time due to different causes including process and operational changes, variability in the effectiveness of corrosion management strategies, uncertainty in expert knowledge estimates and changes in asset conditions due to maintenance activities. Such causes are the source of uncertainties when estimating the model parameters for pit characteristics. Thus, it was concluded that probabilistic approaches are preferred over deterministic methods to enable capturing such uncertainties. Therefore, this thesis uses probabilistic methods to estimate Probability of Failure (POF), Consequences of Failure (COF) and the remaining life of assets attacked by pitting corrosion. The Monte Carlo (MC) simulations are used to integrate the proposed POF and COF models to address the variabilities in the proposed probabilistic models.

7.2.3. Evolving Pitting Behaviours: The Importance of Dynamic Approaches

Pitting corrosion is a complex process and its behaviour can change over time due to changing process and operational conditions. Therefore, developing a static model with assumed model parameters for accurate prediction of pitting corrosion during the entire asset life is ambitious. Moreover, a lack of prior inspection data for new installations and uncertainties associated with expert knowledge add to the unreliability of using static models with constant model parameters. Therefore, it was concluded that a mechanism is required to update and adjust model parameters as new inspection data become available since such data provide better information about the latest pitting corrosion status. The proposed methodology in this thesis incorporates the inspection data in the remaining life analysis by using the Markov Chain Monte Carlo and the Metropolis–Hasting algorithm to carry out the Bayesian updating to revise the prior distribution of maximum pit depth. The application of the proposed method on a real case study in Chapter 6 highlights the fact that the incorporation of inspection data using Bayesian analysis to revise the model parameters for maximum pit depth can provide a more realistic prediction of pit behaviour and failure time.

7.2.4. Resource-Intensive Challenge: The Importance of Corrosion Risk Management

It has been shown in numerous studies that several major losses in the oil and gas industry might have been prevented if a dynamic risk approach like the one presented in this work was integrated into the management framework. The implementation of a dynamic risk assessment approach could be a complex, resource-demanding process. Quantitative and dynamic risk assessment tools are data-intensive and usually involve numerical work, which make them less attractive for practical applications. The integration of the proposed dynamic risk assessment model for pitting corrosion with day-to-day management workflow is used in this thesis to address these limitations by providing management support and resources to collect required data and conduct the evaluations. This objective is achieved by integrating a systematic Plan-Do-Check-Adjust (PDCA) risk management strategy with the proposed pitting corrosion risk assessment model to ensure adequate allocation of resources to support the implementation of each step.

7.2.5. Proactive Decision-Making: The Importance of Predictive FFS Assessments

Fitness-for-Service (FFS) assessments help engineers to make decisions about the structural integrity of an in-service component that may contain a flaw or damage. For time-dependent degradation mechanisms, such as pitting corrosion, a predictive FFS approach is required to ensure effective planning of inspection, repair and maintenance activities. However, having reviewed the existing FFS assessment approaches, it was concluded that the existing methods are based on known damage dimensions. Although FFS assessment based on known damage dimensions is an important decision-making tool for corroded components, such methods cannot be used for proactive inspection and maintenance planning. To address this shortcoming, a predictive FFS assessment for pitting corrosion is proposed by modelling the change in burst pressure capacity of defected components due to growing pits over time. This outcome provides a failure prediction tool for assets susceptible to pitting corrosion by calculating a time-dependent limit state function. This predictive tool can help engineers to make “run, repair, replace and re-rate” decisions regarding defected components. Such predictive tools are of particular importance to track and predict pitting corrosion for places with restricted availability to implement frequent inspections, such as offshore process facilities.

7.2.6. Corrosion Risk-Cost Balance: The Importance of Risk-Based Economic Assessment

Corrosion models that only estimate failure probability cannot be used for effective inspection and maintenance planning as they do not take into account the economic impacts of corrosions such as corrosion management costs and failure consequences. Both probabilities and consequences of failure due to pitting should be considered to ensure safe operations by making risk-informed decisions for deteriorating assets. In addition to the analysis of risk of failure, it was concluded that the risk-cost trade-off should be also taken into consideration by analyzing corrosion management costs. This approach will help both safe and cost effective operation of assets susceptible to pitting corrosion and will ensure the observation of the highest value from an asset during its entire life cycle. Consequently, a methodology is proposed to consider the mitigating impact of corrosion prevention, monitoring, maintenance and management (CPM3) strategies to evaluate the overall economic impact analysis of pitting corrosion. The proposed methodology also helps to estimate more accurate business and accidental losses due to pitting corrosion by considering the decreasing time value of money due to inflation. The case study results in Chapters 5 and 6 highlighted the advantages of the proposed approach to risk-based cost-benefit analysis and the selection of cost-effective CPM3 strategies without compromising plant safety.

7.2.7. High-Risk Operations: The Importance of Quantitative Methods

As discussed earlier, the application of the quantitative risk assessment methods may seem demanding and not practical when dealing with the problem of ranking a large population of assets susceptible to pitting corrosion. It should be noted that quantitative methods like those proposed in this work are meant to complement fast-screening qualitative techniques. While qualitative methods are key to identify high-risk equipment from a large population of susceptible assets, quantitative methods are essential for more rigorous and in-depth analysis of critical equipment. As shown in this thesis, quantitative models can also be used to predict corrosion risk and provide early warnings based on data collected from different sampling, monitoring and inspection tools.

7.2.8. Overall Conclusion: Safe and Productive Operations Through Risk-Based Corrosion Management

Overall, it has been shown in this thesis that the evolving, complex and uncertain pitting corrosion mechanism calls for a predictive risk-informed decision-making tool to ensure safe and cost-effective operation of assets susceptible to pitting corrosion. This thesis has made a leap step toward development of such tool by providing new methods, insights and guidance to:

- Improve understanding of how to model pitting corrosion under dynamic conditions
- Help engineers to make a decision regarding an asset affected by, or susceptible to, pitting corrosion through predictive FFS assessment
- Develop different criteria for remaining life evaluation of equipment affected by pitting corrosion
- Ensure safety and productivity in process operations susceptible to pitting corrosion through dynamic corrosion risk management

7.3. Recommendations

The present work attempts to introduce new concepts and also overcome the limitations of existing techniques in the field of dynamic risk management of assets susceptible to pitting corrosion. This study can be extended further by addressing the following main limitations:

7.3.1. Consideration of Other Damage Mechanisms

It should be noted that the proposed methodology only estimates the risk of failure due to pitting corrosion. Corrosion is a complex process and multiple mechanisms might be present at a same time. For instance, pitting corrosion can occur simultaneously with general corrosion. Moreover, the generated pits can act as stress concentration points, causing or enhancing the rate of stress corrosion cracking. A framework should be developed for cases where multiple damages mechanisms are present to capture the overall effect of active mechanisms on the probability of failure. The estimation of risk due to other damage mechanisms and the aggregation of all estimated risks are required to provide an accurate picture of the overall asset integrity due to different failure mechanisms. The scope of the proposed risk-based pitting corrosion management can be expanded to apply to other corrosion mechanisms.

7.3.2. Further Investigation of Insulation Effect on Pitting Corrosion

This thesis identified the factors that should be taken into consideration to model pitting in insulated equipment. In future work, different aspects of coating and insulation effects on the behaviour of pitting corrosion should be further analyzed using experimental lab results.

7.3.3. Consideration of Dependencies in Degradation Modelling

The Bayesian approach is used in this work to incorporate new inspection data to revise model parameters. However, Bayesian analysis has some restrictions, which are mainly lack of control of the marginal probability distribution of variables and an inability to capture the non-linear dependence structure. The integration of Bayesian analysis with statistical tools such as copula functions can be a subject for future studies to capture dependencies among different factors affecting pitting corrosion[6].

7.3.4. Development of Data Gathering Methodologies

Most of the proposed approaches in this study demand a high amount of quality data which are often difficult to obtain, particularly for remote operations such as offshore and marine facilities. Choosing appropriate data that best represent the asset conditions in a given operation is challenging. To tackle this challenge, potential sources of information and data include:

- Expert experience and knowledge
- Information shared across industries that have operations in similar environments
- Accelerated corrosion tests, such as the one proposed by Caines et al.[7]

The development of advanced data acquisition systems and their integration with the proposed dynamic risk management model for pitting corrosion could be another subject for further studies to systematically gather, share and analyze information.

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[6] Hashemi, S.J., F. Khan, and S. Ahmed, Multivariate probabilistic safety analysis of process facilities using the Copula Bayesian Network model, *Comput. Chem. Eng.* 93 (2016): pp. 128–142.
[7] Caines, S., F. Khan, J. Shirokoff, and W. Qiu, Experimental design to study corrosion under insulation in harsh marine environments. *J. Loss Prev. Process Ind.* 33 (2015): pp. 39–51.

7.3.5. Conducting Uncertainty Modeling

Probability distributions are used in this work to model uncertainties. Uncertainty associated with the selection of proper probability distributions and the estimation of probability distribution parameters can significantly affect the accuracy of risk assessment. Uncertainty analysis investigations have been conducted in different parts of this thesis to address this challenge. However, a more formal uncertainty modelling study, separating the epistemic and aleatory uncertainties, is recommended to ensure consideration of all sources of uncertainty when applying the proposed methods in this thesis. A recent study by Bedford et al.[8] can be used as a guideline to approximate uncertainty modeling in risk analysis.

7.3.6. Development of Commercial Tools

MATLAB® codes are used in this thesis for the development and implementation of the proposed models. However, there is a need to develop a commercial and user-friendly software tool for implementation of proposed models for practical applications. The developed software tool should be compatible with current inspection, maintenance and corrosion monitoring methods in the oil and gas industry to facilitate its application for in-line risk control of aging assets.

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[8] Bedford, T., Daneshkhah, A., Wilson, K.J., 2016. Approximate Uncertainty Modeling in Risk Analysis with Vine Copulas. Risk Anal. 36, 792–815. doi:10.1111/risa.12471