RISK BASED INTEGRITY MODELING FOR THE OPTIMAL MAINTENANCE STRATEGIES OF OFFSHORE PROCESS COMPONENTS

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RISK BASED INTEGRITY MODELING FOR THE OPTIMAL MAINTENANCE STRATEGIES OF OFFSHORE PROCESS COMPONENTS

by

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Dedicated to my

father-Gopalan, mother-Sulochana, and wife-Swapna

ABSTRACT

Ageing of components is a major threat to asset integrity in offshore process facilities. A robust maintenance strategy mitigates the effects of age-based structural degradations and reduces the threat of failure. Failure caused by structural degradations is a stochastic process. For maintenance strategies to be effective, the stochastic nature of failure has to be taken into consideration. Risk based integrity modeling (RBIM) is a newly-developed approach that aims at the protection of human life, financial investment, and the environment against the consequences of failure. RBIM quantifies the risk to which individual components are subjected and uses this as a basis for the design of a maintenance strategy. Risk is a combination of the probability and the consequence of failure. The major age-based structural degradations to be addressed include corrosion; such as uniform, pitting, and erosion mechanisms; and cracking; such as stress corrosion, corrosion fatigue, and hydrogen induced cracking. In this study, component degradation processes are modeled stochastically to estimate the probability of failure using Bayesian analysis methods. Bayesian analysis improves the fidelity on the likelihood of future events by relating with the prior and posterior probabilities. Prior modeling is performed using judgmental studies and analyzing historic databases from similar installations. For the assessment of ageing assets and degradation mechanisms, field non-destructive test (NDT) data is used to establish the likelihood function. The posterior modeling is performed using a simulation-based Metropolis-Hastings algorithm and Laplace approximation since the prior-likelihood combinations are non-conjugate pairs. In this study, the consequences of failure are modeled using economic analysis to estimate the costs of failure, inspection and maintenance. The cost of failure includes lost production,

loss of shutdown, cost of spill cleanup, loss caused by environmental damage and liability. The inspection and maintenance costs are estimated using the inspection and maintenance tasks, access, surface preparation, gauging defects, coating and restoration costs. Maintenance may be either minimal repair or replacement of components. The annual equivalent cost (AEC) of operating and maintaining a facility is the summation of the annual equivalent costs of failure, inspection, and maintenance. The cumulative posterior failure probability is combined with AEC to produce the operational life risk curve for a component. Since the risk curve is a convex function of the maintenance interval, then the optimum interval is the global minimum point. The operational risk is thus reduced to as low as reasonably practicable level by optimal maintenance.

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LIST OF ABBREVIATIONS

A-D	Anderson - Darling
AEC	Annual Equivalent Cost
AHP	Analytical Hierarchy Process
ALARP	As Low As Reasonably Practicable
ANN	Artificial Neural Network
API	American Petroleum Institute
BA	Bayesian Approach
BM	Breakdown Maintenance
CBM	Condition Based Maintenance
CC	Correlation Coefficient
CDF	Cumulative Density Function
CFC	Corrosion Fatigue Cracking
CMMS	Computerized Maintenance Management System
CoF	Consequence of Failure
CRA	Corrosion Risk Assessment
DM	Drilling Mud
EC	Erosion Corrosion
ECM	Effectiveness Centered Maintenance
E-M	Expectation - Maximization
FC	Failure Cost
FORM	First Order Reliability Method
FOSM	First Order Second Moment

GC	Gas Condensate
GE	Gas Export
GNP	Gross National Product
HIC	Hydrogen Induced Cracking
HP	High Pressure
HSE	Health Safety and Environment
IC	Inspection Cost
K-S	Kolmogorov – Smirnov
LA	Laplace Approximation
LCC	Life Cycle Cost
LEM	Lifetime Extending Maintenance
LS	Least Square
LSF	Limit State Function
MC	Maintenance Cost
MCDM	Multiple Criteria Decision Making
McMC	Markov Chain Monte Carlo
M-H	Metropolis-Hastings
MILP	Mixed Integer Linear Programming
MLE	Maximum Likelihood Estimate
MO	Maintenance Outsourcing
MPI	Magnetic Particle Inspection
NDT	Non Destructive Test
PC	Pitting Corrosion

PDF	Probability Density Function
PM	Preventive Maintenance
PoF	Probability of Failure
PP	Probability Plot
QRA	Quantitative Risk Analysis
RBI	Risk Based Inspection
RBIM	Risk Based Integrity Modeling
RBM	Risk Based Maintenance
RCM	Reliability Centered Maintenance
RI	Radiographic Inspection
SCC	Stress Corrosion Cracking
SMM	Strategic Maintenance Management
TPM	Total Productive Maintenance
TSCF	Tanker Structure Co-operative Forum
UC	Uniform Corrosion
USD	United States Dollar
UT	Ultrasonic Testing

LIST OF SYMBOLS

English Symbols

AEC	Annual equivalent cost
$(A/P,i,n)$	Failure recovery factor
$(A/G,i,n)$	Gradient to equal-payment series conversion factor
C	Loss of wall thickness at the start of service
C_0	Fluid discharge coefficient
C_c	Cost of consumables
C_{dp}	Cost of downtime
C_{dnr}	Unit cost of nature damage
C_F	Total cost of failure
C_{fsd}	Cost of shutdown
C_{flp}	Cost of lost product
C_I	Cost of inspection
C_{iga}	Cost of gaining access for inspection
C_{il}	Cost of logistics for inspection
C_{ir}	Cost of radiographic inspection
C_{isp}	Cost of surface preparation for inspection
C_{ita}	Cost of technical assistance for inspection
C_{iut}	Cost of ultrasonic testing (UT)
C_{lcr}	Labor cost for minor repair per hour

C_{li}	Cost of inspection personnel
C_{lds}	Personnel cost for UT defect sizing
C_{lm}	Cost of maintenance personnel per hour
C_{lmp}	Personnel cost of magnetic particle inspection
C_{lri}	Personnel cost for radiographic inspection
C_{lut}	Personnel cost for UT thickness measurements
C_{lvi}	Personnel cost for visual inspection
C_M	Cost of maintenance
C_{mcw}	Repair cost (cutting, welding and fitting)
C_{mga}	Cost of gaining access for maintenance
C_{mgd}	Cost of defects gauging for maintenance
C_{msp}	Cost of surface preparation for maintenance
C_{mta}	Cost of maintenance technical assistance
C_{mmr}	The cost of minor repair
C_{mwt}	Cost of weld quality test and coating restoration
C_r	Cost of equipment rent
C_{st}	Cost of storage and transportation
C_{ta}	Technical expert's consultancy fees
C_u	Unit cost of product
C_{usc}	Unit cost of spill cleanup

d	Loss of material
D_{rp}	Duration of the commodity loss
E	Average number of critical failures in lifetime
$E[g(\theta)]$	Expected value of the function $g(\theta)$
$F[p(\theta / y)]$	CDF of posterior probability of failure
FR	Failure recovery cost
G	Increments in periodic payment for inspection and maintenance
g_c	Gravitational constant
$g(\theta)$	Posterior function in Laplace approximation
i	Annual interest rate
j	Maintenance interval
k	Rate of degradation
$L(y / \theta)$	Conditional likelihood function
n	Service life of component
$nh(\theta)$	Logarithm of unnormalized posterior density
P	Probability of loss of commodity
P_{burst}	Burst pressure
P_g	Gauge pressure
P_{op}	Operating pressure
$p(x')$	Probability of being in new state x'
$p(x^t)$	Probability of being in current state x^t

$p_{MH}(x', x^t)$	Probability of move from current state to next state
$p(\theta)$	Prior probability distribution
$p(y/\theta)$	Likelihood function
$p(\theta/y)$	Posterior probability distribution
Q	Quantity of affected production
Q_m	Mass flow rate through pipe or release rate
Q_{pl}	Quantity of commodity loss per unit time
$q(x', x^t)$	Proposal density in M-H algorithm
$R(j)$	Risk of failure due to degradation
t	Time or duration
T	Exposure period
T_m	Maintenance delay
$u(0,1)$	Uniform distribution
$V[g(\theta)]$	Variance of the function $g(\theta)$
x	Wall loss or pit depth
x_0	Threshold depth of degradation at incubation time T_i
x^t	State of Markov chain at time t
x^{t+1}	Next state of Markov chain at time $t+1$
x'	New proposed sample
Y	Loss of wall thickness

Greek Symbols

θ	Degradation rate parameter
λ	Location parameter of extreme value distribution
γ	Euler's constant = 0.5772
μ	Mean of normal distribution
σ	Standard deviation of normal distribution
$\bar{\mu}$	Posterior mean
$\bar{\sigma}^2$	Posterior variance
α	Scale parameter
β	Shape parameter
$\bar{\alpha}$	Posterior Gamma parameter
$\bar{\beta}$	Posterior Gamma parameter
$\hat{\theta}$	Maximum likelihood estimate for distribution mode
δ	Neighborhood domain value in Laplace approximation
ρ	Fluid density
$\sigma *$	Mode of $-nh*(\theta*)$
σ	Mode of $-nh(\hat{\theta})$
$\pi(\theta)$	Prior distribution
$\alpha(x', x')$	Probability of move (sampling rejection criterion)

CHAPTER I

INTRODUCTION AND BACKGROUND

1.1 INTRODUCTION

Offshore process components fail while operating even though due diligence has been observed during the design and fabrication stages. Failures of these components pose serious threats to human life, financial investment and the environment. Threats to human life include the fatalities and injuries. The threats to financial investment arise from the loss of commodity as a result of shutdown. The threats to the environment consist of pollution caused by spills and other environmental damage. In addition, every failure is associated with liability and bad-reputation. Thus, integrity of process components is of paramount importance to conducting safe operations. The integrity of a component is defined as the ability of the component to perform its required function effectively and efficiently whilst protecting health, safety and the environment (HSE UK, 2009). A good asset integrity management plan ensures that people, systems, processes and resources required to maintain the asset integrity are in place, in use, and will perform when required over the whole lifecycle of the asset. Furthermore, the plan should ensure the prevention of accidents and it should encompass good design, construction and operational practices. Once the offshore process facility is operational, the only way to prevent failure is through frequent inspection and proper maintenance. However, to determine with confidence, the extent and interval of necessary inspection and maintenance based on the condition of the component is a challenging task. Maintenance optimization using mathematical models is one way to reduce the risk of failure of ageing components.

1.2 HOW DO PROCESS COMPONENTS FAIL?

The components of offshore process installations deteriorate with time. During its life cycle, it will be subjected to many potential damages, such as (Stephens et al., 1995): third party damage; ground movement due to seismic acceleration; material and fabrication defects; and human factors. However, studies indicate that majority of failures are contributed by time-dependent structural degradations (Faber, 2002; Straub, 2004; Khan et al., 2006); hence, the quantification of component integrity can be established by understanding the physics of time-dependent failure processes and its adverse consequences. Traditionally, the codes and standards that are used for inspection and maintenance are prescriptive rules based on experience. Most of the time they have been formulated in response to significant failure cases. They neither take into account all types of failures, nor the various sources of uncertainty arising from degradation processes associated with the facility's operation.

API 581 (2000) highlighted the need to develop an industry failure database and software to support the risk based inspection planning and expands the program to fit into several industry initiatives. Leaks and rupture are the principal causes of hydrocarbon release, fire, and explosions in process facilities. Studies indicate that corrosion is the principal cause of about 15% of leakage occurrences (HSE UK, 2002). In nine and a half years, 44.70% of the mechanical failures leading to hydrocarbon releases from offshore facilities in the UK resulted from corrosion or other related degradations (HSR UK, 2002). The direct annual cost of corrosion in the USA is assessed to be 276 billion USD, which represents 3.1% of the GNP, while about 121 billion USD is spent on corrosion control (Koch et al., 2000). The direct cost of corrosion in industrialized countries in billions of USD is reported (Bhaskaran et al., 2005): Japan (59.02), Russia (55.01), Germany (49.26), UK (8.51), Australia (7.32) and Canada (3.38). These figures show that corrosion and related cracking degradation is an economic problem, which needs to be addressed on a priority basis. In Canada, the environmentally induced defects, such as metal corrosion, stress corrosion cracking and hydrogen induced cracking were responsible for 40% of the natural gas pipelines failures and 38% of hazardous liquid releases (Stephens et al., 1995). It is reported that corrosion accounts for 21% of failures in submarine gas pipelines, and erosion-corrosion modes account for 24.6% of pipe leakages in process plants (Googan and Ashworth, 1990). Moreover, 40% of the accidental hydrocarbon releases to the environment are corrosion related. Therefore, the investigation and mitigation of corrosion and cracking and its effects is one of the main actions required to reduce the frequency of hydrocarbon releases, to maximize the production, and to improve the safety of offshore process operations. Better inspection and maintenance optimization need a reliable determination of degradation mechanisms and their consequences. This can be achieved with risk analysis by combining the stochastic degradation modeling with consequence analysis (Faber, 2002).

1.3 HOW TO PREVENT FAILURES?

The time-dependent mechanisms which describe the structural degradation of process components are random processes and hence it will have large uncertainty in the degradation data. Thus, it is appropriate to use stochastic models to accurately describe these mechanisms. Due to this uncertainty in determining the degradation mechanisms, there will always be a certain probability that a given component of the process facility fails during its operation. The life cycle integrity threats may be reduced through well established procedures of design, fabrication, quality assurance and quality control and stringent policies and regulations. However, once the offshore process facility is operational, the age-related or time-dependent degradation processes reduce its strength and material. Therefore, during the operational stage, the best way to predict failure is through inspection and prevent failure is through maintenance.

There are various inspection strategies, such as prescriptive rules, condition/health monitoring and reliability based inspection. In recent years, risk based inspection has emerged as an area of interest in asset integrity management (Faber, 2002; Kallen and Noortwijk, 2002; Straub, 2004; Khan et al., 2006). Risk based inspection may be categorized as qualitative, semi-quantitative, and fully quantitative. A robust, quantitative risk based inspection model based on reliable, probabilistic structural degradation mechanisms and consequences analysis of offshore process components is not yet published in literature (Faber, 2002; Khan et al., 2006).

The various maintenance strategies include reactive and proactive maintenance programs. Reactive maintenance is based on the principle "fix it as it fails", which is costly due to abrupt commodity loss and unplanned shutdowns. The recent developments in maintenance are total productive maintenance (TPM), reliability centered maintenance (RCM) and the condition based maintenance (CBM). However, their applications are limited as they focus on likelihood of failure only. Failures result in direct economic consequences such as loss of commodity, loss due to shutdown, spill cleanup and environmental damage costs. Inspection and maintenance also have direct and indirect economic consequences. Hence, optimizing maintenance on the basis of actual condition and failure consequences is to be investigated. Risk based integrity management models are emerging as a rational choice. The basic questions to be answered in connection with optimization of inspection and maintenance of deteriorating components are:

- What component will fail? (identify critical components).
- How will it fail? (understand the physics of failure).
- When failure becomes critical? (quantification of true risk).
- When to inspect/maintain? (estimation of inspection/maintenance interval).
- What is to be inspected/maintained? (inspection/maintenance activities).

1.4 BACKGROUND

The first initiatives and developments of risk based approaches to the inspection and maintenance planning were directed towards the inspection planning for welded connections subject to fatigue in fixed steel offshore structures (Skjong, 1985; Madsen et al., 1987; Fujita et al., 1989; Moan et al., 2000). Later, the same methodology was adopted to other structures such as tankers (Soares and Garbatov, 1996; Paik et al., 2003); floating, production, storage and off-loading facilities (Lotsberg et al., 1999; Goyet et al., 2002); semi-submersibles and pipelines (Willcocks and Bai, 2000; Desjardins, 2002; Dey and Gupta, 2001). Recently, the risk based approaches were applied to process plants (Geary, 2002; Kallen, 2002; Montgomery and Serratella, 2002; Khan et al., 2006);

bridges (Frangopol et al., 2001) and to breakwaters (Noortwijk and Phajm, 1996). The degradation mechanisms such as, fatigue cracking and, some aspects of corrosion of steel and concrete structures were considered. Throughout these developments, structural reliability methods have played an important role (Straub, 2004; Faber et al., 2005). Melchers (2006) introduced an approach for probabilistic corrosion estimation based on the structural reliability theory. Further, Straub and Faber (2006) discussed the computational aspects of risk based inspection planning for fatigue cracking based on structural reliability theory. The inspection planning for process equipments and marine systems has later evolved from the traditional quantitative risk analysis (QRA) (Khan and Haddara, 2003; Khan et al., 2004; Dey, et al., 2004). Offshore system operators collect inspection data; however there is no proved model that makes use of such data to dynamically update probability of failure, with the arrival of new data. A closer review of literature has shown that little information is published on a robust, holistic and stochastic risk based methodology for the integrity assessment of offshore process components; considering the important threats to structural integrity, such as various types of detrimental corrosion and cracking. What is lacking is the development of a stochastic as well as dynamic model for degradation modeling and economic consequence analysis having predictive capabilities, which is the main focus of this study.

1.5 RISK ANALYSIS AND ASSET INTEGRITY

The risk to a component's life is defined as a combination of the probability of an undesirable event occurrence and its likely consequence. Thus, the operational life risk analysis is reduced to the accurate estimation of probability and consequence of failures. *Integrity* is defined as the quality of being whole and complete. When it is applied to process components, the *structural integrity* is the ability to safely resist the required loads and perform as desired. In other words, it is the soundness and consistency of the process components to resist the operational loads or demands.

The life cycle integrity of process components could be achieved through various stages of design, manufacturing, operation and maintenance. If the integrity has been ensured during the design, fabrication and operational stages through a well-established design, quality control and regulations, then asset integrity depends only on the maintenance. In offshore process facilities, the design and fabrication usually follow certain codes and standards. The codes and standards are based on deterministic models, which will have the model and data uncertainty, thus results in certain probability of failure. Once a plant starts its operation, risk to life is a function of inspection and maintenance.

1.6 RISK BASED STUDIES

The application of risk based approaches to inspection and maintenance of deteriorating structures, engineering installations and production facilities has been increasing over the last decade (Faber, 2002; Straub, 2004; Khan et al., 2006). The components of offshore process facilities are designed to ensure economical operation throughout the anticipated service life in compliance with client's requirements and acceptance criteria. The acceptance criteria are related to minimum code requirements that may be exceeded with consideration of the safety of personnel, risk to environment and the annual operating and maintenance budgets. The time dependent degradation processes such as corrosion and cracking will always be present to some degree. Depending on the adopted design philosophy in terms of degradation allowances and protective measures, the degradation process will reduce the performance of the system causing leak, rupture and contamination. In order to ensure that the acceptance criteria are fulfilled throughout the service life, it is required to control the development of degradation and install proactive maintenance measures, before the failure occurs.

The planning of inspection and maintenance concerns the identification of what to inspect and maintain, how to inspect and maintain, where to inspect and maintain, and how often to inspect and maintain. Even though inspections and maintenance are used as an effective means for controlling the degradation of the process components, they may also have considerable impact on the operation of the facility. It may result in direct and indirect economic consequences in terms of shutdown costs and unavailability. Therefore, it is necessary to plan inspection and maintenance, such that a balance is achieved between the expected benefits of inspection and maintenance and the corresponding economic consequences implied by the inspection and maintenance.

The development of risk based integrity modeling of process facilities is highly necessary to avoid adverse technological incidents, to ensure the safe operation and to extend the operational life of existing facilities. The proposed risk based integrity modeling (RBIM) finds optimal strategy to the inspection and maintenance. The RBIM methodology enables the assessment of the probability of failure of a component and the consequences of that failure. In RBIM, the critical components for the safe operation of facility are prioritized. Using probabilistic models, the RBIM models the degradation mechanisms and estimates the rates of degradation. It optimizes the inspection method and interval, and maintenance resource by adopting risk based maintenance strategy subject to the corporate's acceptance criterion. This result in an improved safety, low risk, fewer shutdown, and reduced operational costs. The risk based integrity modeling approach provides an integrated framework for the maintenance strategy of the facility.

1.7 STRUCTURAL DEGRADATION PROCESSES

Different methods are required for the inspection and maintenance of different degradation processes. Kowaka (1994), Melchers (2001), Goyet et al., (2002), and Khan and Howard (2007) reported that the main threats to the integrity of process facilities are several types of corrosion (Figure 1.1). Further, Kallen (2002), Straub (2004), and Straub and Faber (2005) have reported that the major degradation mechanisms threatening the integrity of structural components consist of various types of cracks (Figure 1.2).

Corrosion is the loss of material as a result of a chemical reaction between a metal and its environment. Based on literature study (Stephens et al., 1995; Kallen, 2002; Khan et al., 2006), the critical structural degradation mechanisms threatening the integrity of assets are uniform corrosion (UC), localized or pitting corrosion (PC), erosion corrosion (EC), stress corrosion cracking (SCC), corrosion fatigue cracking (CFC), and hydrogen induced cracking (HIC). Uniform corrosion is defined as the uniform or regular removal of metals from the surface (Jones, 1996). For uniform corrosion, the corrosive environment must have the same access to all parts of the metal surface, and the metal itself must be uniform in terms of metallurgy and composition. Uniform corrosion results in the thinning of wall thickness until the wall is penetrated leading to leaks or breakdown of equipment (Mansfeld, 1987). The localized attack of corrosive environment on an otherwise resistant surface produces pitting corrosion (Jones, 1996). The combination of the corrosive fluid and high flow velocity results in erosion corrosion. A stagnant or slow flowing fluid will cause a low or modest corrosion rate, but the rapid movement of the corrosive fluid physically erodes and removes the protective corrosion product film, exposing the reactive metal beneath, thus accelerating corrosion. Sand or suspended slurries enhance erosion and accelerate erosion corrosion attack on metal. The attack follows the directions of localized flow and turbulence around surface irregularities.

The brittle fracture of a normally ductile alloy, in presence of a corrosive environment or cyclic loading is known as cracking (Jones, 1996). The amount of cracking per unit time either in length or depth is expressed in terms of cracking rate. Stress corrosion cracking (SCC) is the cracking induced by the combined influence of static tensile stress and a corrosive environment, especially at elevated temperatures. The required tensile stresses may be in the form of directly applied stresses or in the form of residual stresses. The process in which a metal fractures prematurely under conditions of simultaneous corrosion and repeated cyclic loading at lower stress levels or fewer cycles is known as corrosion fatigue cracking (CFC). Hydrogen induced cracking (HIC) means the severe loss of ductility caused by the presence of atomic hydrogen in the metal lattice (Jones, 1996). Hydrogen absorption may occur during electroplating, welding, pickling, cathodic protection or other processes that favor the production of nascent hydrogen at the surface.

Fig.1.1. Material Degradations-Various Types of Corrosion

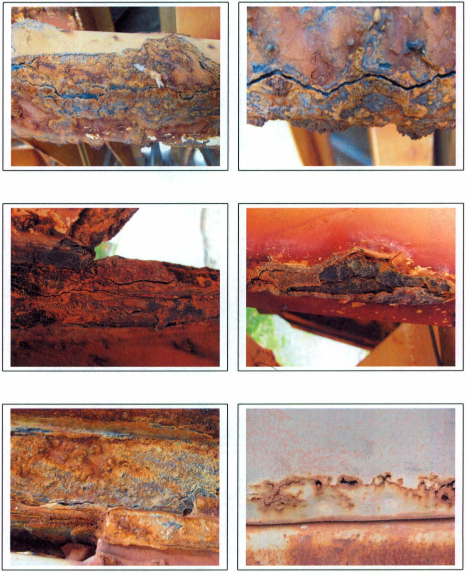

Fig.1.2. Material Degradations-Various Types of Cracking

If structural corrosion or cracking are found during inspections, wasted parts are to be repaired or renewed. Corrosion and cracking result in loss of material as well as structural strength at local and global levels. It leads to leaks and breakage. Decisions regarding the extent of renewal require the knowledge of how much more material will corrode or how long the crack will grow before next inspection and maintenance. Thus, in order to ensure the integrity of process components, it is crucial to estimate how often to inspect and maintain so that risk is reduced to as low as reasonable practicable (ALARP) level. Different inspection and maintenance strategies with different inspection and maintenance effort, quality, and costs will have different effects on the risk. By comparing the risk associated with different inspection and maintenance strategies, the one implying smallest risk, which is acceptable, can be identified.

Though design strategies may attempt to mitigate the effect of degradation processes by choice of materials and dimensions, degradation processes will still occur due to errors or flaws during the manufacturing and operations. The real load carrying capacity and the level of safety of these components will diminish with time. In order to maintain acceptable level of safety, it is necessary to determine the variation of structural properties with time. The rate of degradation may not be uniform in all cases. A constant factor of safety (corrosion allowance/crack resistant material) taken to account for loss of material at the design stage may not be adequate. This necessitates the stochastic degradation modeling updated using the latest inspection data.

The reliability of a component is the probability of its satisfactory performance under specific service conditions within a time period. There are several analytical and simulation methods to estimate the probability of failure. The major analytical methods for the estimation of failure probabilities are the deterministic method and the stochastic method, which lead to the prediction of remaining life. The stochastic methods used in risk analysis include the qualitative and quantitative methods.

The uncertainty in degradation processes may arise from many sources such as, inherent randomness in physical processes, statistical uncertainty and modeling uncertainty. The physical uncertainty means that the repeated measurements of the same physical quantity do not yield the same value due to numerous fluctuations in the environment, test procedure, instruments, and the observer. Statistical uncertainty occurs when one does not have precise information about the variability in the physical quantity of interest due to limited data. Modeling uncertainty occurs due to the limited representation of the system behavior. A computational model strives to capture the essential characteristics of system behavior through idealized mathematical models or numerical procedures.

The stochastic Bayesian theory may be used for the quantification of uncertainty and the prediction of the likelihood of the time-dependent degradations. The Bayesian models are based on a mixture of prior understanding, observations and experience. It is an adaptive approach. The observations of actually occurring degradations obtained by non destructive tests (NDT) may be introduced into models that greatly enhance the precision of their predictions. The probabilistic characteristics of the structural degradations are decisive for the estimation of the future performance of the components. The predicted future degradation will vary considerably if the observed degradation state is used to update the degradation model at the time of the successive inspections. This facilitates the system-learning process with the arrival of new NDT data.

The consequences of failure may be analyzed in terms of the cost incurred as a result of the occurrence of failure and the implementation of inspection and maintenance strategy. The consequences of failure include the loss due to breakdown, loss due to shutdown, cost of spill cleanup, cost of nature damage and liability. The cost of inspection may depend on the method and duration of inspection, type of component, availability of access, and surface preparation costs. The maintenance cost depends mainly on the type of maintenance, availability of access, surface preparation, gauging defects, fitting, welding and coating restoration costs. By developing the annual equivalent cost of operating and maintaining the component, the inspection and maintenance strategy following minimum risk may be developed. For that purpose, the annual equivalent cost shall be combined with Bayesian probability model to develop operational life risk. A model for the cost of degradation caused by corrosion and cracking in typical process piping component is developed. The developed models take into account the effects of the uncertainty in cost estimation using random sampling methods.

1.8 MOTIVATIONS

The safe operation of process components requires accurate modeling of failure modes, understanding uncertainties, and the development of a robust methodology for the quantification of risks. However, using available risk models, it is not possible to quantify accurately the requirements of inspection and maintenance strategy considering the overall risk to facility. Based on the methodological developments in the area of industrial integrity management for components subjected to age-based degradations, a holistic approach is needed to the risk based integrity management of components in offshore process facilities.

In order to protect the public, the financial investment and environment against the consequences of failure of offshore process facilities, a risk based assessment of the existing facility is necessary. Such an assessment should quantify the degradation of the material and provide a basis for the decision making process regarding the optimal inspection and maintenance. The decision making process under uncertainty using Bayesian risk analysis is presented in Figure 1.3, where PoF and CoF refer to the

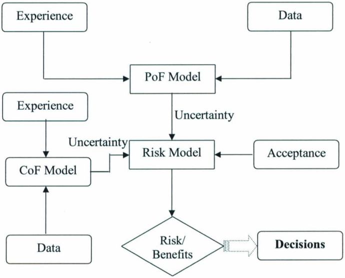

Fig. 1.3. Decision Making Process using Bayesian Risk Analysis

probability of failure and consequence of failure, respectively. Usually, the operational risk in industrial applications is calculated by adding up all the consequence cost elements and, multiplying it by the predicted frequency of the accident probabilities. Further, the use of risk based integrity modeling allows the operating expenditures to be focused on a few critical elements that will give the greatest return on expenditure.

In any integrity modeling efforts, the strategic elements, such as corrosion and cracking mechanism and rate, available remaining life from the inspection data and history of degradation rate, consequences of failure, inspection and maintenance etc. are important to be modeled, which has not addressed so far in literature. Further, many researchers (Faber, 2002; Frangopol et al., 2004; Khan et al., 2006) have reported the need of a holistic procedure to be developed for risk management in offshore process installations.

Most of the risk based approaches reported in the open literature so far deal with the structural reliability methods, and the physical condition of the asset, however, there is no single approach that can be used to address the needs of offshore process facilities. The economic consequence analysis of failure, inspection and maintenance are not well integrated with probability of failure in the existing literature. Therefore, further work is necessary to collect the relevant data, improve the modeling capability and formulate the stochastic decision problems applicable to offshore process standards. The important motivations to undertake this study are discussed in brief below:

- There are a few limitations in the existing models, such as scarce data, gap between theory and practice, models are only mathematical and no convincing case studies. Thus, the applications are limited in industry.

- The risk based repair and replacement models with adequate confidence are scanty. Some literature attempted to model the deterioration with Gamma process that restricts the use of priors and need not reflect the true degradation process based on subjective knowledge, experimental judgment and generic database. There is a need for investigating the use of non-conjugate pairs to obtain reliable posterior distributions in the cases of corrosion and cracking processes.
- The lack of accurate and reliable methods to deal with the uncertainties in the input data. There is a need for accurate and reliable modeling of degradations resulting from pitting, erosion, and stress corrosion as well as corrosion fatigue and hydrogen induced cracking.
- There is a need for developing models which account for the nonlinearity and stochastic degradation growth in cases of corrosion and cracking.
- There is a need to understand the economic consequences of failure, inspection and maintenance and integrate that in risk based maintenance decision making.
- There is a need for a risk based integrity model which is able to predict the operational risk and is adaptive to the current condition of components.
- There is a need to develop quantitative risk models acceptable to the industry and easy to use by maintenance practitioners, based on the operating and maintenance budget towards the risk acceptance criteria.

1.9 ADVANTAGES OF RISK BASED METHODS OVER TRADITIONAL METHODS

The risk based methods are preferred over the traditional deterministic methods, because:

- In traditional methods, the integrity of a component is evaluated by comparing the current operating conditions with a design limit state that often yield conservative results, leading to potentially unnecessary inspections and maintenance, that results in an overall increase in maintenance costs and unavailability.
- The traditional methods do not provide information on potential degradation risks to life and, thus results in unrealistic inspection and maintenance of components. The degradation risk arises from the uncertainty associated with data and modeling; a chosen value of corrosion allowance or crack resistant material at the start service may not be adequate to preclude the operational life-risk due to the random nature of degradation process and uncertainty in data collection.
- The traditional approaches are based on prescriptive rules and leave little possibility to adapt the inspection and maintenance effect to either the actual condition of the components or degrading systems. The risk based approach is a condition based approach and provides a rational basis for adapting the inspection and maintenance using Bayes theorem, to the present condition of components.
- In the operational stage, the traditional methods do not consider the importance of the critical components for the inspection and maintenance of a facility. At the same time, risk based approaches prioritizes the inspection and maintenance in accordance with the importance of components and the criticality of different degradation mechanisms.
- The risk based models minimizes the risk of operating and maintaining the component to as low as reasonably practicable levels.

- The risk based integrity models reduce failures, minimize the operating and maintenance cost and at the same time promote the safe operation of facility.

1.10 ORGANIZATION OF THESIS

This thesis is written in manuscript format. Outline of each chapter is discussed below:

Chapter 2 presents the literature review pertaining to this thesis. The literature review deals with four areas: maintenance optimization using mathematical models; risk based inspection and maintenance models; stochastic degradation models including corrosion and crack models; and failure consequence analysis models.

Chapter 3 reports the development of RBIM framework and thesis overview. The RBIM is developed based on the stochastic degradation modeling using the Bayesian analysis and the economic consequence analysis. Inspection and maintenance is optimized by minimizing risk. The framework for connecting the various chapters of this thesis is also discussed in this chapter.

Chapter 4 reports the development of prior probability models for identified component-degradation mechanisms. This chapter is a published paper in the *Journal of Stochastic Environmental Research and Risk Assessment (2009), 23*(6): 793-809.

Chapter 5 reports the development of Bayesian posterior probability models using the simulation based Metropolis-Hastings algorithm and analytical Laplace approximation methods. The field NDT data are used to estimate the likelihood probability of degradation processes. This chapter is published in the *Journal of Risk Analysis (2010), 30*(3): 400-420.

Chapter 6 focuses on the economic consequence analysis part of the RBIM and the optimization of replacement decisions using the engineering economic analysis. This work is accepted for publication by the *Journal of Quality in Maintenance Engineering*.

Chapter 7 deals with the integration of RBIM and validation of models, using the computed failure probability and consequence reported in chapters 5 and 6. It optimizes the inspection and maintenance decisions under uncertainty. This work is submitted for peer review and publication to the *Journal of Risk Analysis*.

Finally, Chapter 8 reports the summary and conclusions of this thesis. It also includes the novelties of this research and suggests the scope for future work in this area.

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CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

The optimization of maintenance strategies using mathematical models has been a subject of research for many years. The research has been focused primarily on the deterministic and probabilistic approaches. Recently, the importance of the considerations of reliability and cost was recognized. The importance of the impact of the economic considerations on the inspection, maintenance, and replacement strategies cannot be overestimated. Thus, the development of a more rational and cost-effective approach for maintenance strategy is essential. Risk to the life of a component is an outcome of an uncertain event and it may be defined as the product of probability of failure and its likely consequences. Risk reflects the impact of the three factors: condition, reliability and total cost. An approach for the design of maintenance strategies on the basis of risk optimization seems to be in order. In such a model, an accurate structural degradation modeling to estimate probability of failure and a rigorous consequence analysis are two essential components.

A review of the relevant literature related to risk based integrity modeling found in the open literature has been carried out. The research work can be listed under four categories: maintenance optimization models, risk based inspection and maintenance planning models, stochastic degradation models for corrosion and cracking, and consequence analysis models.

2.2 MAINTENANCE OPTIMIZATION MODELS

The history of maintenance in offshore industry goes back to the history of offshore oil and gas production. The earliest known approach in maintenance was reactive maintenance. Up to 1940's, the maintenance cost was considered as an unavoidable cost and the only maintenance carried out was breakdown maintenance. This was less expensive and time consuming with limited number of components and parts. The industrial revolution brought there a huge advancement in automation, machinery and equipments used in offshore industry. This opened the door for the use of complex and costly-components in the system to transport and process the produced hydrocarbons. Thus, the traditional breakdown maintenance was no more attractive nor cost-effective. The evolution of operational research and mathematical optimization after Second World War II lead to the development of preventive maintenance strategies to avoid breakdown. With the rapid growth and development of mathematical models and computational capability in early 1990's, preventive maintenance strategies gained predominance. It was recognized that preventing a failure is always better than recovering from it. Preventive strategy not only prevents failure, but also avoid costly shutdown. Further, it reduces operating and maintenance budgets, making the operation safe, reliable and profitable.

Maintenance optimization using mathematical models has been a subject of research for many years. In the early 1960's, the detection of the degradation of specific component in a system was used to minimize breakdown (Barlow and Hunter, 1960). The degrading components are replaced either under an age-replacement policy or a block replacement policy (Barlow and Proschan, 1965). In age replacement policies, the device is replaced upon failure or at fixed age, whichever occurs first. In block replacement policies, the device is replaced at fixed time intervals and at failure. In both cases, the replacements are done using new and identical devices (Barlow and Proschan, 1965). In 1970's more integrated approach to maintenance involving a close linkage to reliability and maintainability was recognized. Abdel-Hameed (1977) studied an age-replacement policy for which renewal is defined as either a corrective replacement upon failure or preventive replacement upon reaching a predetermined age, which ever occurs first, using a stationary Gamma process with non-negative increments in material wear.

The fatigue reliability updating through inspection of steel bridges is presented in Zhao et al., (1994). An approach using the linear elastic fracture mechanics theory is proposed and the corresponding risk of fatigue damage is evaluated. The overall fatigue reliability can be maintained by undertaking minimal repairs or replacement as necessary. Since degradation is a slow process, the inspection strategy may be more economical from the design point of view and may help to extend the service life of components. A non destructive test (NDT) may be an essential and important tool in the degradation-detection and evaluation. Non-destructive means that component specimen examined remains fit for purpose after inspection. During NDT the material properties could change, but the change will be within allowable level. The NDT results may be utilized in maintenance planning. For that purpose, mathematical models using the NDT data are to be developed to link the degradation process to optimize maintenance planning. For a particular NDT, several factors are expected to affect inspection results, including modeling effects, human errors, and inspection factors (Zhao et al., 1994).

The modeling effects are composed of material characteristics, types of defects, component configuration, and surface conditions including thickness, presence of abrupt geometry changes, and accessibility of critical regions (Zhao et al., 1994). The human factors include variations in inspector skill, interpretation of results, variations in calibration of equipment, variation in inspection procedures, and sequence of operations. The inspection factors are attributed to different inspection environments, including factory, laboratory, and field conditions, and detectability. These factors add uncertainty to the inspection results, which needs to be addressed in the mathematical model.

Various NDT techniques are used for the purpose of detecting degradations. Some of the most common techniques are visual inspection, ultrasonic inspection, liquid penetrant inspection, magnetic particle inspection, eddy current testing and radiographic inspection. The ultrasonic inspection is one of the most commonly used NDT and it is accepted for corrosion and crack detection in components. The main advantage of this method include the relative ease of penetration into materials with engineering application, such as steel, and the ability to test from only one surface and to detect substantial flaws, the sensitivity and comparative accuracy, and the presence of no significant radiation hazards requiring operational precautions. During the operational lifetime of an offshore facility, the NDT could be conducted several times to ensure the integrity of components. The information generated during inspection needs to be incorporated in mathematical model to decide on maintenance actions, which is lacking. Since the inspections are required at intervals, the results may be used to update maintenance of components. Inspection information is beneficial; however, it adds uncertainty to the degradation evaluation process.

With the developments in mathematical modeling, operational research and computers, more sophisticated preventive maintenance strategies such are reliability based and condition based maintenance are developed. An inspection, maintenance and replacement models are discussed by Abdel-Hameed (1995) based on age and block replacement policies. The preventive maintenance with limited historic data has been presented in Silver and Fiechter (1995). Since the breakdowns are costly, it may be attractive to undertake preventive maintenance on a regular basis. The decision making depends on the lifetime distribution of system, current state of system and cost structure of system.

For process components it is useful to base the failure model on the physics of failure and the characteristic of operating environment (Singpurwalla, 1995). The condition based monitoring uses direct monitoring of the mechanical condition, system efficiency and other indicators to predict the actual time to failure or loss of efficiency. It serves two purposes, such as: (i), determine if a problem exists in equipment, how serious the problem is, and how long the equipment can run before failure, (ii), to detect and identify specific components in the system that is degrading (Tsang, 1995). Thus, instead of inspecting and maintaining each and every component in a system, which is rather costly as well as unnecessary, the inspection and maintenance efforts may be focused on those critical (degrading) components to ensure the safety of system operation.

To lower the cost of inspection, maintenance, replacement and failure, mathematical optimization models are increasingly applied in the field of maintenance management (Dekker, 1996; Dekker and Scarf, 1998). The optimization of maintenance is a decision making under uncertainty arising from degradation and cost. In maintenance management, the most important uncertainty is the uncertainty in the rate of degradation. Therefore, it is recommended to model the deterioration in terms of a time-dependent stochastic process. Various classifications of maintenance optimization models and maintenance performances have been presented in Dekker and Scarf (1998), Tsang (1998), and Tsang et al., (1999). Dekker and Scarf (1998) classified the maintenance models as block replacement models, Markov decision models, and delay time models. The maintenance optimization models can be qualitative or quantitative. The former includes the techniques like total productive maintenance (TPM), reliability centered maintenance (RCM), while the latter incorporates various deterministic or stochastic models such as, Markov decision, stochastic deterioration, random processes, Bayesian model etc. The corrective maintenance prevailed in 1940's has been evolved to operational research, reliability, and risk based maintenance models of today.

The maintenance cost may be minimized by basing the maintenance on the condition of the critical components. Since the condition of the component deteriorate randomly, probabilistic models are essential to model its nature. A probabilistic analysis framework to estimate reliability incorporating the impact of inspection and repair activities planned over the service life of a pipeline, vulnerable to corrosion is reported in Pandey (1998). The framework is applied to determine the optimal inspection interval and the repair strategy that would maintain adequate reliability throughout the service life. The maintenance can be either preventive or corrective. The preventive maintenance can be either reliability centered maintenance or condition based maintenance. The corrective maintenance is always less economical than preventive maintenance and all failure can be prevented. Again, the predictive maintenance is more attractive than preventive maintenance as it prevents failures, unnecessary shutdowns and maintenance errors. Reliability centered maintenance (RCM) is a preventive maintenance strategy, and is a structured methodology for determining the maintenance requirements of any physical asset based on target reliability. The primary objective of RCM is to preserve the system to function. It uses systematic technique to rank the criticality of failure modes and provides guidelines for the selection of applicable preventive maintenance tasks that are most effective in preserving system function. The goal of optimal maintenance is to make economically justifiable decision, or it includes the profit or availability maximization, and risk minimization. The development of an optimal maintenance programs based on vibration monitoring of critical bearings on machinery is presented (Jardine et al., 1999).

The lifetime extending maintenance models for offshore structures are discussed in Bakker et al., (1999). The modeling of entire components in an offshore facility are not feasible, however, high risk components may be ranked and analyzed. The general rule of thump in process facility is that, 80% of the system failures are from 20% of the components. The risk based decision model will focus on these high risk components.

With the advent of computers and fast programming, maintenance strategies have witnessed a paradigm shift over the recent decades from breakdown maintenance to more sophisticated strategies like online monitoring, reliability and risk based maintenance. The safety of offshore operation is directly related to the reliability of its components. A robust maintenance program is necessary for process components as it deals with hazardous substances often under harsh operating and environmental conditions. Preventive maintenance (PM) can help to minimize the probability of losses due to accidents and unscheduled failure of process components. However, the predictive maintenance is more advanced as it allows the optimal utilization of maintenance resources. The trade-off is usually in risk and cost balance to achieve the acceptance criteria. Quantitative approaches connect the component degradation to the condition improvement by maintenance to make informed decision under uncertainty. A large number of publications are available on the subject of maintenance through risk based models (Wilcocks and Bai, 2000; Montgomery and Serratella, 2002; Khan and Haddara, 2003; Dey, 2004; Khan et al., 2006). The API (2000) has developed a methodology for aiding the industry to base the maintenance on quantitative risk analysis. It was argued that the existing method of health monitoring, which requires the entire components to be inspected periodically, is both time-wasting and expensive. Risk based model prioritize the critical components to the safe operation. A risk based model for the inspection and maintenance of cross country pipeline is presented in Dey (2001) based on the analytical hierarchy process, a multi criteria decision making techniques. The weightage given to the failure factors based upon subjective experience and available data.

Risk is defined as the product of the probability of an unwanted event occurrence and its likely consequences. Risk assessment may be used as an identification and prioritization tool to assist decision making on the selection of inspection and maintenance to prevent asset failures. It is essential to ensure that the stake holders concerns are adequately addressed and that the system is safe for production. Risk management is a technique used to identify, characterize, quantify, evaluate and reduce losses from actions of decisions that have undesired outcomes. It provides equal priority to low probability-high consequence failures as well as high probability-low consequence failures.

Risk is often viewed as the uncertainty associated with any outcome. Uncertainty can be in the form of probability of potential failures and consequences. The vital risk factors, which correspond to the likelihood of failure, are corrosion: internal and external, external influence: third party activity, free span and vibration, construction and material defects: poor construction and low grade material, errors: human and operational, and natural hazards: earthquakes, storms (Stephens et al., 1995). The literature study reveals that the internal corrosion and cracking are the major causes for likelihood of failure. The environmental and social factors also have more impact on failure.

Wang (2002) reported a survey of maintenance policies of deteriorating systems and has summarized, classified and compared various existing maintenance policies with an emphasis on single unit systems. Risk analysis is one tool the decision makers can use to help with prioritizing maintenance action planning (Backlund and Hannu, 2002). An effective use of resources can be achieved by using risk-based maintenance decisions to guideline where and when to perform maintenance. By conducting a comparative study of three independent risk analyses on a specific hydro-power plant, to make a meaningful decision, it was concluded that careful requirement identification, ensuring the system approach with clear aims and goals are needed when performing risk analysis (Backlund and Hannu, 2002). The client needs to have sufficient competence to evaluate and understand approaches and result from the risk analysis performed. In order to identify risks in terms of where they are located in a system and how serious they are, risk analysis is often used. The results of risk analysis can provide guidance as to where maintenance actions should be directed. Some quality assurance applied to risk analysis process will enhance the conditions for reliable results. Literature on the use of simulation in maintenance planning has been reviewed by Andijani and Duffuaa (2002). Knowledge of the reliability and maintenance engineer may be useful in the design of customized inspection and maintenance concept. An optimal maintenance of systems subjected to deterioration of renewal type has been reported by Abdel-Hameed (2003). The optimization is based on the total discounted cost over the infinite horizon, and the long-run average cost criterion.

The deterioration and maintenance models for insuring safety of civil infrastructures at lowest life cycle cost are presented in van Noortwijk and Frangopol (2004). The model can be applied to determine the best maintenance strategy to insure an adequate level of safety at minimal lifecycle cost while taking the uncertainties in the deterioration process in to account. Without being complete, a time-dependent deterioration process can be modeled as a failure rate function, a Markov model, a stochastic process or a time-dependent reliability index. The pros and cons of the different models considered are discussed (van Noortwijk and Frangopol, 2004). The advantage of reliability based maintenance is that the reliability is explicitly taken to account in decision making. In condition-based deterioration models, the reliability only follows implicitly after transforming condition to reliability. The advantage of condition based models is that conditions can be measured or inspected, whereas reliabilities must be computed and that inspections can naturally included in maintenance models. Ideally, the best way is to base a deterioration model on the time-dependent stochastic processes of resistance and stress and to compute the corresponding lifetime distribution and failure rate function, as well as the time-dependent reliability function (van Noortwijk and Frangopol, 2004).

Offshore process systems usually consist of a large number of components which operate under high pressure and temperature transporting corrosive products. This will degrade the material of component at a faster rate as it ages. The rate of loss of strength and material produce the highest uncertainty in the decision models. Inspections may be used to reduce this uncertainty. An optimal maintenance decision model under imperfect inspection for a steel pressure vessel subjected to corrosion is reported by Kallen and van Noortwijk (2005). It was based on risk analysis and has concluded that a Gamma stochastic process with an adaptive Bayesian approach for incorporating the uncertainty in the degradation process is a viable option to be used in the structural reliability methods, which are commonly used in the process industry. However fitting a Gamma prior-likelihood, thinking of getting a closed form posterior may not always reflect the reality of degradation processes.

The failure probability of offshore process component is scarce, but if a failure occurs, the consequences are severe. A risk based maintenance model for offshore oil and gas pipeline is discussed by Dey et al., (2004). The breakdown maintenance of the pipelines is cost-intensive and time-consuming resulting in huge tangible and intangible loss to the operators. Pipeline health monitoring and integrity analysis have been researched a lot for successful pipeline operation and risk based maintenance model is one of the outcome of those researches. The reasons for optimal maintenance planning are from: stringent environmental protection laws, scarce resource, and excessive inspection and maintenance costs. A clearly focused inspection and maintenance policy that has low investment to benefit ratio should be formulated. The study introduced a tool for predicting the risk factor for pipeline failures, analyzed their effects, and developed a response measure through effective inspection and maintenance methods.

An analytical model for the optimization of maintenance profitability has been presented by Oke (2005). The traditional view of maintenance is changing. Earlier, it has been viewed as a necessary evil, now mangers are visualizing maintenance as a valuable function since it is regarded as the safety line for components. Recently, maintenance function is portrayed as a value-adding activity. There is a need to integrate the cost into the model (Oke, 2005). With cost, a mechanism that links expenses incurred during a financial period with budgeted costs would add great value to the maintenance model.

The optimization of lifetime maintenance strategies for deteriorating structures considering the probabilities of violating safety, condition and cost thresholds is presented by Bucher and Frangopol (2006). Two different maintenance strategies (i.e., time-based and performance-based) are considered and the corresponding cost values are computed on a probabilistic basis in terms of the expected values, standard deviations and probabilities of exceeding prescribed thresholds. The computational analysis of costs and useful key performance indicators for different maintenance policies in order to choose the most advisable applied to a food product plant is presented in Silva et al. (2008). A good maintenance plan will give: reduction of the amount of routine work, planned workload much lower than breakdown maintenance, less overtime work, higher plant availability and reliability, less time given to corrective maintenance and greater safety.

The uncertainty in maintenance models is mainly from the parameter, deterioration rate per unit time (Frangopol et al., 2004). Pandey et al., (2006) has pointed out that time-based variability is not taken into account in the random variable models. For stochastic modeling of monotonic and gradual asset deterioration, a Gamma process is most appropriate (van Noortwijk, 2009). The less developed aspects in the modeling of maintenance under Gamma-process deterioration are variability, dependence, multi-failure mode models including their statistics dependence (van Noortwijk, 2009).

Optimum preventive maintenance schedules may be obtained, using the minimization of total cost incurred in relation to maintenance activities. Cost minimization has been the traditional objective in maintenance planning. However, risk optimization is more attractive as it takes into account both the condition of component through probability of failure and consequences through cost incurred. The preventive maintenance interval is often optimized when the increasing rate of corrective maintenance cost equals the decreasing rate of preventive maintenance costs (Ghosh and Roy, 2009). Flexible maintenance intervals are conceptualized by studying the change in risk over the service life of components. Efficient maintenance policies are of fundamental importance to offshore process systems because of their impact on the safety and economics of facility operation. A survey of the application of Gamma processes in maintenance is presented by van Noortwijk (2009). Gamma processes are increasingly used to model the stochastic deterioration for optimizing maintenance. An extensive literature study of inspection and maintenance models under Gamma process deterioration is presented. However, these litterateurs were tempted to use stationary Gamma process because of the existence of conjugate pairs for updating. The non-conjugate pairs are not covered in any study.

An optimal maintenance and replacement decisions under technological change is presented by Nguyen Thi (2010). There is an intensive research to provide the most appropriate strategies for organizing a set of maintenance actions based on complex degradation models to optimize a decision criterion. The usual maintenance models are considering various maintenance actions such as good as new replacement by an identical item, imperfect maintenance which restores the system to an acceptable condition as bad as old. The literature reviews and directions for maintenance management reported by Garg and Deshmukh (2006) brought out the major gap in knowledge. In offshore process facilities, 30% of the total manpower is utilized in the maintenance and operations departments. The widespread mechanization and automation has reduced the number of personnel and increased the capital employed in the offshore production facilities. As a result, the fraction of employees working in the area of maintenance as well as the fraction of maintenance spending on total operational costs has grown over the years (Garg and Deshmukh, 2006). Next to energy costs, the maintenance cost can be the largest part of any operational budget. The main question faced by the maintenance management, whether its output is produced more effectively, in terms of contribution to company profits and efficiently, in terms of man power and materials employed, is very difficult to answer. The current maintenance optimization model covers the following:

- A description model of the technical system, its function and importance.
- A modeling of the deterioration of the system in time and possible consequences for this system.
- A description of the available information about the system and actions open to management.
- An objective function and an optimization technique, which helps in finding the best balance.

The models are classified into modeling of deterioration as deterministic or stochastic, qualitative or quantitative (Garg and Deshmukh, 2006; Khan et al., 2006). Stochastic models are further classified into stochastic models under uncertainty or warranty. The various maintenance optimization models are classified as (Garg and Deshmukh, 2006):

Bayesian Approach (BA)

A fully Bayesian, i.e., a subjective approach towards straight forward means of presenting uncertainty related to future events to decision makers in the process of decision making on inspection and maintenance. Bayesian model helps to update the inspection and maintenance efforts. This approach is in contrast with the classical probability approach, which assumes the existence of true probability distributions. Kallen and van Noortwijk (2005); Straub and Faber (2006); Khan et al. (2006 has been used this approach to optimize the maintenance performance with new NDT data.

Mixed Integer Linear Programming (MILP)

Goel et al., (2003) presented a new mathematical formulation, MILP for the integrated design, production and maintenance planning for a multi-process plant. In contrast to earlier approaches, which focus mainly on deriving an effective maintenance policy at the operational stage, the proposed integrated approach provides a design with an opportunity to improve the operational availability at design stage itself.

Fuzzy Multiple Criteria Decision Making (MCDM) and Linguistic Approaches

Al-Najjar and Alyouf (2003) assessed and selected the most informative maintenance approach using fuzzy MCDM evaluation methodology.

Simulation and Markovian Probabilistic Models

Chen and Popova (2002) and Barata et al., (2002) used Monte Carlo simulation to determine optimum maintenance policy by minimizing total service cost and for modeling of continuously deteriorating systems. The Markov probability models using random variables for optimizing the maintenance policy has also been discussed in Bruns (2002); Sarkar and Haque (2000); and Balakrishnan (1992).

Analytical Hierarchy Process (AHP) and Artificial Neural Network (ARN)

AHP is used for selecting the best maintenance strategy for oil refineries (Bevilacqua and Braglia, 2000; Shervin, 2000). Further, Bevilacqua et al., (2005) have used artificial neural network (ANN) framework for failure rate prediction for maintenance.

Presently, many researchers are pursuing the development of various mathematical maintenance models to estimate the life cycle risk measures and determine the optimum maintenance policies. However, these models may be useful to maintenance engineers if they are capable of incorporating information about the repair and replacement strategy, the management policies, the methods of failure detection, failure mechanism etc. (Garg and Deshmukh, 2006). Further, the assumptions used in the model and the applicability of model in a given system environment that can give greater confidence in estimates based on small number of NDT data, have to be strictly checked.

2.2.1 Maintenance Strategies

The available maintenance strategies based on Duffuaa et al., (1999); Garg and Deshmukh (2006), and Jardine and Tsang (2006) are reviewed briefly below.

Breakdown Maintenance (BM) or Corrective Maintenance: This type of maintenance is only performed when the equipment is incapable of further operation. There is no element of planning for this as it is a run to failure strategy.

Preventive Maintenance (PM): A series of tasks performed at a frequency dictated by the passage of time, the amount of production, machine condition that either extends the life of an asset or detect that an asset had a critical wear is going to fail or breakdown constitutes PM. It is a planned maintenance to counteract potential failures.

Condition Based Maintenance (CBM): This is a maintenance strategy, in which the maintenance tasks are performed on the basis of component condition. The condition is detected using measurement, such as pressure, temperature, vibration going beyond a predetermined limit. If a machine cannot hold a tolerance, the CBM is initiated. Grall et al (2002) developed a mathematic model for the condition based inspection/replacement policy for a stochastically and continuously deteriorating single unit system.

Total Production Maintenance (TPM): Originating from Japan, it centers on solving maintenance problems using quality circles method. Some of the advantages of TPM are better understanding of the maintenance performance, improved teamwork, less adversarial approach between production and maintenance.

Computerized Maintenance Management System (CMMS): CMMS provide capabilities to store, retrieve and analyze information and help to make informed decision on PM.

Reliability Centered Method (RCM): It was founded in 1960's and initially oriented to aircraft maintenance. It directs maintenance efforts at those parts and units where reliability is critical. High probability of failure components gets more attention.

Predictive Maintenance: Predictive maintenance consists in deciding whether or not to maintain a system according to its expected state. It estimates through diagnostic tools and probabilistic methods, when a component is going to fail and what type of maintenance to perform to prevent the occurrence of failure.

Maintenance Outsourcing (MO): This refers to transferring workload to outsiders with the goal of getting higher quality maintenance at faster, safer and lower costs. The other goals are to reduce the number of fulltime equivalents and concentrate organizations talents, energy and resources in the areas called core competence.

Effectiveness Centered Maintenance (ECM): It emphasizes doing the right things, instead of doing things right. This approach focuses on system functions and customer service and has several features that are designed to enhance the performance of maintenance practices and encompasses core concepts of quality management, TPM and RCM.

Strategic Maintenance Management (SMM): In the SMM approach, maintenance is viewed as a multi-disciplinary activity. It is mostly qualitative or semi quantitative.

Risk Based Maintenance (RBM): Risk based maintenance ensures a sound maintenance strategy meeting the dual objective of minimization of hazards caused by unexpected failure of equipment and reduction of cost. Khan and Haddara (2003) and Khan et al., (2006) outlined this strategy. This methodology is comprehensive and quantitative. The risk to life is used as a criterion for decision making regarding maintenance.

2.3 RISK BASED INSPECTION AND MAINTENANCE PLANNING MODELS

The past risk based inspection (RBI) and risk based maintenance (RBM) efforts and methods have been reviewed based on their application to the various industries such as offshore structures, pipelines, ships, civil structures and process plants. Although the inspection performance models for the detection of crack and flaws were in use in early sixties by McCall (1965) and Barlow and Proschan (1965), the risk based approaches for inspection and maintenance gained predominance since 1980's due to the rapid developments in the field of mathematical computations and programming.

2.3.1 Offshore Structures

The first initiatives and developments towards the inspection planning for welded connections subjected to fatigue in fixed offshore steel structures has reported in Skjong (1985); Madsen et al., (1987); Fujita et al., (1989), and Moan et al., (2000). Later, the same methodology was adopted to other structures such as tankers, Soares and Garbatov (1996); Paik et al., (2000); floating, production, storage and off-loading facilities, Lotsberg et al., (1999), and Goyet et al., (2002, 2004); and to semi-submersibles, Lotsberg et al., (2000). The structural reliability method has played a vital role in these developments. Recently, a generic and simplified approach for the risk based inspection planning has been reported in Straub and Faber (2005a). A comprehensive documentation of this approach has been observed in Straub (2004), considering the fatigue crack growth between hot spots as the degradation mechanism. The reliability updating for structures subjected to localized corrosion defects, based on the fatigue crack models has been found in Straub and Faber (2005). For localized corrosion defects, the actual measurements as well as the possibility of missing the largest defect are accounted in reliability updating of inspections (Straub and Faber, 2005).

The theoretical framework for risk based inspection planning, consequence assessment, modeling of uncertainties, assessment of probabilities, modeling of inspections, modeling of engineering systems in terms of logical systems, modeling of deterioration processes and the acceptance criteria for RBI has been published in Faber (2002). This paper has outlined the problem of inspection planning and summarized the theoretical basis for its systematic treatment within the framework of Bayesian decision theory. The need of implementing the robust and efficient algorithms for future developments in enhancing the use of RBI planning into industrial practice has been emphasized.

A unified approach to the risk based inspection planning of offshore facilities comprising of both structural and process type components and systems was published by Faber et al., (2003), based on a generic modeling of risk based inspection planning for components subjected to fatigue degradation. Methodology for the derivation of acceptance criteria for inspection planning purposes at component level taking basis in the overall facility acceptance criteria specified in terms of risk to personnel, environment and economy by the responsible authorities has been proposed. The same probabilistic model was then applied for steel components subject to corrosion; thereby enhancing the

RBI planning for process type components of offshore facilities. The generic approach described is promising for practical use of risk based inspection planning of components. However, in regard to probabilistic modeling of various corrosion and cracking phenomena much work is still required, Faber et al., (2003). The detailed case study and calibration needs to be performed for degradation rates to validate the model for different degradation phenomena. Inspections based on Bayesian theory must be performed to ensure that the assumptions prevailing the modeling of the ideal age-based deterioration are satisfied.

A simplified and practically applicable approach for risk based inspection planning of fatigue sensitive structural details have been reported in Bloch et al., (2000). The fatigue sensitive details are categorized according to their stress intensity factors and their fatigue design life to reserve strength ratio. When the reserve strength ratio and the corresponding probability of total structural failure given fatigue failure of the considered detail is known, it is possible to develop pre-made inspection plans, which depend on relative cost of inspections, repairs and failures. Due to simplicity of the format of the developed inspection plans, it is reported that the proposed approach has a high potential in making codes for the design and maintenance of steel structures, Engelund et al., (2000). The generic inspection plans have been established in Sorensen and Faber (2002) for representative fatigue sensitive detail in terms of fatigue design factor and reserve strength ratio. How the generic inspection plans can be used for code making purpose in connection with the inspection of steel structures, has been reported in this paper. Two approximations to determine inspection times have been described in the paper; namely equidistant inspections plan and constant thresholds plan and it greatly simplified the inspection planning problems and facilitated the development of inspection plans which are generic in the sense that they are representative for a range of different detail designs. The generic inspection plans may be applied as a decision tool for evaluating the effect of service life extensions, load increases and strengthening on the required inspection and maintenance efforts. Both approaches result in inspection plans that are sub-optimal, but the numerical calculations are reduced significantly for practical situations.

A combination of proactive, reactive and interactive approaches, employing strategies to (i) reduce the likelihood of malfunction, (ii) increase detection and correction of malfunction and (iii) decrease the effects and consequences of mal-function, have been reported in Bea (2001). The approach developed for estimating fatigue crack growth may be used in the risk based inspection planning of offshore systems, Straub and Faber (2005a, b). The method has been applied by several industries, Faber et al., (2005); Chakrabarti et al., (2005), and Goyet et al., (2002 and 2004). The benefits of risk based inspection planning for offshore structures can be found in Straub et al., (2006). A unified approach to the risk based inspection planning of an offshore production facility has been reported in Faber et al., (2003), the assumptions of which limited its application. The computational aspects of risk based inspection planning based on Bayesian updating of fatigue, reported in Straub and Faber (2006), is quite complex and time-consuming.

The development of a reliability-based management of inspection, monitoring, maintenance and repair has been reported by Moan (2005), for various types of offshore structure, with focus on management of hull damage due to crack growth and corrosion. It is shown that different inspection and repair strategies may be relevant for different types of offshore structures, because the existing structure poses different degree of vulnerability to fatigue and robustness. The deterioration due to combined fatigue cracking and corrosion wastage of structural components has been addressed to certain extent. The reliability framework allowed for explicit accounting of uncertainties as well as the effect of inspections. A series of inspection events are defined to update the reliability level based on the detection of fatigue cracks and thickness measurements, both before and after the vessel has changed its location and sea environment. The analyses showed that the reliability may be maintained at the target level for a significant period of time beyond documented fatigue life; provided that adequate inspections are carried out at prescribed intervals and that any defects found are repaired to an acceptable standard. It has shown that the inspection interval needs to be reduced from 5 to 2.5 years to maintain the reliability level when through-thickness cracks are detected after 15-20 years for a welded joint with a 20 years fatigue life. However, by introducing additional safety measures such as weld profiling and toe grinding, the reliability and inspection intervals may be greatly enhanced.

2.3.2 Civil Infrastructures

A comparison and description of the deterioration and maintenance models for civil infrastructures has been reported in van Noortwijk and Frangopol (2004). It is reported that, the time-dependent, uncertain deterioration process can be modeled as: a failure rate function, a Markov model, a stochastic process and, a time-dependent reliability index method. In condition based deterioration models, the reliability follows implicitly or explicitly after transforming the condition to reliability. The best way is to base a deterioration model on the time dependent stochastic process of stress and resistance and compute the corresponding lifetime distribution and failure rate function.

A review of the probabilistic models for life cycle performance of deteriorating structures is presented in Frangopol et al., (2004). In comparison with the well-researched field of analysis and design of structural systems, the life cycle performance prediction of these systems under no maintenance as well as under various maintenance scenarios is far more complex and is a rapidly emerging field in structural failure engineering. As structures become older and maintenance costs become higher, different agencies and administrations in charge of civil infrastructure systems are facing challenges related to the implementation of structural maintenance and management systems based on life cycle cost. This paper reviewed the research to date related to probabilistic models for maintaining and optimizing the life cycle performance of deteriorating structures and formulated future directions in this field. Some of the modeling approaches dealt with the reliability index, whereas the others are concerned with the physical condition of a structure. No single approach has yet proven to be generally applicable. The use of reliability index to model the performance of a structure is a classic approach in engineering, and has resulted in many design codes. The Markov model, which is purely a condition-based is the most commonly used in bridge maintenance models.

The Gamma process model has been the subject of many scientific publications with a few applications to real maintenance problems in civil engineering (van Noortwijk and

Pandey, 2004; Pandey and van Noortwijk, 2005; Kallen and van Noortwijk, 2005). Further work is necessary to collect the relevant data, improve the modeling capability and formulate the probabilistic decision problems as follows: (i) establish an acceptable and consistent methodology for probabilistic modeling of deterioration processes of structural performance in terms of both condition and reliability, (ii) improve the understanding of the effects of maintenance actions on structural performance and their probabilistic modeling; improve the incorporation of measurement data from imperfect inspections into the deterioration models, (iii) develop consistent probabilistic methodologies for evaluating maintenance and management strategies for structures and, (iv) use optimization for finding the best strategy through balancing of competing objective such as reliability, condition and cost. Two probabilistic life-cycle maintenance models for deteriorating civil infrastructure were discussed in van Noortwijk and Frangopol (2004); (i) Rijkswaterstaat's model, which has applied to the public works and water management by Netherlands ministry of transport, used for the justification and optimization of maintenance measures and, (ii) Frangopol's model, which has applied to the development of bridge management methodology that has been set up by UK highway agency. Although the maintenance models are quite similar, the former model is reliability based and treats the multi component, multi-failure mode and multi-uncertainty case. The latter model is condition based and treats only single component, single failure mode and uncertainty. The Frangopol model uses Monte Carlo simulation with stochastic process, whereas, the Rijkswaterstaat model is analytic with uncertain parameters.

A model for lifetime-extending maintenance (LEM) has been reported by Bakker et al., (1999) in which both the interval of life time extension and preventive replacement is optimized. The proposed LEM may be used to optimize the maintenance in both design and operating phase of deteriorating structures. In the design phase, the initial cost of investment can be optimally balanced against the future cost of maintenance. In the operating phase, the cost of preventive maintenance (lifetime extension and replacement) can be optimally balanced against the cost of corrective replacement and failure.

Other relevant works in this area are by Dekker (1996); Wang (2002), and on bridges by, Frangopol and Estes (1999); Frangopol et al., (2001), and Frangopol and Neves (2004). Further, on optimal decision making for sea-bed protection, by van Noortwijk et al., (1997); on breakwaters, by van Noortwijk and Phajm (1996); on bridge structures, by van Noortwijk (1998); on nuclear plants by Ellingwood and Mori (1993); and a condition based maintenance by Grall et al., (2002). A reliability based inspection optimization technique for use in complex structures, such as offshore and bridge structures has been found in Onoufriou and Frangopol (2002). The engineering systems are exposed to a variety of operational stresses and aging related degradation mechanisms which will affect the overall system life, safety and efficiency. A probabilistic approach to minimize the life-cycle cost of inspection and refurbishment of engineering components in large infrastructure systems has been reported in Datla and Pandey (2005). The probabilistic methodology is based on the lifetime distribution of components, though its estimation is hampered by the lack of data. The advantage of the methodology is demonstrated by applying it to the analysis of wood poles in a large electrical distribution network.

2.3.3 Oil and Gas Pipelines

In pipeline industry, the objective of a risk based inspection management is to ensure and maintain the required confidence in the pipelines integrity and hence maximize its operating availability. It essentially includes the optimization of resources to ensure pipeline integrity, such as planning of inspection intervals and methods, repairs etc. A versatile methodology for the RBI of pipelines has been published by Willcocks and Bai (2000), which consists of: defining a required level of confidence in the pipeline integrity, establish a database of operating conditions, evaluate and rank the risks of each potential failure modes, study the time-dependent degradation failure models and finding optimal solutions to reduce the risks and uncertainties to an acceptable level. The designs of pipeline systems are being optimized through probabilistic methods to reduce the cost. Since, the major cause of failures are extreme loading, corrosion, third party defects and fatigue damage; it requires the monitoring and controlling of these factors to eliminate potential risks. A good understanding and management of risks is of vital importance in ensuring the integrity of pipeline transporting oil and gas to terminals. It showed that the adoption of risk based inspection can reduce design, inspection and repair costs whilst ensuring that the required levels of pipeline integrity. By identifying, understanding and addressing the hazards to the pipelines integrity and evaluating the consequence of failure, a high availability of the pipelines can be ensured at an optimum cost. The model discussed was unable to predict the impact of maintenance and replacement plans and lacked the implementation of stochastic models.

The identification of potential hazards and their elimination is critical to the effective risk management of pipeline systems. The corrosion management studies with RBI methodology will instantaneously provide the pipeline risk which can be useful in anomaly assessment and in scheduling inspection interval. Venkatesh and Farinha (2004) presented a corrosion risk assessment (CRA) and its importance in the RBI approach based on the hypothetical data analyzed by various statistical techniques. A holistic approach is proposed based on corrosion inspection strategies and statistical approach. In order to judge the reliability of the statistical approach, corrosion failure prediction models have been created by simple trend, Weibull and survivability techniques. The degradation rate has been estimated for the failure mechanisms that are considered to be inspectable (corrosion, pitting, erosion-corrosion). Following the calculation of critical defect size, the predicted service life is determined by extrapolating existing inspection data, where there is a history of deterioration, or by probabilistic methods (Monte Carlo simulation), where there is no history of deterioration. By multiplying the predicted remaining service life with a risk factor, the approximate inspection interval has been determined. This risk based factor was semi-quantitatively derived using matrices incorporating likelihood predictability and consequence of failure. Pro-active monitoring methods need to be maintained and implemented including good corrosion house keeping, such as routine sampling, on-line monitoring and review of the operator logs, such as proper corrosion monitoring techniques, suitable inhibitor and biocide regime, with the corrosion data will help in predicting reliable asset remaining life. The traditional process data recording should be extended to integrity-related data recording. Cost of risk and its effects on the integrity management of pipelines has been reported by

Laughlin (2004). It is argued that the current tool specifications make the determination of actual risk difficult and hence the cost of risk is underestimated.

The optimal inspection and replacement decisions for multiple failure modes are presented by Kallen and van Noortwijk (2004). The cost function associated with Gamma process for modeling deterioration has been extended to multiple failure modes, which limit the use of priors. An elbow in a pipeline which is susceptible to thinning due to corrosion and stress corrosion cracking has been considered in the modeling, and effect of data availability is discussed. The optimal maintenance decision under imperfect inspection has been published by Kallen and van Noortwijk (2005). A risk based model for the inspection and maintenance of cross-country petroleum pipeline has been reported in Dey (2001). A risk based model using an analytic hierarchy process, a multiple attribute decision making technique, to identify the factors influencing failure on specific segments and analyzed their effects by determining the probability of risk factors, Cagno et al., (2000). Another risk based maintenance model for offshore oil and gas pipeline has been reported in Dey et al., (2004). Some of the risk assessment methods for formalizing the pipeline integrity for operating companies will find in Biagiotti and Gosse (2000).

2.3.4 Process Installations

The proper inspection and maintenance of process plants, which deals with hazardous chemicals at extreme temperature and pressure, are highly important to ensure the safe and continuous operation of the facility. A risk based methodology for the integrity and inspection modeling of such a facility has been presented by Khan et al., (2006) based on Kallen (2002). The Gamma distribution has been used to model the material degradation and a Bayesian updating method to improve the distribution based on real inspection results. The risk is calculated using the probability of failure and, the consequence is assessed in terms of cost as a function of time. The risk function is used to determine an optimal inspection and replacement interval and, that inspection interval has subsequently been used in the design of the integrity inspection plan. This method takes into account the random nature of the material degradation of components and it allows the updating of the probability density function using Bayesian approach. The maintenance interval has been optimized based on risk associated with component failure and the optimization criterion is based on the level of risk that satisfies the acceptance criteria. The study was limited to Gamma distribution that fits the material degradation processes, but may not always in-line with the subjective information or historical database of different degradation processes. It is showed that the method gives reliable estimates for inspection intervals that are comparable with literature, but, the critical degradation mechanisms, such as pitting, erosion corrosion and cracking (CFC, HIC) were not included in the study. Further, the method is computationally intensive and time consuming.

Kallen and van Noortwijk (2005) proposed an adaptive Bayesian decision model to determine the optimal inspection plans under uncertain deterioration. A Gamma stochastic process has been used to model the corrosion damage mechanism, similar way of fatigue cracks based on hot spots and, a Bayes theorem to update the prior knowledge over the corrosion rate with imperfect wall thickness measurements. Since the current non destructive inspection techniques are not capable of measuring the exact material thickness, the imperfect inspection modeling is very important in process plants. The decision model in Kallen (2002) finds a periodic inspection and replacement policy which minimizes the expected average costs per year. The failure condition has assumed to be random and depends on uncertain operation conditions and material properties. The combined deterioration and decision model has been illustrated by using actual plant inspection data for pressurized vessel in Kallen and van Noortwijk (2005); for a pressurized steel pipeline elbow in Kallen and van Noortwijk (2004); and hydrogen dryer in Kallen and van Noortwijk (2003). In all these models, the choice of prior is restricted to Gamma stochastic process, which is not true in the case of all degradation priors. It doesn't reflect the subjective knowledge and experimental data for all degradation priors.

Material Degradation Mechanisms

Material degradation is one of the main causes of process component's failure and it may be caused by one or more mechanisms. The mechanism of failure includes: internal and external thinning due to corrosion, stress corrosion cracking, brittle fracture, and fatigue due to vibration, Kallen (2002), and Khan et al., (2006). These mechanisms cause material deterioration and thus affect the ability of the component to withstand the applied load. The two models reported were a thinning model and a stress corrosion crack model (Kallen, 2002). The thinning model has been used to describe the reduction in material thickness of components as a result of internal or external corrosion and wear. The cracking model has been used to describe the reduction in the load carrying capacity of the components as a result of cracks (Kallen, 2002). Such cracks may results from stress induced corrosion, brittle fracture or fatigue. The stress corrosion cracking (SCC) failure occurs when applied stress on a component generates a field of localized surface crack along the grain boundaries, which yield the component incapable of performing its function. The SCC includes caustic cracking, amine cracking, carbonate cracking, sulfide stress cracking, hydrogen induced cracking, polythionic acid cracking and chloride cracking. At low temperatures the carbon steels suffers brittle fracture at loads significantly below the design loads because of its ductility loss at low temperatures. Vibration also causes components to fail prematurely. Improperly supported piping near vibration sources is prone to fatigue. The net degradation of the material is the total sum of degradations that take place as a result of the above mentioned mechanisms (Kallen 2002; Khan et al., 2006). Although these mechanisms are deterministic, there is a level of uncertainty associated with some of their variables and hence, those variables have to be considered random and degradation process is expected to be a stochastic process. It has been assumed that the incremental material deterioration is independent, exponentially distributed random variables. Then, the cumulative degradation from the start to end of service is a Gamma distributed stochastic process with stationary increments. The results of inspection can effectively be used in updating the prior knowledge of the average degradation rate using the Bayesian updating. The inspection updating modeling involves two steps: (i) selection of an appropriate prior and, (ii) Bayesian updating of the prior using the likelihood function of new inspection data (Kallen, 2002). In order to calculate the risk, consequence analysis associated with the failure needs to be estimated. The consequence has been estimated in terms of the cost incurred as a result of failure (Kallen, 2002; Khan et al., 2006). The expected average costs per cycle are determined by the expected number of inspections during cycle and the expected costs due to either preventive or corrective replacement.

2.4 STOCHASTIC DEGRADATION MODELS FOR CORROSION AND CRACKING

2.4.1 Probabilistic Corrosion Models

The probabilistic deterioration of structural strength and the multiple applied loadings are the main criteria needs to be considered for the life assessment of the existing assets using the reliability theory. Various corrosion models have been reviewed in Melchers (2003a) using the data pooled from many sources and, it has been found that most of them are statistical only with little theoretical insight. They provided poor quality mean value information with very high statistical uncertainties. In practice, corrosion is not an independent deterioration mechanism for remaining life assessment of aging systems as it interacts with applied stresses, fatigue, mechanical damages, with protective systems and management practices. The interaction with each of these phenomena or materials is a matter that cannot be ignored in practice, even though the interactions are not fully understood in all cases. In Melchers (2003a), more attention and efforts has been given to marine corrosion to develop statistical models. The marine corrosion is not a linear function of time and the variability in the data is very large and it increases with time. It is further argued that there is an urgent need for better quality models to adequately represent the deterioration mechanism for corrosion. It must be based on sound understanding of the corrosion mechanism and would require calibration to field data and in turn, new data collection with better supplementation of existing data. A probabilistic model needs to be developed and it should follow the deterministic physiochemical corrosion models. These must reflect a reasonable degree of physical reality if they are to have predictive power beyond the data from which they are calibrated.

Considering the probabilistic corrosion modeling based on corrosion mechanics principles and including the effect of environments, another paper has been published by Melchers (2003b). The environmental effects include temperature, dissolved oxygen, salinity, calcium carbonate, pH, water velocity and marine growth. A new multi-phase, non-linear mean value model has been developed for the corrosion of mild and low alloy steel under "at sea" immersion conditions. The model consists of four stages: (i) largely linear phase during which oxygen controls governs, (ii) a phase during which the corrosion rate diminishes rapidly due to buildup of corrosion products and corrosion is governed by diffusion, and (iii) and (iv) governed by anaerobic conditions. The influence of factors that may affect the model under coastal and near shore conditions, such as temperature, dissolved oxygen, salinity, calcium carbonate, pH, water velocity and marine growth are included. The application of basic corrosion understanding and models will help in the development of more specific models for practical applications.

In general, the extreme value statistics are used to model the pitting corrosion (Shibata 2007; Kowaka, 1994; Khan and Howard, 2007). There is likely to be a high degree of dependence among the depths of extreme pits and, the statistical population describing such pits is likely to be different from that of the remaining pits, Melchers (2005). These observations questioned the conventional use of extreme value distributions for modeling the uncertainty in maximum pit depth since such distributions are based on the assumption of independent statistical events. The empirical observations suggest that extreme pit depths appear to be representable by a normal distribution. This provides a basis for a review of probability theory to be used for dealing with systems of highly dependent events. Significantly lower probabilities of occurrence of extreme depth pits are predicted while it is applied to the probabilistic modeling of the maximum pit depths.

Melcher (2005) proposed that the deepest pits are drawn from a different population being the result of super-stable pitting. The probability distribution for all pit depths is bi-model and that for the deeper pit is approximately normally distributed. There is likely to be a high degree of dependence between the depths of external pits is based on the use of experiments of near uniform but homogeneous material properties and similar environmental conditions. The actual degree of correlation between external pit depths and its variability with separation distance between pits has not been addressed specifically. On the basis of near-uniform but essentially homogeneous material properties and similar environmental conditions, a high degree of dependence is expected between the deepest depths that occur on a corroding metal surface. Series system probability theory shows that the probability distribution for all pits is approximately normal for deeper pits. A similar result was found from the consideration of the uncertainty associated with estimating the theoretical upper pit depth cut-off value in the application of the generalized extreme value theory. The implication for practical analysis of pitting data is that if the external pitting is highly correlated, there is no need to consider individual coupons but only a sufficiently large area so as to capture the deepest pits with a high degree of confidence. In this approach, the probability estimates that have much less uncertainty than those estimated by conventional approaches (i.e., Gumbel Extreme Values). These propositions are based on the assumption that the extreme pits are formed through super-stable pitting, the external pits are likely to be those that initiate immediately on the metal being exposed and then continue to grow in a stable pitting mode without entering a meta-stable state.

The asset integrity management is the management of assets such that availability is maximized at optimum cost without compromising the safety to environment and legislative standards. This is achieved when the risk of failure endangering the safety of personnel, environment and asset value are as low as reasonably practicable.

One of the primary life–limiting threats is the internal corrosion and therefore the effective corrosion management is vital. The two approaches for corrosion management: probabilistic, and the traditional, deterministic approach have been compared in Lawson (2005). The probabilistic approach to the assessment of pipeline corrosion risks dealt with many of the uncertainties that are common in the corrosion data. Rather than considering each input parameters as an average value, this approach considered the inputs as a series of probability density functions, the collective use during the assessment of risks yields a risk profile that is quantified on the basis of uncertain data. The variability in pipeline failure probability with time has been predicted using both the FORM and Monte Carlo simulation and it was observed that the failure probability increases over the time periods considered, consistent with an increased level of damage with time. This approach differs from the traditional deterministic assessment in that the output yields a curve that shows how the risk of failure increases with time. The asset operator simply chooses the level of risk that is acceptable and then devises a strategy to deal with those risks.

The probabilistic methods reduces the weakness in the deterministic method concerning the assumptions made with regard to the input variables, but it doesn't remove the possibility that important parameters are omitted, or perhaps even misjudged, Lawson (2005). The probabilistic methods are computationally intensive, time consuming and can be very complex in many cases. The inherent strength of probabilistic method is compromised in two areas. The first one is the data available to support the calculation of risks and the calculation method itself. Second one is the choice of target level of risk.

A probabilistic analysis framework capable of evaluating the condition of a corroding pipeline and the evolution of its probability of failure with time has been outlined in Hallen et al., (2003). The uncertainties associated with the inspection tool, corrosion growth rate, pipeline geometry, material strength and operating pressure were modeled. The results of these evaluations were compared with target reliability levels derived by risk analysis in order to formulate optimal re-inspection intervals, corrosion growth rate control measures, re-rating strategies and repair/replacement actions over the targeted pipeline service life. The proposed methodology (Hallen et al., 2003) ensures the current and future safe operation of the pipeline based on minimizing the cost of repair while maintaining at least the minimum safety goals projected for the pipeline. The probability of failure has been determined for the entire pipeline, ranked by segment between joints or for a given characteristic length. Then, it is compared with target probabilities which are established either from historic failure rates or from risk criteria. This comparison allows the operator to formulate cost effective strategies for future safe operation.

Corrosion is the most prevalent time dependent safety threat to a pipeline and continues to be the most important cause of failure for the oil and gas pipeline (Hallen et al., 2003). Significant effort has been made in order to assess the condition of corroding pipelines using data obtained from high resolution magnetic flux leakage or ultrasonic technology based in-line inspection tools. The reliability assessment framework used in the paper can identify the relevant failure modes and establish the corresponding limit states. Two limit states were established as immediate integrity concerns: (i) burst or rupture state and, (ii) leak state. Burst threaten the pipeline integrity when the operating pressure (P_{op}) exceeds predicted burst pressure (P_{burst}) and leak threatens the pipeline integrity when a metal loss (d) exceeds a given percentage of the pipeline wall thickness. Once the PDF's of P_{op}, P_{burst} and d are established through uncertainty analysis, the probability of failure associated with each corrosion defect can be calculated for these two limit states.

A study on the probabilistic methodology for the estimation of the remaining life of pressurized pipelines containing active corrosion defects has been presented in Caleyo et al., (2002). The First Order Second Moment (FOSM) method, the Monte Carlo integration techniques and the first order Tyler series expansion of the limit state function are used in order to estimate the probability of failure associated with each corrosion defect over time. The uncertainty of the statistical variables on which the limit state function depends is modeled using the normal and lognormal distributions and the sensitivity of pipeline reliability to these variables has evaluated. The extended probabilistic analysis framework has been applied to a sample operating pipeline which is inspected using a high resolution magnetic flux leakage inspection tool. The failure probability model considered to define the limit state function lead to similar failure probabilities for short pipeline service periods. The expected numbers of repair actions predicted by the probabilistic and deterministic methodologies are similar if the normalization factor PF_{thresh} is used to define the global safety factor, for the pipeline failure probability is assumed to be unity. PF_{thresh} is a key parameter in planning inspections and maintenance strategies and can be estimated from the global safety factor for pipeline as established by the regulating safety codes. The FOSM and Monte Carlo integration reliability algorithms produce similar results when the LSF can be linearized and the load and resistance variables have normal probability distributions. If the probabilistic distribution of a load or resistance parameter is not experimentally available, then sensitivity of pipeline reliability to this variable is the key to assume its distribution type. The probabilistic analysis of a pipeline must be carried out separately for deep and shallow defects in pipelines containing a large number of corroded sections to ensure a correct repair strategy for short and long term exposure periods (Caleyo et al., 2002).

Wang et al., (2003) published an estimation of corrosion rates of structural members in oil tankers using a probabilistic model and a corrosion wastage database. The corrosion rates could be described by Weibull distribution; the mean, standard deviation and maximum values of the corrosion rates for the structural members are obtained based on the entire population of the database. The salient observations made are: corrosion rates scatter in wide ranges, the maximum corrosion rate is much higher than average and the average corrosion rates do not seem to depend on the usage space on ship. The predicted corrosion rates presented may be generalized to the tanker fleets in the world and can be used as a reference when planning maintenance and inspection for a group of ships. The analysis is based on a corrosion wastage database that contains over 110 000 thickness measurements. Upon comparisons of the estimated corrosion rates with TSCF (Tanker Structure Co-operative Forum) estimations, the estimated mean corrosion rates has been found generally higher than or close to the high end of the TSCF ranges. The estimated corrosion rate can be used for establishing corrosion allowances for structural designs, planning for inspections and scheduling for maintenance optimization.

The risk of failure for a tank vessel type during its serviceable life is associated with structure's strength, corrosion and cracking defects, Anghel and Lazar (2005). The simulation techniques of the performance function and a well known reliability method (FORM) have been used in the analysis. The professional analysis package, crystal ball has been used for the former and a developed procedure built on the principle of FORM implemented in MATLAB has been used for the latter to perform the simulations. The corrosion decay model is based on experimental values from the published failure models. The uncertainty and variability of the variables and parameters on which the model depends are evaluated by sensitivity analysis.

A large number of technological structures like, pressure vessels are deteriorating by corrosion, with time, due to process exposure. As a result, the carrying capacity diminishes with time and hence, the level of risk of these structures increases. Using a corrosion decay model, based on experimental data and a probabilistic assessment, it is possible, more realistic to decide when the structure becomes unsafe or the level of risk becomes too high. The sampling and probabilistic algorithms for calculating the risk of failure, for corrosion deteriorating pressure vessel at any time during the service life has been discussed. The study has offered a greater reliability in life prediction. The excessive safety margin in design and more cumbersome experimental and analytical approach has thus reduced. The active corrosion defects are major conditions for the risks of failure or the reduction in safety. This type of study is necessary for integrity engineers to work out the optimal safety decisions, inspection and maintenance schedules.

A critical evaluation of empirical and mechanistically based modeling of pit propagation kinetics has been found in Turnbull (1993). The extreme value statistics applied to materials exposed for varying periods of time provide a more effective method of prediction of maximum pit depth at a given time. The statistical characterization of pitting corrosion, for probabilistic modeling of maximum pit depth has been reported in Melchers (2005); Scarf and Laycock (1996), and Laycock et al., (1990).

2.4.2 Probabilistic Crack Models

The earlier works reported in Skjong (1985); Madsen et al., (1987); Fujita et al., (1989), and Moan et al., (2000) attempted to model the fatigue cracks in structures. The fatigue modeling was further extended to other structures, Soares and Garbatov (1996); Paik et al., (2001), Lotsberg et al., (1999, 2000), and Goyet et al., (2002, 2004). Recently, generic and simplified approaches for the risk based inspection planning have been formulated by Straub and Faber (2005 a, b) and, comprehensive documentation of the approach has seen in Straub (2004), considering the fatigue crack degradation mechanism. The modeling of crack mechanisms and acceptance criteria for RBI has been found in Faber et al., (2005).

A unified approach to the risk based inspection planning of offshore facilities comprising of both structural and process systems has been published in Faber et al., (2003) based on a generic modeling of risk based inspection planning for components subjected to fatigue degradation. A simplified and practically applicable approach for risk based inspection planning of fatigue sensitive structural details is presented in Bloch et al., (2000). A combination of proactive, reactive and interactive approaches for RBI has been proposed by Bea (2001). The generic approach developed for fatigue crack growth renders a potential to risk based inspection planning of systems, Straub and Faber (2005a,b), and the method has been applied by industries as reported in Faber et al., (2005); Chakrabarti et al., (2005), and Goyet et al., (2002 and 2004). A unified approach to the risk based inspection planning of an offshore production facility has been reported in Faber et al., (2003). Generic inspections plans has established in Sorensen and Faber (2002) for representative fatigue sensitive detail in terms of fatigue design factor and reserve strength ratio. It has shown how the generic inspection can be used for codification purpose in connection with the inspection planning of steel structures. The computational aspects of risk based inspection, based on Gamma process and Bayesian updating through a generic fatigue approach has been reported in Straub and Faber (2006).

The development of a reliability-based management of inspection, monitoring, maintenance and repair has been reported by Moan (2005), for various types of offshore structure, with focus on management of hull damage due to crack growth. A risk based methodology for the integrity and inspection modeling of a process facility, with respect to stress corrosion cracking has been presented by Khan et al., (2006) based on Kallen (2002). The combined deterioration and decision model has been illustrated by using actual plant inspection data for pressurized vessel in Kallen and van Noortwijk (2005), for a pressurized steel pipeline elbow in Kallen and van Noortwijk (2004); and a hydrogen dryer in Kallen and van Noortwijk (2003). There is a little information on modeling SSC, but little information on hydrogen induced cracking or combined corrosion-fatigue cracking.

An approach to the estimation of variability cased by the material microstructural inhomogeneities has been presented by Shen et al., (2001). The approach was based on the results of a combined experimental and analytical study of the probabilistic nature of fatigue crack growth in Ti-6Al-4V. A simplified experimental fracture mechanics framework has been used for the determination of statistical fatigue crack growth parameters from fatigue tests. The experimental study showed that the variabilities in fatigue crack growth data and the Paris coefficient are well described by the lognormal distributions. The variabilities in the Paris exponent are also known to be well characterized by a normal distribution. These statistical distributions are incorporated into a probabilistic fracture mechanics framework for the estimation of material reliability.

2.5 ECONOMIC CONSEQUENCE ANALYSIS

When a failure occurs there is an instantaneous loss of profits and combination costs. In addition to the lost profit, the fixed and variable costs during the time of repair are paid by the business, yet they have been wasted without production. This cost of shutdown can be really high in offshore process facilities. This could be modeled using the unit cost of product and the total quantity of affected production with maintenance delay time. Knowing the total cost of failure is only useful if the failure can be prevented. The best protection against failure is prevention. Once the asset ages, the economic consequences of failure are to be assessed. Then the management can take informed decisions on maintenance to prevent them failing. The failure costing will show that vast amount of money and resources are wasted throughout a company whenever failure happens. The bigger the failure, the more resources and money are lost. The cost of process component failure due to degradation encumbers billions of dollars in offshore industry. It is not only financially damaging the economies, but also wasting the limited natural resources, damaging environment and causing a great deal of human suffering (Jackson, 2003). The understanding of degradation with correct engineering application could greatly reduce the damaging effects and cost of degradation, such as corrosion and cracking.

A guideline for the life cycle costing of corrosion in the oil and gas industry is presented in Jackson (2003). It provides structured guidance on establishing a system for gathering cost of corrosion data during the life of a facility. It is useful for analysts in the life cycle costing studies for new facilities which are similar. This study indicates that the cost of corrosion can be estimated in terms of dollar with respect to: capital costs, operating costs, cost of lost production caused by equipment failure and the material residual value (Jackson (2003). The capital cost includes the costs for hydrocarbon systems, utility systems and structures and covers the design and construction phases. In the operational phase, the cost to recover from a failure may also be included in the capital cost. The operating cost includes the preventive and corrective maintenance, energy consumption and routine operating services. The preventive maintenance costs include one or any combination of the following: personnel costs to maintain and inspect the systems and equipments, such as cost of extra materials for corrosion allowance together with the extra cost of transport, storage and fabrication, cost of corrosion inhibitors for mitigating the fluids corrosivity, cost of painting and coating restoration including the cost of cost of personnel, products, surface preparation, inspection and scaffolding, the cost of purchasing, installing and commissioning corrosion monitoring systems, including data storage, processing and analysis equipment, including planned shutdowns (Jackson (2003). The costs of replacement parts and materials associated with a degraded item, where component failures have critical effects are to be accounted.

Consideration may be given to predictive maintenance. This could be based on previous experience and an assessment of the risk of defects and failures caused by degradation. It includes: the cost of failure analysis and studies to solve degradation problems in the operating phase, the personnel costs required to rectify degradation related defects and failures within the facility, including the cost of unplanned shutdown, the cost of spare parts and materials associated with repair and replacement, the consequential costs associated with a failure due to corrosion and cracking, including injury to personnel and equipment, damage to the environment and necessary clean-up operations and other safety issues, the energy consumption costs should include those costs for systems and equipments. The lost productions costs are financial losses or penalty charges which are associated with loosing production because of degradation related failures and include the cost associated with lost revenue. The method of calculating the cost of lost production needs to be defined as it may vary for each operating company.

At the end of the facility's life, it may be possible to recover some or part of the value of material used, known as the residual value. This is valuable when the degradation resistant materials are used. Benefits derived from this recovery may be used to offset the initial costs. The life cycle cost (LCC) calculation method given in Jackson (2003) is used in this thesis. The aim of LCC analysis is to maximize the profit from the operation of facility by minimizing or eliminating the costs associated with degradations. The LCC analysis will only be good as the data and experience used for the analysis. By operating a system of life-time data accumulation, the degree of accuracy should be increased with time and experience. This is true especially in the case of ageing offshore assets.

A case study of the cost of corrosion in fertilizer industry is presented in Bhaskaran et al. (2004). A cost of corrosion survey has been undertaken using the net present value method to estimate the direct annual cost due to corrosion. The risk factor is an important consideration in the evaluation of a maintenance strategy under uncertain degradation processes. Unfortunately, the present procedures for considering risk have not been entirely satisfactory as they overlook at the failure consequences. This assumption has high impact when the event probability is less, however the consequences are severe.

Certain explicit formulas for both the expected value and variance of discounted life-cycle costs over an unbounded horizon are presented by van Noortwijk (2003). In life cycle costing analysis, the optimal design is achieved by minimizing the expected value of the discounted costs. The variance of the discounted cost is useful to determine uncertainty bounds. Uncertainty in the cost estimated has to be accurately modeled.

The cost of failure estimation should take the following factors into account: the cost of lost commodity, shutdown, spill cleanup, nature damage and liability.

2.5.1 Factors Influencing the Spill Cleanup and Nature Damage

It is important to estimate the cost consequences of an oil spill in offshore, as it is necessary for insurance company, corporate administration to allocate recovery measures. The cost associated with failure includes economic losses, environmental damages and mitigation expenses (White and Molloy, 2003; Etkin, 2000; Purnell, 1999). The expenses related to the cost of spill are divided into direct cost and indirect costs. The direct expenses include: cost of personnel and their expenses during cleanup, cost of contractors and other direct cleanup, fees and fines from state agencies, cost of litigation and litigation defense. Indirect costs includes: the increased attention by regulators, permit for new activities cost more, more drills and training, increased cost of new equipment and other preparation cost, new local, state and federal laws and taxes, business cost by diverting key personnel to spill control, stock price and stockholder pressure, higher insurance costs, loss of sale of products. The best way to estimate the cost of spill cleanup is considering per unit cost and the duration and rate of spillage. Obtaining the cost data for spill is difficult as many aspects of cleanup operations and damage claims are confidential business agreements between claimants and the operators. However, the published data in literature may provide some guidelines (Etkin, 2000; White, 2000).

One of the most important factors is the type of oil, coupled with the physical, biological and economic characteristics of the spill location (White and Molloy, 2003). The other factors such as the amount spilled and the rate of spillage, weather and sea conditions, time of the year and the effectiveness of cleanup can also be crucial in determining the overall cost of an incident. Each spill involves a unique set of circumstances that determines the clean up cost (Etkin, 1999). Estimating a per-unit cleanup cost is meaningless without taking into consideration factors such as location and type of oil, which can be profoundly influence the cost. An understanding of the relative importance of these various factors can help focus the spill prevention programs, the development of realistic spill contingency plans and the delivery of cost-effective response. Trend in costs associated with various low technology shoreline clean-up methods by drawing on information gathered during the response and subsequent claims for compensation from the local government councils is presented in Purnell (1999). It should be recognized that complete removal of every trace of oil is neither achievable in practice nor technically reasonable. Etkin (2000) reported the marine oil spill cleanup costs on the basis of country, proximity to shoreline, spill size, oil type, degree of shoreline oiling, and cleanup methodology to determine how each of this factors impacts per unit cleanup costs. It is reported that the oil spill response in different countries and regions of the world vary considerably in their costs most likely due to the differences in cultural values, socio-economic factors, and labor costs. A model has been developed from cost data collected from case studies of over 300 spills in 40 nations. It has taken into account the oil type, location, spill size, cleanup methodology and shoreline oiling to deduce a per-unit cleanup cost value.

2.5.2 Liability Consequences

Accident costs are used in economic analysis for choosing among alternate improvements to the existing systems. Estimates of costs that results from an offshore accident are not available in open literature. However, the estimates of costs that results from motor vehicle accidents are routinely published by several public and private organizations. They are often derived from different bases, which often results in significantly different estimates. Comprehensive cost is a measurement of motor vehicle accident cost that includes effects of injury on people's lives. The injuries and deaths caused by a system failure have the most severe implications possible. The loss of life or pain of an injury is impossible to quantify, however, the cost implied due to worker's compensation and corporate liabilities shall be taken into account (Jones, 1995). Apart from that, safety related system failures have other immediate implications, such as legal fines and penalties of professional negligence. The US department of transportation published a technical note (Judycki, 1994) on comprehensive motor vehicle accident costs. The components of the comprehensive costs includes medical costs, emergency services, vocational rehabilitation, lost earnings, administrative costs, legal consulting fees, pain and lost quality of life. The seven categories of liability costs and their descriptions are presented in Chapter VII.

2.6 CRITICAL REVIEW OF LITERATURE

Most of the modeling approaches dealt with the structural reliability methods, whereas the others are concerned with the physical condition of the asset. No single approach has yet proven to be generally applicable and each model has its own advantages and disadvantages. It is found that further work is necessary to collect the relevant data, improve the modeling capability and formulate the probabilistic decision problems applicable to industry standards. A critical review of literature has been given below.

2.6.1 Maintenance Optimization Models

- There are a few problems in applying quantitative optimization models, such as decision support systems are needed for maintenance optimization, scarce data, gap between theory and practice. Thus, the applications are limited in industry.
- The models are published as mathematical discipline with operational research, the applications are very limited, and no convincing case studies are reported.
- Engineers need to learn economics of maintenance, statistical data analysis and principles of optimization. That is, a multi-disciplinary risk analysis is needed.
- The existing models may be useful to maintenance engineers if they are capable of incorporating risk information about the repair and replacement strategy, the methods of failure detection, accurate failure mechanism and consequences that can give greater confidence in estimates based on small number of NDT data.
- Maintenance is increasingly viewed as a multi disciplinary activity and is evident from the emergence of new approaches, like RBM. However, No convincing risk based models for maintenance and replacement optimization is available.

2.6.2 Risk Based Inspection and Maintenance Planning Models

- Preventive and condition based maintenance continue to be the areas where most of the research has been focused. Various simulation tools and mathematical models are attempted in recent years to reduce the cost. Risk based inspection, maintenance and replacement models with adequate confidence are limited.
- Most of the models described in literature were unable to predict the impact of recommended maintenance strategy and Bayesian updating using latest NDT data.
- Some literature attempted to model the deterioration with Gamma process that restricts the use of priors and need not reflect the true degradation process based on subjective knowledge, experimental judgment and generic database.
- It is observed that, developments are still needed in enhancing the use of risk based inspection and maintenance planning into practice. A pre-requisite for the practical implementation of risk based inspection and maintenance planning is that numerical operations are simplified and automated and adapted specifically to the special requirements of the different industry's acceptable risk levels.
- The inherent strength of existing risk based models is compromised in three areas which limit its application, needs to be explored further. The first one is the data available to support the model; the second one is the calculation method of risk itself, and the third one is the choice of acceptable level of risk.
- Since the quantitative models available are computationally intensive, only skilled engineers can use them in industrial applications. A generally acceptable, efficient and easy to apply tool has not yet been reported in open literature.

2.6.3 Stochastic Degradation Models for Corrosion and Cracking

- The outputs from the deterministic assessment are highly uncertain and variable. Thus, they fail to capture the true risk to life of components.
- The inaccuracies and the inabilities to deal with uncertainties in the input data would lead to an underestimation/overestimation of the likelihood or consequence of failure and hence the true risk associated with component operations.
- It is observed that the major types of corrosion and cracks are not a linear function of time and the variability in the data is very large and it increases with time. Therefore, probabilistic assessments are necessary to model it accurately.
- It is argued by many researchers that there is an urgent need for better quality models to adequately represent the uncertainty and variability in structural degradation processes and to make use of it to predict the future degradation.
- In regard to probabilistic modeling of various relevant corrosion and cracking phenomena much work is still required. The calibration of the existing model was done with limited data; detailed case study using field data needs to be done to validate the model for different corrosion and crack phenomena.
- There are a little information reported on the probabilistic modeling of uniform corrosion and localized pitting, but little information is reported on the modeling of erosion corrosion. Similarly, the fatigue cracks are modeled in isolated cases, but little information has been observed on the modeling hydrogen induced cracking and corrosion fatigue cracking degradations.

2.6.4 Economic Consequence Analysis

- The direct economic consequences of failure, inspection and maintenance of offshore process components are not estimated and published in literature.
- The economic consequences of failure are not well understood and integrated in the risk based decision making on maintenance and replacement of components.
- In the available risk based models, due consideration has not been given to the low probability-high consequence models, which needs to be explored further.
- An easy to use tool for engineering management to make informed decision, based on the operating and maintenance budget in dollar, which can estimate the operational life risk from ageing components, is not available in literature.

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CHAPTER III

OVERVIEW OF RISK BASED INTEGRITY MODELING (RBIM)

3.1 INTRODUCTION

This chapter outlines the framework for the development of a methodology for risk based integrity modeling of process components. The framework outlines the use of Bayes theorem to obtain stochastic degradation models for the various degradation processes which affect process component. An outline of the consequence analysis is also given. The consequence analysis consists of modeling the consequences of failure, inspection and maintenance. Finally, the optimization of the inspection and maintenance, and replacement intervals are carried out using the operational risk analysis. This chapter provides an integration and overview of the entire thesis.

3.2 OBJECTIVES

The main objective of this research is to develop a risk based methodology which can be used to design optimal maintenance strategies. This objective will be achieved by completing the following steps:

- Identify the potential degradation processes in offshore process components.
- Develop stochastic degradation models, for the degradation processes which affect process components, using a Bayesian analysis.
- Determine failure consequences using an economic consequence analysis.
- Combine the probability of failure and the consequence to develop an RBIM methodology.

- Optimize inspection, maintenance, and replacement strategies.
- Demonstrate the application of developed methodology and models for the integrity assessment of an aging facility operating in the North Sea.

3.3 SCOPE

A risk based integrity modeling methodology is based on a stochastic modeling of structural degradation processes to estimate the probability of failure and the engineering economic analysis to estimate the consequences of failure. An optimum inspection and maintenance strategy will be developed as a tradeoff between risk and benefits. The structural degradation processes, such as corrosion: uniform corrosion (UC), pitting corrosion (PC) and erosion corrosion (EC); and cracking: stress corrosion cracking (SCC), corrosion fatigue cracking (CFC) and hydrogen induced cracking (HIC) are modeled using the stochastic Bayesian models.

The study of physical degradation processes, such as abrasion or cavitations, and process degradations, such as leak, rupture or contamination will not be considered in this study. The modeling of minor laps, hook cracks and girth weld cracks are also excluded. Similarly, the other non-age dependent causes of component failures, such as third party damage, natural disasters, seismic vibrations, and human errors are also beyond the scope of this study. Mathematical modeling of failure consequences using fault tree/event tree analysis are not included, but rather failure consequences are estimated using the economic analysis. This study is conducted at component level and not the system level.

3.4 ASSUMPTIONS

The study is based on the following assumptions:

- Structural degradation processes are statistically independent.
- Failure consequences are isolated and independent.
- Components have crossed the early stages of degradation or infant mortality.
- Failure rate of components is increasing, i.e., components are in wear-out region.
- After each minor repair, the components return to a state just before failure.
- After each replacement, the components behave as good as new condition.
- Components' failure will cause the system failure, but will not result in a chain reaction, which may lead to the loss of entire facility.
- Risk acceptance criteria depend on the maintenance budget, the individual, societal and environmental safety expectations are included in the maintenance budget.
- The cost of maintenance is very high after failure than before.

3.5 ASSET INTEGRITY THREATS IN PROCESS COMPONENTS

Asset integrity is defined as the ability of an asset to perform its required function effectively and efficiently whilst protecting health, safety and environment (HSE UK, 2009). Failure of the management of offshore facilities to adequately monitor the asset integrity often leads to poor decision making. Past studies indicate that the major asset integrity threats in process components are (Stephens et al., 1995): third party damage, environmentally induced defects, material and fabrication defects, and operational errors. Integrity threats may be functions of the age of component or it may be independent of the age. The non-age dependent failure processes may be reduced through establishing adequate design procedures, effective quality assurance and quality control programs, training personnel and imposing stringent policies and regulations, and hence are not considered in this study. Moreover, the review of published literature (Khan et al., 2006; Straub, 2004; Kallen and Noortwijk, 2002; Stephens, et al., 1995) indicates that the most critical asset integrity threats in offshore process components are age-dependent and environmentally-induced defects. The potential environmentally-induced degradation processes threatening the integrity of assets are various types of corrosion and cracking. The typical age-dependent asset integrity threats in process components are illustrated in Figure 3.1. Also, the literature data indicates that several corrosion and cracking processes are stochastic in nature. Therefore, their accurate modeling with predictive capability is a challenging task for engineers, which is addressed in this thesis.

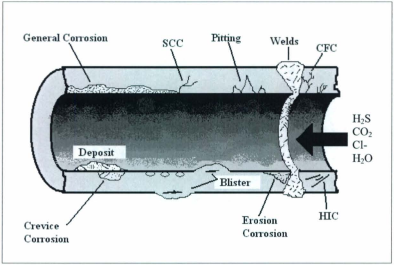

Fig. 3.1. Process Component Integrity Threats

3.5.1 Corrosion Degradation Processes

Corrosion is the loss of material as a destructive result of chemical reaction between a metal or alloy and its environment (Jones, 1996). Corrosion has been viewed from three perspectives as electrochemical reaction, penetration theory and breakdown theory.

Most corrosion processes are of electrochemical in nature. The corrosion rate depends on the surface structure of the substrate, i. e., the density of steps and kinks on the surface. The surface structure is determined by the orientation of crystal faces exposed to the electrolyte, by dislocations and grain boundaries in the metal, and by segregation of impurities from the metal by chemical absorptions of various substances from electrolyte (Mansfield, 1987). The absorbed substances from the electrolyte change the structure of the interphase metal/electrolyte, catalyze of inhibit metal dissolution and may change the reaction path. The changes of interphase may also arise by the formation of uniform or non uniform or porous or non porous 2D or 3D films of intermediates and reaction products on the surface. For example, under galvanic conditions, it has been observed that the iron electrode is subjects to polarization in one step influenced by crystallization phenomena: $Fe \Leftrightarrow Fe_{sol}{}^{2+} + 2e-$

With increasing pH, the consecutive mechanism of iron dissolution with hydroxyl ion participating in the formation of intermediates and products, such as;

$Fe + OH^{-} \Leftrightarrow Fe(OH)_{ads} + e^{-}$ and, $Fe(OH)_{ads} + OH^{-} \Leftrightarrow FeO_{ads} + H_2O + e^{-}$

$FeO_{ads} + OH^{-} \Leftrightarrow HFeO_2{}^{-}$ and, $HFeO_2{}^{-} + H_2O \Leftrightarrow Fe(OH)_2 + OH^{-}$

The kinetics of iron dissolution orders a catalytic mechanism involving the transfer of Fe (II) leading to the loss of metal, called corrosion. The corrosion may be either, atmospheric corrosion (uniform corrosion) or localized corrosion (pitting and erosion).

According to the penetration theory, the aggressive anions adsorbed on the oxide film enter and penetrate the film when the electrostatic field across the film or solution interface reaches a critical value corresponding to the critical breakdown potential. Thus, a contaminated oxide film is produced, which is much better ion conductor than the original passive layer. Rapid cation egress occurs and corrosion can proceed.

Mechanical breakdown of the passive films is a principal step in pit initiation, giving direct access of the electrolyte to reach the base metal within the crack. The thin films always contain a significant film pressure mainly due to electrostriction. When this pressure exceeds the critical compressive strength of the oxides or hydroxides, the film could easily deform or break, leading to loss of material. Three types of critical corrosion mechanisms are studied and modeled in this thesis: the uniform or general corrosion, the localized or pitting corrosion, and the erosion corrosion.

Uniform Corrosion

Uniform corrosion is defined as the uniform or regular removal of metals from the surface (Jones, 1996). For uniform corrosion, the corrosive environment must have the same access to all parts of the metal surface, and the metal itself must be uniform in terms of metallurgy and composition. Uniform corrosion results in the thinning of wall thickness of components until the wall is penetrated leading to leaks or rupture. The extent of deterioration per unit time is expressed in terms of corrosion rate. The breakdown of passive oxide layer is the main cause of uniform corrosion. Usually, its rate is very slow in process components and may be measured using ultrasonic testing. Being slow and uniform, it can be predicted in most cases and necessary measures shall be taken in the design stage itself, in terms of corrosion allowances. However, in the operational life, the rate of corrosion may be random due to environmental exposure. The most critical corrosive environment is the presence of H_2S, CO_2, Cl^- and H_2O.

Pitting Corrosion

The localized attack of corrosive environment on an otherwise resistant surface produces pitting corrosion (Jones, 1996). It is confined to a point or small surface area that takes the form of cavities. Pitting is the localized form of attack that results in relatively rapid penetration at small discrete areas. Pits are quite small at the surface and may easily be hidden by inoffensive corrosion products and process streams. Pitting often remains undetected until leaks results from penetration of the wall thickness. Pitting of stainless steel alloys containing various proportions of iron, chromium, nickel and sometimes molybdenum are common. The iron and aluminum pit in the alkaline chloride solution by similar mechanism in less aggressive condition prevails in offshore process components. Pitting corrosion results from the failure of passive film, by the adsorption of aggressive anions at energetically preferred places. Susceptibility increases with chloride solutions in high temperatures. Pitting is unpredictable, especially in conditions forming deep pits. The rate is variable, depending on uncertain migration of corrodents into and out of the pits. Pits may be initiated by a number of surface discontinuities, including sulphide inclusions, insufficient inhibitor coverage, scratches in coatings, and deposits of slag, scale, dust, mud or sand. Depending on the metallurgy of the alloy and chemistry of environment, pits may be shallow, elliptical, deep, undercut or subsurface. Pit initiates at the critical pitting potential, with the presence of chlorides in an acid solution. Once it is initiated, it propagates in the direction of least resistance.

Erosion Corrosion

The combination of the corrosive fluid and high flow velocity results in erosion corrosion. The same stagnant or slow flowing fluid will cause a low or modest corrosion rate, but the rapid movement of the corrosive fluid physically erodes or abrades and removes the protective corrosion product film, exposes the reactive alloy beneath, thus accelerates corrosion (Jones, 1996). The corrosivity of the flowing corrodent has a significant effect. Sand or suspended slurries enhance erosion and accelerate erosion corrosion attack on metal or alloy. The attack generally follows the directions of localized flow and turbulence around surface irregularities. Removal of protective surface film by erosion due to flowing stream results in accelerated corrosion. The attack is accelerated at elbows, turbines, pumps, tees, reducers and other structural features that alter flow direction or speed and increase turbulence. Erosion corrosion often occurs when the corrodent is in the liquid phase. Suspended solids further aggravate the erosion of surface films and increase erosion corrosion. The lower strength, less corrosion resistance alloys, such as carbon steel, copper and aluminum are highly susceptible to erosion corrosion. Erosion corrosion takes the form of grooves, waves, gullies, tear-drop shaped pits and horse-shoe shaped depressions in the component surface. The turbulent eddies facilitates to thin the protective film locally to account for downstream undercutting.

3.5.2 Cracking Degradation Processes

The brittle fracture of a normally ductile alloy in the presence of an environment or loading is known as environmentally-induced cracking (Jones, 1996). Three distinct types of cracking are studied and modeled in this thesis: stress corrosion cracking, corrosion fatigue cracking and hydrogen induced cracking. The amount of cracking per unit time either in length or depth is expressed in terms of cracking rate.

Stress Corrosion Cracking

The stress corrosion cracking occurs in metals or alloys with static tensile stress in the presence of specific corrosive environmental condition (Jones, 1996). SCC is the brittle failure at relatively low, constant tensile stress of an alloy exposed to a corrosive media. Pure metals are relatively resistant to SCC. Three conditions must be present simultaneously to produce SCC: a critical environment, a susceptible alloy, and a tensile stress. Environmental conditions are specific to the alloys system and many not have an effect on other alloys of different type. For e.g., the hot aqueous solutions readily crack stainless steel, but do not have the same effect on carbon steel or aluminum. The required tensile stresses may be in the form of directly applied stresses or residual stresses. Tensile stresses even below yield are sufficient to cause SCC and that may result from bolting and fastening parts that fit together imperfectly. Uneven thermal expansion and contraction can also produce tensile stress after welding and other heat treatments. SCC may be either transgranular or intergranular, but the cracks follows a general macroscopic path and is always normal to the tensile component of stress. In transgranular failures, the crack propagates across the grains usually in specific crystal planes. The intergranular crack follows the grain boundaries in the intergranular mode. The cracking is primarily by mechanical fracture, with a little electrochemical dissolution during fracture process. The intergranular failure mode is due to inhomogenity at the grain boundaries. The electrochemical potential has a critical effect in the SCC.

Corrosion Fatigue Cracking

The process in which a metal fractures prematurely under conditions of simultaneous corrosion and repeated cyclic loading at lower stress levels or fewer cycles is known as corrosion fatigue cracking (Jones, 1996). Corrosion products typically present in cracks grow slowly during service life. Fracture surfaces from CFC shows macroscopic bench marks, where corrosion products accumulate at discontinuous crack advance fronts. On the microscopic scale, stripy pattern are often evident, where each cycle produces a discontinuous advance on the crack front. The cyclic stress is also important as low frequency leads to greater crack propagation per cycle. Stress raisers such as notches or surface roughness increase the susceptibility to CFC. Cracks are observed to initiate from corrosion pits, which again serve as surface for stress concentration. The endurance limit to cause fatigue failure is reduced in a corrosive environment. CFC cracks propagate perpendicular to the principal tensile stress component of cyclic stress. CFC crack usually form more slowly and corrosion products are likely to present in the crack. CFC is confined to the crystallographic features of grains and do not follow grain boundaries.

Hydrogen Induced Cracking

Hydrogen induced cracking is caused by hydrogen diffusing into the alloy lattice when the hydrogen evolution reaction produces atomic hydrogen at the surface (Jones, 1996). HIC means the severe loss of ductility in material, leading to failure. Hydrogen absorption may occur during electroplating, welding, pickling, cathodic protection or other processes that favor the production of nascent hydrogen at the surface. Because of its small size, atomic hydrogen can enter into the lattice to produce HIC. The necessary atomic hydrogen can also be provided by dissociation of hydrogen gas on the surface during exposure to elevated temperature gases. HIC is prevalent in iron alloys because of the restricted slip capabilities in the predominantly body centered cubic structure. Cathodic polarization initiates or enhances the HIC. HIC cracks are brittles, fast growing and unbranched. HIC cracks are more often transgranular.

3.6 BAYES' THEOREM

Degradation modeling is often viewed as an iterative process of integrating, accumulating and interpreting information capturing the physics of failure process. The analysts can assess the current state of knowledge regarding the degradation level, gather new integrity data to infer the question of future degradation, and then update and refine the current understanding to incorporate new data. Bayesian inference provides a logical and quantitative framework for this. Bayesian approach to degradation modeling starts with the formulation of a model that is expected to describe the degradation process. The prior distributions of unknown parameters of the model may then be formulated, which is meant to capture the beliefs about the degradation before actually seeing the data. After observing data, the Bayes theorem may be applied to obtain the posterior distributions for those unknowns, which takes account of both the prior and system data. From these posterior distributions, predictive distributions for future observations may be computed.

Probability is a degree of belief, that is, how much one thinks that something is true based on the evidence at hand. In the face of uncertainty in degradations, one can make the best inference based on the inspection data and any prior knowledge that one might have, reserving the right to revise the present knowledge if new information comes to light. Bayes theorem allows this process of learning as more data becomes available. It states how to update the prior probability distribution, $p(\theta)$, with a likelihood function, $p(y/\theta)$, mathematically, to obtain the posterior distribution as:

$$p(\theta / y) = \frac{p(\theta)p(y/\theta)}{\int p(\theta)p(y/\theta)d\theta} \tag{3.1}$$

The posterior density $p(\theta / y)$ summarizes the total information, after viewing the data and provides a basis for inference regarding the parameter, θ. Denominator of (3.1), i.e., $\int p(\theta)p(y/\theta)d\theta$ is known as the normalizing factor. The application of the Bayesian methods in risk analysis is limited due to the challenge of computing normalizing factor.

3.6.1 Conjugate Pair Distributions

The conjugate pairs are those distributions, whose posterior can be directly obtained from the prior and likelihood parameters and hence no computations are needed. For example, the Gamma prior and likelihood provides a Gamma posterior with a combination of the prior and likelihood parameters. The natural conjugate pairs for exponential families are presented in Table 3.1. The use of conjugate pair makes it simple to carry out the process of Bayesian updating. However, in some cases the concept of conjugate pairs does not yield realistic posteriors. Some literature conveniently assumes there are conjugate pairs for degradation process, for easy computation of posteriors, which is not the case in real life. This introduces significant uncertainty in the analysis. Distributions like, Weibull, lognormal, extreme value, do not lend themselves easily to the Bayesian updating. Another alternative is the use of simulation methods to determine the posterior distributions (Robert and Casella, 1999). In this study, simulation methods, such as Metropolis-Hastings algorithm will be used for the posterior development. To compare the results of simulation methods, analytical approximation, such as numerical integration technique or Laplace approximation method may also be used.

Table 3.1 Natural Conjugate Pairs for Exponential Family (Bedford and Cooke, 2001)

Prior Distribution $\pi(\theta)$	Likelihood $f(y/\theta)$	Posterior Distribution $\pi(\theta/y)$
Normal $N(\mu,\tau^2)$	Normal $N(\theta,\sigma^2)$	$N(\rho(\sigma^2\mu+\tau^2 y),\rho\sigma^2\tau^2)$ $\rho^{-1}=\sigma^2+\tau^2$
Gamma $G(\alpha,\beta)$	Poisson $P(\theta)$	$G(\alpha+y,\beta+1)$
Gamma $G(\alpha,\beta)$	Gamma $G(\nu,\theta)$	$G(\alpha+\upsilon,\beta+y)$
Beta $Be(\alpha,\beta)$	Binomial $B(n,\theta)$	$Be(\alpha+y,\beta+n-y)$
Beta $Be(\alpha,\beta)$	Negative Binomial $Neg(m,\theta)$	$Be(\alpha+m,\beta+y)$
Dirichlet $D(\alpha_1,...,\alpha_k)$	Multinomial $M_k(\theta_1,...\theta_k)$	$D(\alpha_1+x_1,...,\alpha_k+x_k)$
Gamma $Ga(\alpha,\beta)$	Normal $N(\mu,1/\theta)$	$G(\alpha+0.5,\beta+(\mu-y)^2/2)$

3.7 DEVELOPMENT OF RBIM FRAMEWORK

The risk based integrity modeling provides a framework to quantify the risks posed by aging components, based on structural degradation processes. Risk is defined as a combination of the probability of failure and its consequences. The integrity refers to the soundness of the component to perform its desired functions. The major threats to asset integrity in process components have been identified earlier. These are age-based degradation processes, such as corrosion and cracking. Based on detailed literature review, the critical structural degradation processes threatening the integrity of process components are identified as UC, PC, EC, SCC, CFC and HIC. Thus, the essential steps of the risk based integrity modeling are the estimation of probability of these degradation failures and consequences. The overall framework for the risk based integrity modeling has been presented in Figure 3.2. The probability of failure is estimated using Bayesian modeling of potential degradation processes. The consequence analysis estimates the consequence of an undesirable event occurrence in terms of cost of failure, damage to human life, and environment. The consequences of failure are expressed in terms of cost (in dollars) associated with failure, inspection and maintenance.

The annual equivalent cost (AEC) of failure consequence is combined with cumulative density function (CDF) of failure probability to estimate the operational life risk profile as given below.

$$R(j) = F[p(\theta / y, j)] \times AEC(j) \tag{3.2}$$

where, $R(j)$ is the risk of failure due to a degradation (in dollar) in the j^{th} interval, $F[p(\theta / y), j]$ is the CDF of posterior probability of failure and $AEC(j)$ is the annual equivalent cost, corresponding to the inspection and maintenance interval, j. The AEC may be computed from the equivalent rate costs of failure, inspection and maintenance.

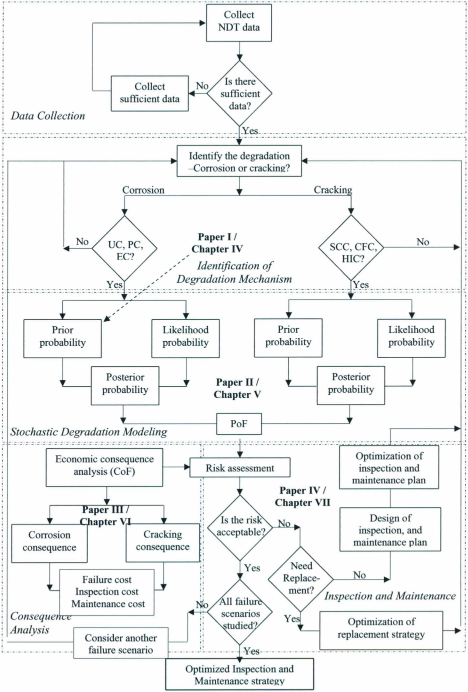

Fig.3.2. Framework for Risk based Integrity Modeling

Thus, finding the optimal inspection and maintenance interval reduces to finding a value of maintenance interval that minimizes the operational risk. At the optimal risk point, the risk will be reduced to as low as reasonably practicable (ALARP) level and at the same time the maintenance interval is maximized, thus avoiding unwanted maintenance, and its associated costs. The risk in dollar is compared with the company's operating budget (as risk acceptance criteria) to make a decision on maintenance. The risk acceptance criteria typically relate to the safety of personnel and risk to environment. They will be reflected in the corporate's annual operating and maintenance budgets. By plotting the operational risk curve over maintenance intervals, the optimum interval may be obtained as the period corresponding to the minimum risk.

An engineering replacement analysis is used to obtain an optimal replacement strategy. The same formula as in equation (3.2), with j being the replacement interval may be used. The annual equivalent cost (AEC) is computed as a summation of the annual equivalent of failure recovery, inspection and maintenance cost. The annual equivalent of failure recovery cost may be estimated using the annuity factor, indicating a series of future payments towards the failure cost for a specified number of years. The expected cost of inspection and maintenance involves periodic payments that increase by a constant amount from period to period, as a function of the age of component. This increasing trend may be modeled using arithmetic gradient (Park, 2007). Then, the AEC is combined with CDF of posterior probability of failure to estimate the operational life risk and economic service life of components. The optimum replacement interval will be obtained from the economic service life analysis of components.

The overall framework presented in Figure 3.2 consists of four parts; identification of potential degradation mechanisms, stochastic degradation modeling for estimating the likelihood of failure, economic consequence analysis for estimating the consequences of failure, optimization of maintenance strategy and, testing and validation.

3.8 IDENTIFICATION OF DEGRADATION PROCESSES

To identify the potential degradation mechanisms, the functional details of the system, subsystem and component are analyzed by subject experts. The data to be analyzed includes the material of component, the service (sweet or sour), the product being used or transported, and the environmental conditions, such as pressure, temperature and humidity. Furthermore, the wall thickness data obtained using NDT is used to identify the degradations. Analyzing the generic failure database and literature also helps to identify degradation processes. If the degradation is a uniform loss of material over the entire surface, the uniform corrosion is predominant. If it is localized attack in the form of pits at key points, the localized pitting, and if the loss of wall material follows the flow pattern of muddy fluid boundary layer, then the erosion corrosion may be dominant.

3.9 STOCHASTIC DEGRADATION MODELING

The stochastic degradation modeling has been carried out using the Bayesian analysis. The Bayesian analysis consists of computation of the prior, likelihood and posterior models for degradation processes; i. e., corrosion and cracking.

3.9.1 Prior Probability Modeling

The corrosion and cracking process are studied in detail and their mathematical modeling is attempted using probabilistic methods. The data extracted from the literature, pertaining to different types of degradations, such as UC, PC and EC, and SCC, CFC and HIC are considered in the probabilistic prior modeling. The data is tested with standard probability distributions to check for their suitability. A goodness of fit test is conducted using the probability plot and Anderson Darling (A-D) test. The method of least squares and maximum likelihood estimate are used for the parameter estimation. At the end of this study, best suited prior models for each degradation mechanism are obtained. Chapter III deals with the development of corrosion prior distributions in RBIM, which is published in the journal of stochastic environmental research and risk assessment.

The probabilistic modeling of degradation processes is essential to quantify the uncertainty and variability in the data. In order to develop the most appropriate prior distributions for degradations modeling, the following procedure has been followed:

- A study of the properties of standard probability distributions, such as exponential, normal, lognormal, Weibull, extreme value, Gamma and beta, which may be suitable for modeling the degradation processes in process components, was conducted.
- Minitab and self-developed subroutines in Matlab were used for testing and to assessing the goodness of fits using data obtained from the literature.
- Selected priors were validated using the field NDT data from an ageing facility.
- The best suitable prior models were identified using goodness of fit tests and the distribution parameters are estimated.

3.9.2 Likelihood Probability Modeling

In Bayesian analysis, the likelihood refers to the evidence from field that is supporting the prior information. If the likelihood is not supporting the prior, then the Bayesian posterior diverges. In that case, the chosen prior may be incorrect. If evidence supports the prior information, then the posterior obtained provides an accurate description of the degradation process.

The non-destructive test (NDT) data obtained from an offshore production facility operating in the North Sea has been used to model the likelihood probability of corrosion degradations. The data includes the minimum and average wall thickness measurements acquired during the period 1997 to 2003. The nominal diameters of its components varied from 19.05 to 508 mm. In the absence of such field data for cracking, the data from literature is used instead. From the piping system, the data obtained from the Gas Condensate (GC) system is observed to follow a uniform wall loss. Also, it is observed that the data obtained for the Gas Export (GE) system, in the above mentioned facility, follows the localized pitting corrosion. The data associated with high pressure Drilling Mud (DM) system has been observed to follow the erosion pattern. For precise estimation of corrosion and cracking rates, inspection data has been divided into several groups, namely, straight pipes and features. Features include bends, tees, reducers, flanges and valves. Three major components, straight pipes, bends and tees are considered in the analysis.

The statistical analysis has been divided into two groups, one is the precise estimation of degradation rates and the second is testing of the degradation rates with standard probability distributions. The method outlined in Khan and Howard (2007) and HSE UK

(2002) has been used to compute the corrosion rates from the wall loss data. The collected data is first analyzed to identify uniform or localized degradation. In the case of uniform degradation, time dependent regression analysis and in the case of localized degradation, an extreme value analysis has been carried out for estimating the rates of degradation. Further, the estimated degradation rates are tested with probability distributions and the best suitable likelihood models are concluded.

3.9.3 Posterior Probability Modeling

Prior probability models provide initial description of the degradation mechanisms. As more inspection data become available from field, these prior probability models can be revised to posterior probability models, which represent the current system and can be used to predict future failures. Since the priors and likelihoods of degradations may be of non-conjugate pairs, closed form solution for posteriors may not be possible. Thus, simulation methods or analytical approximations are required to estimate the posteriors.

In this study, a rejection sampling based Metropolis-Hastings (M-H) algorithm is used to develop posterior distributions. The M-H algorithm is a Markov chain Monte Carlo algorithm used to generate a sequence of posterior samples without actually knowing the normalizing constant. Ignoring the transient samples in the generated Markov chain, the steady state samples are rejected or accepted based on an acceptance criterion. To validate the estimated parameters of posterior models, analytical Laplace approximation method is used to compute the integrals involved in the posterior function. Results of the M-H algorithm and Laplace approximations are compared with conjugate pair estimations of known prior and likelihood combinations, and thus, the best suitable method will be recommended. The conjugate-pairs, such as normal-normal, Gamma-Gamma, Gamma-normal and Gamma-Poisson will be used to test and compare the results. The revised posterior model is a system-learned model and hence can be used for the accurate predictions of future probability of failure from degradations. This work is presented in detail in Chapter VI, which is published in the journal of risk analysis.

3.10 ECONOMIC CONSEQUENCE ANALYSIS

The purpose of RBIM is to minimize the risk arising from degradation processes. By operating a dynamic system of life-time data accumulation and processing, the accuracy will be improved with time and experience. To provide a consistent measure of risk, all consequence categories should be in the same units. Otherwise, the overall risk from many contributing sources cannot be computed. A standard choice of unit to represent all consequence categories is dollar, because risk can be interpreted as the expected loss due to a certain event or group of events (Jones, 1995). Therefore, the failure consequences are expressed in terms of dollar in this study. To minimize the likelihood of failure, components need to be inspected and maintained at very small interval. However, if the maintenance is performed too frequently, it will involve large costs and if it is performed too rarely, it will result in failure followed by unplanned shutdown and costly corrective maintenance. Sometimes, performing maintenance may not be an ideal choice from the economic perspective, in such a case; the replacement strategy should be considered. Replacement is a maintenance strategy that entails the replacement of component rather than performing maintenance based on the economic service life. Therefore, the purpose of this module is to develop a consequence analysis to find an optimal maintenance strategy taking the component's operational risk into account.

The failure consequences include the economic consequences of component failure, inspection and maintenance. The consequences of failure include the loss of commodity due to breakdown, loss due to shutdown, cost of spill cleanup, cost of nature damage and liability. The inspection cost depends on the method of NDT inspection, type of component, cost of gaining access, surface preparation and logistics costs. The maintenance cost depends mainly on the type of repair, i.e., minimal repair or component replacement, along with gaining access, surface preparation, gauging and coating restoration costs. Further, the total cost, also known as AEC, of operating and maintaining the component is computed. The AEC is a summation of the annual equivalent costs of failure, inspection and maintenance and may be estimated using (3.3):

$$AEC(j) = FC(j) + IC(j) + MC(j) \tag{3.3}$$

where, FC is the failure cost, IC is the inspection cost, MC is the maintenance cost and j represents the maintenance interval. Further details of the economic consequence analysis are presented in Chapters VI and VII.

3.10.1 Consequences of Failure

Failure cost is the cost associated with the loss of a facility due to degradation processes, such as corrosion and cracking. It is assumed that a component failure is followed by an immediate repair to prevent any system failure scenario with much higher consequences. Degradation-related failures may lead to increased risk of loss of the entire unit through a chain of reactions, in such cases the event tree analysis will be required to assess the system-level consequences. In this study, the component will be assumed as independent and isolated. The cost consequences of component failure includes loss of commodity due to breakdown, loss due to shutdown, cost of spill cleanup, legal fees and penalties due to environmental damage and liability.

Loss due to Breakdown

The loss of wall thickness by degradation leading to rupture is the main cause of breakdown. The breakdown costs are the financial losses, which are associated with loosing commodity. This cost depends upon what product is being processed, the rate of leakage and its current market value when the failure occurs. The focus in this thesis is on a process piping component in the North Sea and the product considered is crude oil. Unit cost of crude oil is extracted from the market value. The cost of breakdown will be estimated using the unit cost, rate and duration of release.

Loss of Production due to Shutdown

The main factor influencing the cost of failure is the facility's unavailability for production. Inspection and maintenance can be planned, whereas failures may lead to an unplanned, immediate shutdown of the facility. The cost of such a shutdown is dependent on the number of days of shutdown, the rate of loss of production and the value of products at the time of failure. Thus, the shutdown cost may be estimated by combining the unit cost of product, loss of affected production and maintenance delay time.

Cost of Spill Cleanup

The cost of oil spill cleanup depends on a number of factors, such as, the type of oil, the amount spilled and rate of spillage, the characteristics of affected area, weather and sea conditions, local and national laws, time of the year and the spill cleanup strategy (Etkin, 2000). Predicting the unit cost of spill response is possible, though it is complex. In this study, the crude oil spillage in offshore is considered. The average per-unit offshore oil spill cleanup cost may be taken from literature. The necessary formula for cleanup cost will be developed from first principles comprising the unit cost of spill cleanup and the total quantity released due to failures caused by degradations.

Loss due to Environmental Damage

The size of penalty as a result of damaging the environment is difficult to estimate, because costs increase with the scope of failure. The failure modes developed could escalate to more complex system failures leading to significant environmental damages. However, approximate assessments considering the quantity released and unit penalty rate are possible. The environment damage due to oil spillage includes loss of marine as well as coastal habitat, soil pollution, damage to agriculture land and adverse health impact (Purnell, 1999). The cost of environmental damage comprises the unit cost of nature damage, the rate and duration of product release. The per-unit cleanup cost of environmental damage may be obtained from literature.

Cost of Liability

The injuries and deaths caused by the failure of process components have the most severe implications possible. The loss of life or pain of an injury is impossible to quantify, yet, the cost implied due to worker's compensation and corporate liabilities shall be taken into account. The safety-related system failures have other immediate implications, such as legal fines and penalties for professional negligence. The estimates of liability costs that result from accidents are routinely published by several organizations. For component failure, liability cost may be estimated based on these reports. The liability cost typically include medical costs, emergency services, vocational rehabilitation, lost earnings, administrative costs, legal consulting fees, pain and lost quality of life.

Total Cost of Failure

The total cost of failure is the summation of loss of breakdown, loss due to shutdown, cost of spill cleanup, costs of environmental damage and liability. This total cost is based on two assumptions; the component is isolated, and the component failure leads to a system failure with subsequent unavailability for production.

3.10.2 Consequences of Inspection

The NDT techniques are used for the detection and quantification of discontinuities and separations in materials due to degradations. The integrity data is achieved by detecting, locating and sizing of detected flaws, such as corrosion, cracking and holes. Defect quantification requires considerable skill and experience, and the use of more than one NDT technique. The best suitable inspection methods for corrosion and cracking may be identified and their corresponding dollar costs may be estimated. The unit costs for the NDT techniques may be obtained from inspection industry.

Cost of Degradation Inspection

The NDT technique is used to detect and quantify the extent of wall loss, pit depth and surface crack as well as coating breakage. The inspection costs depend on how much area has to inspect from a risk perspective. The inspection cost includes the cost for gaining access to the component, the cost for surface preparation, personnel cost for inspection, cost associated with technical assistance, the cost of consumables and chemicals, and the logistics cost. In this thesis, it is assumed that the proposed inspection method is able to detect the presence of corrosion discontinuities, and surface or subsurface cracks. The cost of each inspection activity may be estimated using the per-unit personnel cost and the total duration of inspection.

3.10.3 Consequences of Maintenance

Inspection can detect the potential failure; however it is the maintenance that does the risk reduction. Maintenance cost is the cost associated with restoring a facility. To ensure safe operation, the maintenance needs to be performed at very small intervals. However, it is impractical to have frequent maintenance due to large costs, the possibility of maintenance-induced errors, and the associated plant unavailability for production. To optimize the maintenance, the following necessary conditions are to be satisfied; the cost of maintenance should be greater after failure than before, and the hazard rate of component should be increasing, i.e., component should be in the wear-out region. This thesis focuses on predictive maintenance of process components. It estimates through diagnostic tools, when a component or part is about to fail and should be repaired or replaced; thus reducing the costly corrective maintenance. This section covers the cost of necessary repair, replacement and material costs associated with the maintenance.

Cost of Degradation Maintenance

The maintenance may be either a minor patch repair work or the complete replacement of degraded component. For all types of corrosion, minor patch repair work of the affected area is considered, and for any types of cracking, immediate component replacement with necessary repair is considered. The maintenance task includes the access to degraded component, surface preparation, cutting and removal of parts, assembling, welding, testing and restoring the protective coating. Thus, in addition to the cost of repair and replacement, the personnel and logistics cost related to transportation, storage and rent of facilities also must be included. The cost of each maintenance activity may be estimated using a unit cost of maintenance task and total duration of maintenance. Refer to

Chapters VI and VII for further details on modeling the failure inspection, and maintenance costs.

3.11 OPTIMIZATION OF MAINTENANCE STRATEGY

Maintenance is a combination of activities by which a component is kept in, or restored to a state in which it can perform its designed functions. Application of the correct maintenance strategy optimizes the use of maintenance resources in the best interests of corporations. Determination of an optimal inspection and maintenance strategy is a problem of optimization under uncertainty. The ideal approach for such optimization will be the use of risk based analysis as it provides a predictive mechanism to evaluate the alternatives and identify the optimal choice. The operational risk estimated will be used to determine the maximum length of time between two consecutive inspection and maintenance, or to compute optimum time to replace the component in a cost-effective manner that will result in a minimum acceptable risk.

The cumulative probability density (CDF) of structural degradations is combined with the AEC of operating and maintaining the component to produce the operational risk over the varying maintenance interval. From the operational risk curve, optimal inspection and maintenance strategy is obtained by minimizing the overall risk. The optimum inspection and maintenance interval thus obtained satisfy the two necessary criteria of maintenance: first, the risk is reduced to ALARP level, and second, the maintenance interval is maximized, thus avoiding unwanted maintenance and its associated costs. The developed inspection and maintenance risk are compared with the company's operating and maintenance budget, as risk acceptance criteria. It is assumed that the component returns a condition just before failure after each minimal repair. This quantitative, risk-based model rationalizes the inspection and maintenance decision. Chapter VI discusses the various aspects of risk based inspection and maintenance optimization.

The decision to repair or replace the ageing component is based on economic analysis. The best time to make replacement decisions for repairable components is during the operational phase. The likelihood of failure and the life cycle costs are used in the replacement analysis. The decision to replace the components can be taken as it starts ageing, mainly due to the evidence of degradation or breakdown or obsolescence. In that case, the varying operational costs, such as failure, inspection and maintenance costs must be taken into consideration. The replacement of failed assemblies with spares often require less time out of service, but require the stocking in inventory. The failure mechanism influences the selection of appropriate course of action to be taken for the component replacement. The time-based replacement cannot be applied for truly random processes, following exponential models. However, degradation processes are observed to be a time-dependent process, enabling one to use the models such as Weibull, lognormal or Extreme Values. The economic decision about repair or replacement would be needed to determine the action to take for the failed or degrading components. Chapter VII discusses the various aspects of risk based replacement optimization.

3.12 SUMMARY

This chapter provides an overview and integration of the entire thesis. It started with the objective and scope, and the assumptions made in this study. The critical asset integrity threats in process components are further discussed. Later, it is argued that the statistical

Bayes theorem is an ideal choice to model the uncertain degradation processes. Further, the challenges of using Bayes theorem in quantitative risk analysis are discussed. In life cycle, the failure, inspection and maintenance of component may result in economic consequences. Furthermore, a robust RBIM framework is developed based on the stochastic degradation modeling and economic consequence analysis. Finally, the optimization of maintenance strategy is briefly outlined in this Chapter. Although, environmentally induced degradations are only one major part of complete asset integrity spectrum, it is only considered in this thesis for optimizing inspection and maintenance.

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CHAPTER IV

THE SELECTION OF CORROSION PRIOR DISTRIBUTIONS FOR RISK BASED INTEGRITY MODELING

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PREFACE

This chapter presents the selection of best suitable prior probability models for critical structural degradation processes in offshore process components. Although the choice of prior is often subjective, a rational consensus has been achieved here by analyzing generic data from similar installations. This paper has been published in the Journal of Stochastic Environmental Research and Risk Assessment (2009), 23(6): 793-809.

The principal author conducted an independent literature review to understand the potential integrity threats for offshore process components. The framework is designed and structured by the principal author. The major integrity threats in process components are observed to be several corrosion processes, namely: uniform, pitting and erosion corrosion; and cracking, namely: stress corrosion, corrosion fatigue and hydrogen induced cracking. The principal author collected generic data from literature for each of these degradation processes. He analyzed the properties of standard probability distributions and tested the collected data with exponential, normal, lognormal, Weibull, Extreme Value, Gamma and beta distributions. A Matlab subroutine *probfit* has been developed by the principal author to test the candidate distributions using the maximum likelihood estimates. The statistical software Minitab is also used for analyzing the data. How well the data fit with the distribution has been measured using the statistical goodness of fit tests. In this study, the principal author used the Anderson Darling (A-D) test for all random variables; the Chi-square and Kolmogorov-Smirnov (K-S) test are applied only for normal random variables. The A-D test is used mainly as it gives more weight to the tails of distribution than the K-S test, so it is better to model the uncertainty in degradation data. Once the type of probability distribution has been selected, the least square and maximum likelihood estimates are used to estimate the parameters.

The selected priors of the degradation processes are validated using a case study by the principal author. With request from the principal author, the second author collected the field non-destructive test data from Lloyd's register, UK. The principal author categorized and analyzed the data by system, subsystem and component level, considering the product and operating conditions. The co-authors provided review and feedback. The regression and extreme value analysis are used to estimate the rates of degradation and the estimated rates are tested with standard probability distributions by the principal author. This study concluded that the best suitable prior probability models that could handle uniform, pitting and erosion corrosion were 3P Weibull and 3P lognormal; Type 1 Extreme Value and 3P Weibull; and 3P Weibull and 3P lognormal distributions, respectively.

ABSTRACT

The deterioration of the condition of process plants assets has a major negative impact on the safety of its operation. Risk based integrity modeling provides a methodology to quantify the risks posed by an aging asset. This provides a means for the protection of human life, financial investment and the environmental damage from the consequences of its failures. This methodology is based on modeling the uncertainty in material degradations using probability distributions, known as priors. Using Bayes theorem, one may improve the prior distribution to obtain a posterior distribution using actual inspection data. Although the choice of priors is often subjective, a rational consensus can be achieved by judgmental studies and analyzing the generic data from the same or similar installations. The first part of this paper presents a framework for a risk based integrity modeling. This includes a methodology to select the prior distributions for the various types of corrosion degradation mechanisms, namely, the uniform, localized and erosion corrosion. Several statistical tests were conducted based on the data extracted from the literature to check which of the prior distributions follows data the best. Once the underlying distribution has been confirmed, one can estimate the parameters of the distributions. In the second part, the selected priors are tested and validated using actual plant inspection data obtained from existing assets in operation. It is found that uniform corrosion can be best described using 3P-Weibull and 3P-Lognormal distributions. Localized corrosion can be best described using Type1 Extreme Value and 3P-Weibull, while erosion corrosion can best be described using the 3P-Weibull, Type1 Extreme Value, or 3P-Lognormal distributions.

Keywords: Corrosion degradation, risk, prior probability, asset integrity, goodness of fit.

4.1 INTRODUCTION

The deterioration of assets of oil and gas and process plants has a major negative impact on the safety of their operation. Maintaining the integrity of process components has been a subject of research for many years (Khan and Howard, 2007). Plant assets are subject to deterioration processes, such as corrosion and fatigue crack growth (Kallen, 2002; Straub, 2004). For assets in operation, design changes are often difficult. Inspection and maintenance are only the feasible measures for risk reduction (Straub, 2004). Risk based integrity modeling (RBIM) provides a framework to quantify the risks posed by an aging asset. In the RBIM, the uncertainty in assets' degradations is modeled using a probability distribution, known as a prior that is based on the knowledge and expertise of the model maker. Using Bayes theorem one may combine a prior distribution with the results of real life inspection data to obtain a posterior distribution (Bedford and Cooke, 2001). The new distribution can be useful in quantifying the risk to the installations. Even though many researchers have indicated a need for a formal process of eliciting a prior distribution, there is no standard method (Ahn et al., 2007). The lack of uniqueness and objectivity associated with the prior probability can be reduced with models of invariance principle and maximum entropy concepts (Baker and Christakos, 2007). One of the major concerns with Bayesian analysis is the daunting task of prior estimation (Tesfamariam and Sadiq, 2008). Although the choice of a prior is often subjective, a rational consensus can be achieved by judgmental studies and analysis of material degradation data obtained from similar existing plants.

Hydrocarbon leak poses a serious threat to the safety of operation in chemical installations. Leaks are the principal cause of fire and explosions in chemical installations. Studies indicate that corrosion is the principal cause of about 15% of leakage occurrences (HSE UK, 2002). The direct annual cost of corrosion in the USA is assessed by Koch et al. (2001) to be 276 billion USD, which represents 3.1% of the GNP, while about 121 billion USD is spent on corrosion control. Googan and Ashworth (1990) reported that corrosion accounts for 21% of failures in submarine gas pipelines, and erosion-corrosion modes account for 24.6% of pipe leakages in process plants. Moreover, 40% of the accidental hydrocarbon releases to the environment are corrosion related. Usually, inspections are carried out for internal as well as external corrosion by means of non-destructive tests (NDT) to estimate the loss of material. Although, the use of statistical methods to estimate the corrosion rates and probabilistic methods to predict plant life have been reported over the past four decades but they have been applied in a few isolated cases. Better inspection planning and maintenance optimization needs a reliable prediction of degradation mechanisms and rate. This can be achieved by combining the statistical techniques with reliability models (Melchers, 2003a and b; Khan and Howard, 2007).

This paper proposes a framework for proposed risk based inspection and maintenance methodology. The first step in this methodology is to select suitable prior distributions for various types of corrosion in process components, namely uniform, localized/pitting and erosion corrosion. Statistical tests were conducted on the short listed distributions to check their applicability. The short listed priors were tested and validated using real life inspection data obtained from an operating asset.

4.2 THEORETICAL BACKGROUND

The first initiatives for the developments of risk based approaches to the inspection and maintenance planning were directed towards the inspection planning for welded connections subject to fatigue in fixed steel offshore structures (Skjong, 1985; Madsen et al., 1987; Fujita et al., 1989). Later, the same methodology was applied to other structures such as ships and tankers (Soares and Garbatov, 1996; Paik et al., 2003), floating, production, storage and off-loading facilities (Lotsberg et al., 1999; Goyet et al., 2002), semi-submersibles, pipelines (Willcocks and Bai, 2000; Desjardins, 2002; Dey and Gupta, 2001), process plants (Geary, 2002; Montgomery and Serratella, 2002; Kallen and Noortwijk, 2005; Khan et al., 2006), bridges (Frangopol et al., 2004), and breakwaters (Noortwijk, 1996). The degradation mechanisms such as fatigue cracking and corrosion of steel and concrete structures were also considered (Faber, 2002). A generic approach for the probabilistic corrosion estimation, based on the structural reliability theory, has been introduced by Melchers (2003a and b). The recent progress in the modeling of corrosion of structural steel immersed in seawaters has been reported by Melchers (2005, 2006). Straub and Faber (2005) reported the reliability updating for structures subject to localized corrosion defects based on a generic approach developed for fatigue crack growth. The computational aspects of their study are complex and time consuming. Similarly, the use of priors has been restricted to the Gamma distribution, which may not reflect the actual degradations in all cases. Inspection planning for process equipments and systems evolved from the traditional quantitative risk analysis (Khan et al., 2004; Dey, 2004; Khan et al., 2006). A closer look at the literature has shown that little information has been published on a robust RBIM methodology using stochastic degradation models.

A theoretical framework for the RBIM is proposed in Figure 4.1. The framework consists of four parts: (a) the comparison of different models for selecting the most appropriate prior distributions for structural degradations, (b) the development of posterior probabilistic models and the analysis of their consequences, (c) optimization of risks and inspection and maintenance intervals, and finally, (d) testing and validation. This paper is an attempt to discuss the first part of the overall RBIM framework (Figure 4.1). Based on literature study (Kallen, 2002; Straub, 2004; Khan et al., 2006), the critical structural degradation mechanisms threatening the integrity of assets are corrosion (uniform corrosion (UC), localized or pitting (PC), and erosion corrosion (EC)) and cracks (stress corrosion cracks (SCC), corrosion fatigue cracks (CFC) and hydrogen induced cracks (HIC)).

Risk is defined as the product of probability of failure of an undesirable event and its likely consequences. Therefore, the main steps in risk based integrity modeling are the estimation of the probability of structural failure and its consequences. The probability of failure could be estimated by the stochastic modeling of individual corrosion and cracking mechanisms using the Bayesian prior-posterior analysis. The consequence analysis estimates the cost incurred as result of failure including the cost of corrective repair or replacement and the proposed inspection and maintenance plan. The risk acceptance criteria based on the ALARP principle will be discussed later. Statistical decision theory will be used for the optimization of inspection intervals. Design of additional safety measures will be considered if the estimated risk exceeds the acceptable criteria. The developed stochastic model will be tested and validated using case studies of an aging process facility.

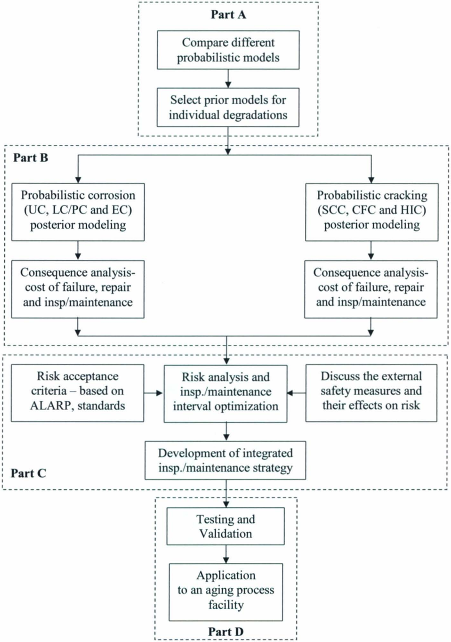


Fig. 4.1. Methodology for Risk Based Integrity Modeling

4.3 TYPES OF CORROSION

Corrosion is the loss of material as a result of chemical reaction between a metal or metal alloy and its environment (Jones, 1996). Three important types of asset corrosion mechanisms will be discussed in this section: the uniform or general corrosion, the localized or pitting corrosion, and the erosion corrosion.

Uniform corrosion is defined as the uniform or regular removal of metals from the surface (Jones, 1996). For uniform corrosion, the corrosive environment must have the same access to all parts of the metal surface, and the metal itself must be uniform in terms of metallurgy and composition. Uniform corrosion results in the thinning of wall thickness until the wall is penetrated leading to leaks or breakdown of equipment (Mansfeld, 1987). The localized attack of corrosive environment on an otherwise resistant surface produces pitting corrosion (Jones, 1996). The combination of the corrosive fluid and high flow velocity results in erosion corrosion. The same stagnant or slow flowing fluid will cause a low or modest corrosion rate, but the rapid movement of the corrosive fluid physically erodes or abrades and removes the protective corrosion product film, exposes the reactive alloy beneath, thus accelerates corrosion. Sand or suspended slurries enhance erosion and accelerate erosion corrosion attack on metal or alloy. The attack generally follows the directions of localized flow and turbulence around surface irregularities.

4.4 ANALYSIS OF CORROSION DEGRADATION MODELS

The different probabilistic models which can be used to describe major corrosion degradation mechanisms will be discussed in this section. The distributions of corrosion samples can be established in several ways; including frequency diagrams, plotting data using probability graphs, and conducting the goodness of fit tests for the distributions (Halder and Mahadevan, 2000). The parameters of distribution can be estimated using the methods of least squares, moments and maximum likelihood estimates.

4.4.1 Goodness of Fit Tests

The goodness of fit test determines how well a particular distribution fits the observed data. The commonly used statistical tests for goodness of fit are Chi-square, Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D) tests. The Chi-square test is based on the error between the observed and assumed probability density functions (PDF) of the distribution. In the Chi-square test, the range of observed data is divided into intervals, and the number of times the random variable is observed in a particular interval is counted. Details of the tests can be obtained from statistical text books such as, D'Agostino and Stephens (1986). The K-S test is based on the error between the observed and assumed cumulative distribution functions (CDF) of the distribution (Halder and Mahadevan, 2000). The A-D test is a modification of the K-S test and it gives more weight to the tails than the K-S test. The K-S test is distribution free in the sense that the critical values do not depend on the specific distribution being tested. The critical values for the A-D test are dependent on the specific distribution that is being tested. The critical values for various distributions, for different significance levels (say, 1% and 5%) have been adopted from D'Agostino and Stephens (1986) and are presented in Table 4.1. Using the A-D statistic, one can compare the fit of competing distributions as opposed to an absolute measure of how a particular distribution fits the data. The A-D statistic is calculated for the probability plots (PP's), maximum likelihood (MLE) and the least square (LSXY) estimates. If several distributions provide a close fit to the data, the distribution with smallest A-D value will be reported or, the collection of more meaningful information is sought. In this paper, the goodness of fit test has been carried out using A-D test for all distributions as it is more sensitive on tails; the K-S and chi-square tests have been applied only for the normal distributions.

Table 4.1. Critical Values of A-D Statistic for Distributions (D'Agostino & Stephens, 1986)

Types of Distribution	Significance Level	Critical Value of A-D Statistic
Normal	0.05	1.087
	0.01	1.551
Lognormal	0.05	1.087
	0.01	1.551
Exponential	0.05	2.492
	0.01	3.857
Extr. Value	0.05	1.321
	0.01	1.959
Weibull	0.05	1.321
	0.01	1.959
Gamma	0.05	1.562
	0.01	1.562
Logistic	0.05	1.046
	0.01	1.505

4.4.2 Estimation of Parameters

Once a probability distribution has been identified for a degradation mechanism, its parameters need to be assessed. The accuracy in estimating these parameters is based on the ability of observed data in representing the uncertainty in the corrosion data (Halder and Mahadevan, 2000). In the present study, parameters have been estimated using least square method and the method of maximum likelihood.

Least square estimates are calculated by fitting a regression line to the points in a probability plot. The line is formed by regressing time to failure or log (time to failure) on the transformed percent (Johnson, 2005). The maximum likelihood parameter is calculated by maximizing the likelihood function, where the likelihood function represents the probability that the true distribution has said parameters based on the sample. The detailed principle behind the maximum likelihood method for parameter estimation can be found in Halder and Mahadevan (2000).

4.5 DATA SUMMARY AND ANALYSIS PROCEDURE

In order to select the prior probability distributions for different corrosion mechanisms, several distributions have been tested using data extracted from the literature. For this purpose, the uniform corrosion data has been extracted from Anghel and Lazar (2005), Melchers (2003), Lawson (2005), McLaughlan and Stuetz (2004) and Paik et al. (2003). For pitting corrosion, the data has been extracted from Melchers (2005), Scarf and Laycock (1996), Laycock et al. (1990) and Sankaran et al. (2001). For erosion corrosion, the data has been extracted from Vinod et al. (2003), Melchers (2006), Salama (2000) and Abdusalam and Stanley (1993). The extracted data has been tested with standard probability distributions, like Normal, Lognormal, 3P-Lognormal, Weibull, 3P-Weibull, Exponential, 2P-Exponential, Type1 Extreme Value, Gamma and Beta using the statistical software Minitab and developed subroutines in Matlab. The goodness of fit test has then been performed using the adjusted A-D statistic and the best fit is reported as the one with smallest A-D statistic. The more and less relevant prior distributions with A-D statistic for probability plot method have been presented in Table 4.2; Table 4.3 reports the maximum likelihood estimates and Table 4.4 reports results of the method of least squares. The sample probability plots are presented for uniform corrosion (data extracted from Anghel and Lazar, 2005) in Figures 4.2a and b, the pitting corrosion (data extracted from Scarf and Laycock, 1996) in Figures 4.3a and b, and the erosion corrosion (data extracted from Melchers, 2006) in Figures 4.4a and b.

A Matlab subroutine, *Probfit* has been developed for testing the candidate distributions using maximum likelihood estimates. The log-likelihood statistic has been used to compare the goodness of fits and to estimate the parameters of the distributions (Table 4.3). The parameters, such as, location and scale parameters are estimated using 95% confidence intervals. The interactive distribution fit tool, *dfittool* has been used to prepare the probability plots of the data and to estimate the log-likelihood parameter. The sample PDF and CDF plots corresponding to the data extracted from Anghel and Lazar (2005) for maximum likelihood estimation are shown in Figures 4.5a and b.

The probability plots have been developed using the least square estimate (LSXY) also. The A-D test statistic and correlation coefficient (CC) statistic have been used for comparing the goodness of fits (Table 4.4). The lower value of A-D statistic and higher value of CC statistic suggested better fit. The mean, standard error, 95% of upper and lower bounds of the probability have also been computed. The sample least square plots with their corresponding CC values (for data extracted from Anghel and Lazar, 2005) have presented in Figures 4.6a and b.

Table 4.2. Summary of Probabilistic Corrosion Prior Modeling using Probability Plots

Types of Corrosion	Data Extracted From	Fitting Summary by Probability Plot Method			
		More Relevant	Statistics	Less Relevant	Statistics
Uniform Corrosion	Anghel and Lazar (2005)	3P-Lognormal	1.738	Normal	1.790
		Weibull	1.739	Lognormal	1.849
		3P-Weibull	1.752	Ext. Value	1.965
	Melchers (2003)	3P-Weibull	1.511	Normal	1.537
		Ext. Value	1.514	Weibull	1.591
		3P-Lognormal	1.537	Lognormal	1.830
	Lawson (2005)	3P-Weibull	1.441	Lognormal	1.518
		3P-Lognormal	1.479	Weibull	1.634
		3P-Loglogistic	1.479	Normal	1.751
	McLaughlan and Stuetz (2004)	3P-Lognormal	1.319	3P-Weibull	1.476
		Lognormal	1.389	2P-Exponential	1.575
		Weibull	1.474	Exponential	1.832
	Paik et al., (2003)	3P-Lognormal	1.199	Ext. Value	1.289
		Normal	1.200	Weibull	1.313
		3P-Weibull	1.203	Lognormal	1.768
Pitting Corrosion	Melchers (2005)	Ext Value	1.742	3P-Lognormal	1.796
		3P-Weibull	1.742	Weibull	2.245
		Normal	1.794	Lognormal	2.543
	Scarf and Laycock (1996)	Ext. Value	1.451	Normal	1.543
		3P-Weibull	1.445	3P-Lognormal	1.543

Types of Corrosion	Data Extracted From	Fitting Summary by Probability Plot Method			
		More Relevant	Statistics	Less Relevant	Statistics
		Weibull	1.506	Lognormal	1.693
	Laycock et al., (1990)	Ext Value	1.297	Normal	1.393
		3P-Weibull	1.297	3P-Lognormal	1.396
		Weibull	1.378	Lognormal	1.689
	Sankaran et al., (2001)	Ext Value	1.453	Normal	1.571
		3P-Weibull	1.453	Weibull	1.645
		3P-Lognormal	1.571	Lognormal	1.945
Erosion Corrosion	Vinod et al., (2003)	Ext Value	1.173	3P-Lognormal	1.219
		3P-Weibull	1.197	Normal	1.319
		Weibull	1.216	Lognormal	1.430
	Melchers (2006)	Weibull	1.095	Normal	1.101
		3P-Weibull	1.101	Ext Value	1.225
		3P-Lognormal	1.101	Lognormal	1.246
	Salama (2000)	3P-Weibull	1.109	Lognormal	1.253
		3P-Lognormal	1.171	2P-Exponential	1.395
		Weibull	1.126	Exponential	1.564
	Abdusalam and Stanley (1993)	Weibull	1.058	3P-Lognormal	1.081
		3P-Weibull	1.067	Ext Value	1.101
		Normal	1.078	Lognormal	1.247

Table 4.3. Probabilistic Corrosion Prior Modeling using Maximum Likelihood Estimates

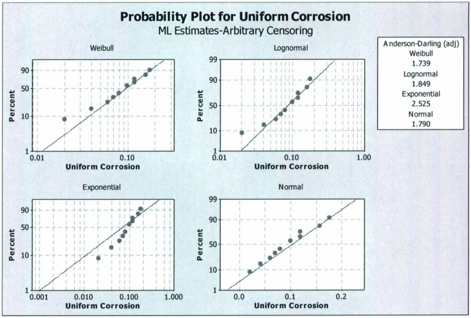
Types of Corrosion	Data Extracted From	Fitting Summary by Maximum Likelihood Method			
		More Relevant	Log likelihood	Less Relevant	Log likelihood
Uniform Corrosion	Anghel and Lazar (2005)	Weibull	18.6565	Gamma	18.4352
		Beta	18.5341	Normal	18.0010
	Melchers (2003)	Ext Value	6.0722	Weibull	5.7341
		Beta	5.8790	Normal	5.6763
	Lawson (2005)	Lognormal	-16.3408	Weibull	-17.5002
		Gamma	-16.6827	Normal	-18.2951
	McLaughlan and Stuetz (2004)	Gamma	16.7484	Weibull	16.3820
		Lognormal	16.5554	Beta	16.0780
	Paik et al., (2003)	Weibull	-22.9423	Ext Value	-23.8987
		Normal	-23.2055	Gamma	-24.0077
Pitting Corrosion	Melchers (2005)	Ext Value	-25.7766	Weibull	-27.9618
		Normal	-27.2373	Gamma	-29.3530
	Scarf and Laycock (1993)	Ext Value	-2.8491	Normal	-4.0541
		Weibull	-3.1969	Gamma	-4.8803
	Laycock et al., (1990)	Ext Value	-36.5267	Normal	-37.858
		Weibull	-37.1421	Gamma	-39.2315
	Sankaran et al., (2001)	Ext Value	58.7858	Normal	57.5830
		Weibull	57.9119	Beta	56.2077

Types of Corrosion	Data Extracted From	Fitting Summary by Maximum Likelihood Method			
		More Relevant	Log likelihood	Less Relevant	Log likelihood
Erosion Corrosion	Vinod et al., (2003)	Weibull	68.2410	Normal	67.7708
		Ext Value	67.9288	Beta	67.1419
	Melchers (2006)	Weibull	37.5092	Beta	37.3557
		Normal	37.5075	Gamma	37.1616
	Salama (2000)	Beta	46.6300	Gamma	46.0812
		Weibull	46.5867	Exponential	43.9436
	Abdusalam and Stanley (1993)	Weibull	-20.6869	Ext Value	-21.3339
		Normal	-21.0715	Gamma	-21.6241

Table 4.4. Probabilistic Corrosion Prior Modeling using the Least Square Estimate

Types of Corr.	Data Extracted From	Fitting Summary by Least Square Estimates					
		More Relevant	A-D Statistic	CC	Less Relevant	A-D Statistic	CC
Uniform Corrosion	Anghel and Lazar (2005)	3P-Weibull	1.857	0.996	Logistic	1.853	0.992
		3P-Lognormal	1.853	0.995	Normal	1.863	0.992
	Melchers (2003)	3P-Weibull	1.537	0.997	Normal	1.580	0.990
		Ext. Value	1.552	0.996	3P-Lognormal	1.581	0.989
	Lawson (2005)	3P-Weibull	1.451	0.997	Lognormal	1.517	0.991
		3P-Lognormal	1.483	0.994	Loglogistic	1.542	0.986

Types of Corr.	Data Extracted From	Fitting Summary by Least Square Estimates					
		More Relevant	A-D Statistic	CC	Less Relevant	A-D Statistic	CC
	McLaughlan & Stuetz (2004)	3P-Lognormal	1.393	0.975	Loglogistic	1.509	0.969
		3P-Weibull	1.519	0.976	Weibull	1.522	0.976
	Paik et al., (2003)	3P-Weibull	1.156	0.995	Normal	1.170	0.992
		3P-Lognormal	1.169	0.992	Logistic	1.235	0.986
Pitting Corrosion	Melchers (2005)	Ext Value	1.601	0.967	Normal	1.712	0.957
		3P-Weibull	1.604	0.966	3P-Lognormal	1.719	0.956
	Scarf and Laycock (1996)	Ext Value	1.471	0.997	Weibull	1.541	0.988
		3P-Weibull	1.472	0.996	Normal	1.603	0.976
	Laycock et al., (1990)	Ext Value	1.300	0.998	Weibull	1.447	0.983
		3P-Weibull	1.301	0.998	Normal	1.453	0.979
	Sankaran et al., (2001)	Ext Value	1.438	0.990	3P-Lognormal	1.582	0.975
		3P-Weibull	1.438	0.990	Normal	1.582	0.975
Erosion Corrosion	Vinod et al., (2003)	3P-Weibull	1.189	0.992	Normal	1.216	0.989
		Weibull	1.193	0.992	Ext Value	1.236	0.985
	Melchers (2006)	Weibull	1.156	0.994	Normal	1.191	0.991
		3P-Weibull	1.159	0.994	3P-Lognormal	1.192	0.991
	Salama (2000)	Weibull	1.012	0.988	3P-Lognormal	1.145	0.981
		3P-Weibull	1.054	0.990	Loglogistic	1.342	0.954
	Abdusalam and Stanley (1993)	Weibull	1.074	0.997	Normal	1.101	0.994
		3PWeibull	1.074	0.997	3P-Lognormal	1.102	0.994



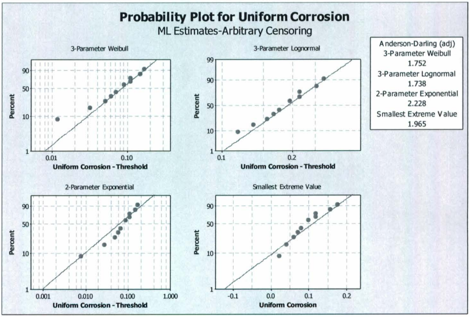
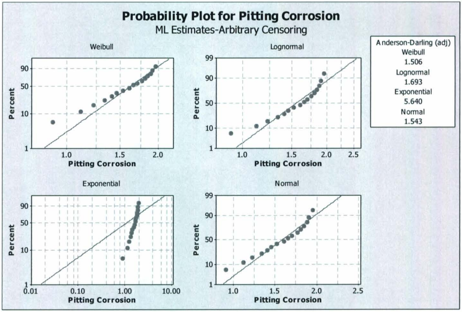


Fig. 4. 2. Sample Probability Plots for Uniform Corrosion, Data from Anghel and Lazar (2005)



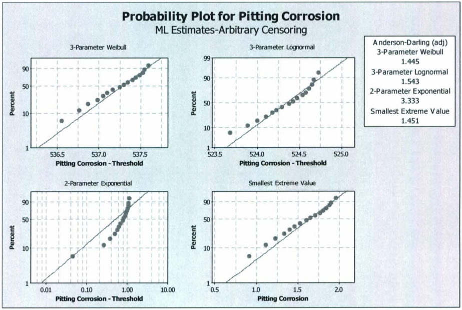


Fig. 4.3. Sample Probability Plots for Pitting Corrosion, Data from Scarf and Laycock (1996)

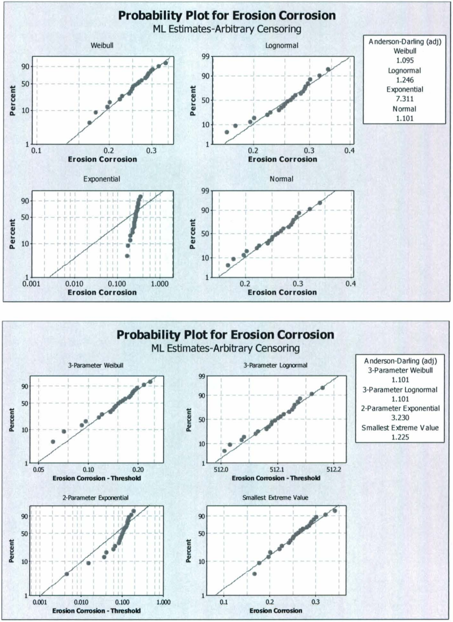


Fig. 4.4. Sample Probability Plots for Erosion Corrosion, Data from Melchers (2006)

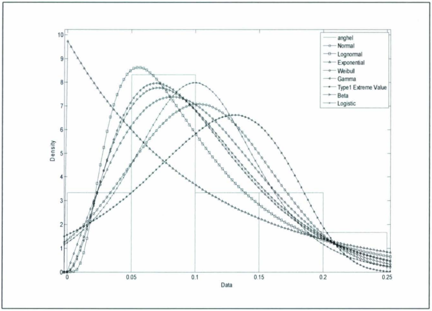


Fig. 4.5a. Sample PDF Plots for Uniform Corrosion, Data from Anghel and Lazar (2005)

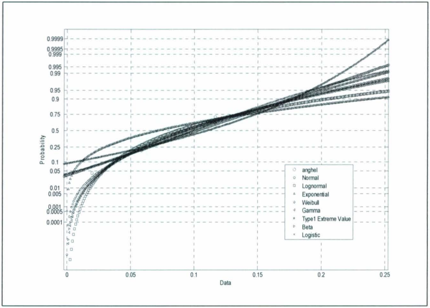
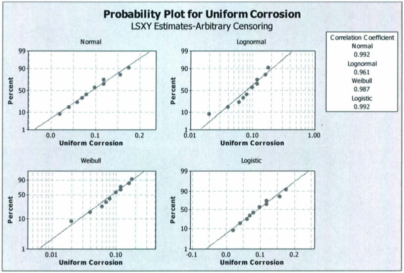


Fig. 4.5b. Sample CDF Plots for Uniform Corrosion, Data from Anghel and Lazar (2005)



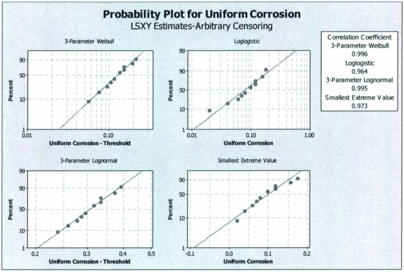


Fig. 4.6. Sample Least Square Plots (LSXY), Data from Anghel and Lazar (2005)

4.6 RESULTS AND DISCUSSIONS

The summary of more relevant and less relevant models for uniform corrosion, pitting corrosion and erosion corrosion prior selection are reported in Table 4.5. The more appropriate distributions that can be used to describe the uniform corrosion are 3P-Weibull and 3P-Lognormal. Type1 Extreme Value and 3P-Weibull distributions are the best to model pitting corrosion, and the 3P-Weibull, Type 1 Extreme Value or 3P-Lognormal distributions are the best to model erosion corrosion priors. The less relevant, but still usable distribution for uniform corrosion include Normal, Gamma and Beta distributions; for pitting corrosion, Gamma, Beta, Normal and Loglogistic distributions; and for erosion corrosion, Normal, Gamma and Beta distributions.

Table 4.5. Summary of Relevant Prior Probability Models for the Corrosion Degradation

Types of Material Degradations	More Relevant Prior Probability Models	Less Relevant Prior Probability Models
Uniform Corrosion	3P-Weibull and 3P-Lognormal	Normal, Gamma, Beta and Ext. Value
Localized/Pitting Corrosion	Type 1 Extreme Value and 3P-Weibull	Normal, Gamma, Beta and Loglogistic
Erosion Corrosion	3P-Weibull, Type 1 Extreme Value or 3P-Lognormal	Normal, Gamma and Beta

The short listed corrosion priors were further tested and validated using the case study of a plant life inspection data. A brief discussion on this validation is reported in Section 4.7.

4.7 VALIDATION OF SELECTED CORROSION PRIORS WITH CASE STUDY

The inspection data obtained from an offshore production facility operating in the North Sea has been used to validate the selected priors for each type of corrosion degradations. The data used for uniform corrosion is the data obtained for the Gas Condensate (GC) system. This data is used to obtain the distribution for uniform corrosion as the data is observed to follow a uniform wall loss. The data includes the minimum and average wall thickness readings acquired during the period 1997 to 2002. The nominal diameters of its components varied from 25.4 to 304.8 mm.

It was observed that data obtained for the Gas Export (GE) system, in the above mentioned facility, follows the localized or pitting corrosion. The data includes the minimum and average inspection readings acquired during the period 1997 to 2002. The nominal diameter of its components varied from 19.05 to 508 mm.

The data associated with HP Drilling Mud (HP) system, which has flow lines of several diameters, has been observed to follow the erosion pattern. The data includes the inspection readings acquired during the period 1999 to 2003. The nominal diameters of its components varied from 50.8 to 127 mm. For precise estimation of corrosion rates, inspection data has been divided into several groups, namely, straight pipes and features. Features include bends, tees, reducers, flanges and valves (Khan and Howard, 2007). Three major components: straight pipes, bends and tees were considered in the analysis.

4.7.1 Subsystem Description

In present study, the flow lines of GC, where uniform wall loss is observed were considered for uniform corrosion; it consists of flow lines from high pressure compressor K1301 to Cooler E1303 of nominal wall thickness varying from 5.54 to 17.48 mm. Further, the system GE has been considered for pitting corrosion as the data observed were localized in nature. For illustration purpose, the subsystem 6 of GE flow lines is presented. The sample wall loss data used for the analysis has been provided in Table 4.6 and the corresponding subsystem 6 isometrics is included in Figure 4.7. The subsystem 6 essentially consists of gas export lines from K3201B to first stage after cooler (0.75, 1.0, 1.5, 6 and 8 inch lines), K3201C to after coolers, K3201 A/B (0.75, 1.0, 1.5 and 6 inch lines), K3201A, first stage compressor (3 and 6 inch lines), and K-3201A to after/inter coolers (6, 8 inch lines). The nominal wall thickness of its components varied from 3.91 to 23.01 mm. The flow lines in HP Drilling Mud for erosion corrosion consists of high pressure mud lines of module 2 and 16, with wall thickness of components varying from 5.49 to 19.05 mm.

4.7.2 Analysis Methodology

The statistical analysis task has been divided into two groups, one is the precise estimation of corrosion rates and the second is testing of these corrosion rates with standard probability distributions. The method outlined in Khan and Howard (2007) has been used to compute the corrosion rates from the available wall loss data. The collected data is first analyzed to identify uniform or localized degradation. In the case of uniform degradation, time dependent regression analysis and in the case of localized degradation, the extreme value analysis has been carried out for estimating the rates of degradation. The HSE UK (2002) guideline for use of statistics for the analysis of corrosion inspection sample has also been referred for general guidance to estimate the corrosion rates using extreme value analysis.

In the regression analysis, regressor variable considered is the period of exposure (T) of each system and the response variable is the loss of wall thickness (Y) over such duration. The inspected data is then regressed to get the degradation rate, k which is represented by the slope of the regression line, $Y = kT + C$, where C is referred as the wall thickness loss $(C = 0)$ at the start of service, i. e., at $(T = 0)$.

Corrosion rates for localized material degradation were estimated using an extreme value model (Khan and Howard, 2007; Melchers, 2005). In constructing an extreme value distribution, an underlying random variable, corrosion rate, with a particular distribution is necessary (Halder and Mahadevan, 2000). If different set of samples are obtained through inspection, one can select the extreme values from each sample set and then construct a distribution for the extreme value analysis. The extreme value equations are summarized in Table 4.7, the detailed mathematical aspects of distributions can be found in Gumbel (1958).

Table 4.6. Wall Loss Data for Pipes of Subsystem 6 (mm)

1997	2000	2001	2002
0	0	0	0
0	0	0.1	0
0.1	0	0.1	0
0.1	0	0.1	0
0.1	0	0.1	0
0.2	0	0.1	0.1

0.4	0.1	0.1	0.2
	0.1	0.3	0.3
	0.1	0.5	0.6
	0.1	0.6	0.7
	0.1	0.6	0.7
	0.1	0.6	1.5
	0.1	0.7	
	0.3	0.7	
	0.3	1.2	
	0.4		
	0.4		
	0.4		
	0.4		
	0.5		
	0.5		
	0.5		
	0.5		
	0.6		
	0.7		
	0.8		
	1.5		
	1.5		
	1.7		

	1.7		
	1.7		

Table 4.7. Extreme Value Distributions (Gumbel distribution)

Maximum value	Minimum value
$f(y) = \frac{1}{\alpha}\exp[-y - \exp(-y)]$ $F(y) = \exp[-\exp(-y)]$ Where $y = \frac{x-\lambda}{\alpha}$; $\alpha > 0$	$f^{-1}(y) = \frac{1}{\alpha}\exp[y - \exp(y)]$ $F^{-1}(y) = 1 - \exp[-\exp(y)]$ Where $y = \frac{x-\lambda}{\alpha}$; $\alpha > 0$

where, x is wall loss or pit depth, λ is location parameter, and α is scale parameter.

The Gumbel distribution is widely used for extreme value analysis including the localized corrosion and stress corrosion crack inspection data analysis (HSE UK, 2002; Kowaka, 1994; Melchers, 2005). Once y is known, the representative location parameter (λ) and scale parameter (α) may be estimated by plotting function of F(y) versus x. Using these values statistical corrosion parameters may be estimated (Khan and Howard, 2007) as:

Mean wall loss $= \alpha + \gamma\lambda$, where γ is Euler's constant and has a value of = 0.5772.

Standard deviation = $\frac{\Pi}{\sqrt{6}}\alpha$, Median wall loss = $\lambda - \alpha \ln(\ln(2))$ and Most likely loss = λ

The degradation rate for localized corrosion may be expressed either by linear, power law, or logarithmic extreme value models (Kowaka, 1994) as:

Linear model: $\mathrm{x} - \mathrm{x}_0 = \mathrm{k}(\mathrm{T} - \mathrm{T}_i)$

Power law model: $x - x_0 = k(T - T_i)^n$

Logarithmic law model: $x - x_0 = k.\log(T - T_i)$

where, x_0 is the threshold depth of degradation (i.e., pit depth) at incubation time T_i, x is measured depth at time T and k is degradation rate. Depths exceeding x_0 would grow, whereas depths lower than x_0 may fail to grow with exposure period.

4.7.3 Procedure and Illustration

The annual wall losses were plotted using the simple regression method for uniform corrosion and the extreme value distribution for localized and erosion corrosion data. For illustration purposes, the straight pipe inspection data of subsystem 6 of the GE lines (i.e., pitting corrosion) has been presented in this section. The sample extreme value probability plot which is obtained by plotting the ordered wall loss versus the cumulative probability, i.e., $(-\ln(-\ln(f(wall\ loss)))$ for the year 2001, for straight pipe is shown in Figure 4.8. Similarly, the data can be plotted for the years 1997, 2001 and 2002. The observation of a good linear fit, suggested the appropriateness of choosing extreme value distributions for such data. These plots can then be used to estimate the location and scale parameters, mean, median and most likely wall losses and the yearly wall loss corresponding to 95% confidence intervals. The cumulative exposure times and the corresponding wall loss values for the 95% confidence interval is used for the estimation of corrosion rates.

The predicted wall losses corresponding to the confidence intervals of 0.95 over several inspection years were then plotted against the cumulative exposure times to estimate the actual corrosion rate of components either by linear or power law model. The sample corrosion rate plot for straight pipes of subsystem 6 (GE) is shown in Figure 4.9.

The estimated corrosion rate data has been tested with probability distribution models like, Normal, Lognormal, 3P-Lognormal, Weibull, 3P-Weibull, Exponential, 2P-Exponential and Type 1 Extreme Value using Minitab. The goodness of fit test has been performed using the A-D statistics and the best fit is reported as the one with smallest A-D statistic. The tested models with their A-D test statistics are summarized in Table 4.8.

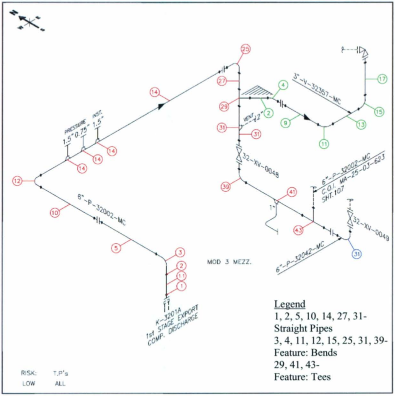


Fig.4.7. Sample Subsystem 6 (of Gas Export Lines) Isometric Drawing

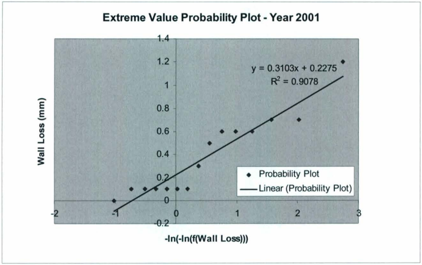


Fig. 4.8. Sample Extreme Value Probability Plot (Year: 2001) for Pipes of Subsystem 6

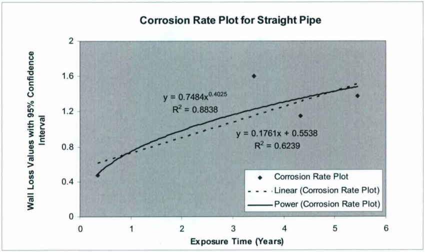


Fig. 4.9. Sample Corrosion Rate (PC) Plots for Straight Pipes of Subsystem 6 (GE)

Table 4.8. Summary of Probabilistic Corrosion Prior Modeling for Case Study NDT Data

Type of Feature	Standard Probability Distributions	Uniform Corrosion			Pitting Corrosion			Erosion Corrosion		
		A-D test Parameter	Sample Mean	Standard Error	A-D test Parameter	Sample Mean	Standard Error	A-D test Parameter	Sample Mean	Standard Error
Pipes	Normal	3.816	0.3280	0.1608	2.627	0.9472	0.1682	4.832	0.2080	0.0685
	Lognormal	3.061	0.3106	0.2038	2.958	1.1048	0.4177	4.886	0.2386	0.1501
	Exponential	4.092	0.3280	0.1160	2.973	0.9472	0.3157	4.828	0.2080	0.1040
	Weibull	3.214	0.3168	0.1572	2.824	0.9335	0.1809	4.869	0.2066	0.0759
	Extreme Value	3.745	0.2785	0.2341	2.603	0.9546	0.1718	4.826	0.2086	0.0744
	3P-Weibull	2.961	0.3420	0.2330	2.603	0.9561	0.1705	4.826	0.2087	0.0742
	3P- Lognormal	3.033	1.2907	2.2777	2.626	0.9497	0.1686	4.833	0.2080	0.0685
	2P-Exponential	5.054	0.3280	0.1085	3.242	0.9472	0.2898	5.485	0.2080	0.0902
Bends	Normal	3.651	0.4112	0.1682	2.980	0.1373	0.0243	5.056	2.1169	0.5171
	Lognormal	2.896	0.4325	0.2585	3.087	0.1429	0.0374	5.038	2.1315	0.6111
	Exponential	3.316	0.4112	0.1454	3.269	0.1373	0.0485	5.053	2.1169	1.0585
	Weibull	3.023	0.4077	0.1727	3.055	0.1372	0.0241	5.057	2.1305	0.5030
	Extreme Value	3.682	0.3715	0.2332	2.964	0.1382	0.0253	5.059	2.1296	0.5586
	3P-Weibull	2.911	0.4418	0.2647	2.964	0.1382	0.0253	4.944	2.2331	1.0759
	3P- Lognormal	3.051	2.0465	3.5906	2.980	0.1373	0.0243	4.910	4.4472	7.0987
	2P-Exponential	3.986	0.4112	0.1356	3.372	0.1373	0.0361	5.530	2.1169	0.5599
Tees	Normal	3.487	0.3582	0.1247	3.612	0.6710	0.1811	4.959	1.5237	0.8036
	Lognormal	3.297	0.3991	0.2371	3.795	0.8025	0.4482	4.797	1.5372	1.0645
	Exponential	3.381	0.3582	0.1354	3.709	0.6710	0.2739	4.835	1.5237	0.7618
	Weibull	3.345	0.3581	0.1403	3.749	0.6652	0.2046	4.814	1.5200	0.8017
	Extreme Value	3.435	0.3424	0.1567	3.594	0.6536	0.2157	5.001	1.3931	1.1069
	3P-Weibull	3.256	0.3977	0.2480	3.975	0.7451	0.4336	4.779	1.7816	1.7819
	3P- Lognormal	3.320	1.9640	3.7715	3.623	0.6710	0.1814	4.830	9.2579	27.4754
	2P-Exponential	4.115	0.3582	0.1224	4.225	0.6710	0.2492	5.734	1.5237	0.6378

4.7.4 Case Study Results

The statistical reliability tests have been performed for the estimation of degradation rates for the data extracted from an oil and gas production facility (offshore, North Sea). The summary of uniform corrosion, pitting corrosion and erosion corrosion prior validation has shown in Table 4.9. For uniform corrosion, the representative straight pipes of the gas condensate system; for pitting corrosion, the bends of gas export system; and for erosion corrosion, the tees of the HP drilling mud system are presented. The column 3 shows the results from first part using data from literature; and column 4 shows the results from case study. Identical observations prove that the selected priors from literature and case study are the best to model the various corrosion degradation mechanisms under consideration.

Table 4.9. Summary of the Study and Validation

Type of Corrosion	Systems or Component	Most Relevant Distributions	
		From Literature Study	From Case Study
Uniform Corrosion	Straight Pipes	3P-Weibull, 3P-Lognormal	3P-Weibull, 3P-Lognormal
Pitting Corrosion	Feature-Bends	Type 1 Extreme Value, 3P-Weibull	Type 1 Extreme Value and 3P-Weibull
Erosion Corrosion	Feature-Tees	3P-Weibull, 3P-Lognormal, Type 1 Extreme Value,	3P-Weibull, Lognormal, or Type 1 Extreme Value

4.8 SUMMARY AND CONCLUSIONS

In risk based integrity assessments, the uncertainty in the material degradations is modeled using prior distributions, which are subsequently updated to a posterior distribution using Bayes theorem and actual inspection data. This updated distribution is useful in assessing the potential risk to installations. The life threatening structural degradations observed are several types of metal corrosion and cracking. The major corrosion mechanisms include uniform corrosion, pitting corrosion and erosion corrosion. Therefore, the selection and validation of the prior models for each type of corrosion is inevitable in the integrity assessment of assets.

The first part of this paper discussed the development of an RBIM framework and the selection of probabilistic prior distributions for various corrosion degradation mechanisms. Several statistical tests were conducted based on the data extracted from literature to check which of the prior distributions best describes the data. The relative accuracy of such fits is tested using probability plots and A-D tests, and the underlying parameters are estimated using the method of least squares and maximum likelihood estimates.

The second part of this paper dealt with the validation of the selected priors through a case study, using life inspection data associated with the operation of an oil and gas production facility, operating in the North Sea. For uniform corrosion, the regression analysis and, for localized pitting or erosion corrosion, the extreme value analysis has been used for estimating the corrosion rates.

A summary of the results is presented in Table 4.9. It is concluded that the most appropriate prior distributions that can be used to describe uniform corrosion are 3P-Weibull and 3P-Lognormal distributions; the pitting corrosion priors is best modeled using Type1 Extreme Value and 3P-Weibull and, the erosion corrosion using 3P-Weibull, 3P-Lognormal or Type 1 Extreme Value distributions.

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CHAPTER V

THE DEVELOPMENT OF POSTERIOR PROBABILITY MODELS IN RISK BASED INTEGRITY MODELING

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PREFACE

This paper presents the development of Bayesian posterior probability models for the identified degradation processes. The prior and likelihood models for the critical structural degradation processes obtained in Chapter IV are observed to be non-conjugate pairs. Thus, their Bayesian posterior estimation cannot be performed in closed form. One of the main challenges of Bayesian analysis, i.e., the posterior estimation of non-conjugate pairs is addressed in this Chapter. This work is published in the Journal of Risk Analysis (2010), 30(3): 400-420.

The potential asset integrity threats are identified by the principal author; the data have had large uncertainty and variability. It has been suggested by the co-authors that the Bayes theorem may be employed to model the uncertainty and to predict the future degradation. The prior model is based on generic data and the likelihood is based on field NDT data from an ageing process component as discussed in Chapter IV. The principal author conducted extensive literature review to identify the best suitable methods to develop the Bayesian posteriors of non-conjugate pairs. The simulation based Metropolis-Hastings (M-H) algorithm and the analytical Laplace approximation methods are identified by the principal author as the best suitable methods for posterior estimation. The M-H algorithm is a rejection sampling based algorithm, which is used to generate a sequence of Markov chain Monte Carlo (McMC) that is difficult sample directly. This sequence is used to approximate the posterior distribution. The ability to generate the posterior samples without actually knowing the normalizing factor is a major virtue of this algorithm. The Laplace method is used for approximating the parameters of the posteriors when direct estimations are difficult and if a normal approximation is reasonable. The basic idea is to carry out a Taylor series expansion around the maximum likelihood estimate value (i.e., mode), ignore the negligible terms and normalize. The principal author investigated the theory behind M-H algorithm and the Laplace approximation, and programmed these two methods in Matlab software, and demonstrated the use for developing the posteriors of non-conjugate degradation priors.

The known conjugate posterior estimates are used to validate the Matlab code. The conjugate parameter estimates are used as true values. The Normal-Normal, Gamma-Poisson, Gamma-Gamma and Gamma-Normal combinations are tested. The Laplace approximation functions for each combination are derived by the principal author and are presented in Appendix. For developing the posteriors of degradations in process facilities, the M-H algorithm is recommended. Since the posterior models are based on real-life NDT data, they provide more reliable and accurate predictions for the future degradations of components in offshore process facilities. The principal author prepared the initial draft of this manuscript, which was later consecutively revised and improved based on comments from the co-authors.

ABSTRACT

There is a need for accurate modeling of mechanisms causing material degradation of equipment in process installation, to ensure safety and reliability of the equipment. Degradation mechanisms are stochastic processes. They can be best described using risk based approaches. Risk based integrity assessment quantifies the level of risk to which the individual components are subjected and provides means to mitigate them in a safe and cost effective manner. The uncertainty and variability in structural degradations can be best modeled by probability distributions. Prior probability models provide initial description of the degradation mechanisms. As more inspection data become available, these prior probability models can be revised to obtain posterior probability models which represent the current system and can be used to predict future failures. In this paper, a rejection sampling based Metropolis-Hastings (M-H) algorithm is used to develop posterior distributions. The M-H algorithm is a Markov chain Monte Carlo algorithm used to generate a sequence of posterior samples without actually knowing the normalizing constant. Ignoring the transient samples in the generated Markov chain, the steady state samples are rejected or accepted based on an acceptance criterion. To validate the estimated parameters of posterior models, analytical Laplace approximation method is used to compute the integrals involved in the posterior function. Results of the M-H algorithm and Laplace approximations are compared with conjugate pair estimations of known prior and likelihood combinations. The M-H algorithm provides better results and hence it is used for posterior development of the selected priors for corrosion and cracking.

Keywords: Asset integrity, corrosion, cracking, prior, Bayes theorem, posterior

5.1 INTRODUCTION

Asset integrity management of process installation equipments is a burgeoning area of research. Research has been focused on the study of damage mechanisms, failure occurrences, and developing models for failure prediction. The major causes of asset failures can be generally classified into (Stephens et al., 1995): third party damage, environmentally induced defects, material and fabrication defects, and operational errors. Third party damage includes mechanical damage and ground movement. Environmental effects cause corrosion and cracking. Surface and weld defect result from bad manufacturing practices. Operational errors result from components failure and human factors. The major share of process components and pipelines failure are attributed to environmentally induced defects such as corrosion and cracking (Khan et al., 2006; Straub, 2004; Kallen, 2002).

Leaks are the principal cause of hydrocarbon release, fire and explosions in process installations. Studies indicate that corrosion is the principal cause of about 15% of leakage occurrences (HSE UK, 2002). In nine and half years, 44.70% of the mechanical failures leading to hydrocarbon release from offshore facilities in the UK were due to corrosion or other related degradations (HSR UK, 2003). The direct annual cost of corrosion in the USA is assessed to be 276 billion USD, which represents 3.1% of the GNP, while about 121 billion USD is spent on corrosion control (Koch et al., 2001). In Canada, the environmentally induced defects, such as metal corrosion, stress corrosion cracking, hydrogen induced cracking etc. has caused for 40% of the natural gas pipelines failures and 38% of hazardous liquid releases (Stephens et al., 1995). It is reported that corrosion accounts for 21% of failures in submarine gas pipelines, and erosion-corrosion modes account for 24.6% of pipe leakages in process plants (Googan and

Ashworth, 1990). Moreover, 40% of the accidental hydrocarbon releases to the environment are corrosion related. Therefore, the investigation and mitigation of corrosion and cracking, and its effects is one of the main actions required to reduce the frequency of hydrocarbon releases, to maximize the production, and to improve the safety of the operations.

Usually, inspections are carried out for internal as well as external corrosion and cracking by means of non-destructive tests (NDT) to estimate the loss of wall thickness and detect the cracking. Although a few probabilistic methods are available to predict plant life, these have been applied in a few isolated cases. Better integrity inspection planning and maintenance optimization needs a reliable and adaptable prediction of degradation mechanisms and rates. This can be achieved by combining the statistical techniques within the risk assessment and decision making framework. This paper presents a methodology for risk based integrity modeling (RBIM) and the development of posterior probabilistic models for structural degradations. The prior models are taken from available literature dealing with assets from different industries (Thodi et al., 2009). The posterior models are developed for the selected priors using the simulation based Metropolis-Hastings (M-H) algorithm and analytical Laplace approximations. The conjugate prior-posterior parameters are used to calibrate the Matlab code. This study summarizes the development of posterior models for identified degradations in order to estimate the probability of failure in risk based integrity modeling (RBIM).

5.2 RISK BASED INTEGRITY MODELING

Risk is the product of the probability of failure and its consequence. Therefore, the major tasks in risk based asset integrity modeling are the estimation of the probability of structural failure (PoF) and the consequence of this failure (CoF). The probability of failure is estimated using stochastic modeling of all identified degradations, such as corrosion and cracking. The consequence analysis estimates the consequence of failure in terms of the costs of failure, preventive repair or replacement, and implementing the proposed inspection and maintenance plan. The developed stochastic probability of failure and consequence of failure models will be tested and validated using case studies of an ageing process facility operating in the North Sea.

An overall framework for the RBIM is proposed in Figure 5.1. The framework consists of the following tasks: identification of potential degradation mechanisms, development of most appropriate prior and likelihood models, development of posterior probability models and the analysis of consequences, determine inspection and maintenance intervals which optimize the risk and finally, testing and validation of the models. In the overall framework, the development of posterior probability model using the M-H algorithm and Laplace approximation is discussed in this paper. For real life applications, the expert's initial knowledge will form the prior models. Subsequently it will be updated using the ageing data (field NDT, as likelihood probability model) to obtain the posteriors, which describe the dynamic model of the current system. These posterior models describe the degradation processes accurately and hence posses better predictive capabilities of future failures.

5.3 ASSET INTEGRITY THREATS

The review of published literature (Khan et al., 2006; Straub, 2004; Kallen, 2002; Stephens et al., 1995) indicates that the most critical environmentally-induced degradation mechanisms threatening the integrity of assets are various types of internal/external corrosion and cracking. Corrosion includes uniform corrosion (UC), localized or pitting corrosion (PC), and erosion corrosion (EC). Cracking includes stress corrosion cracking (SCC), corrosion fatigue cracking

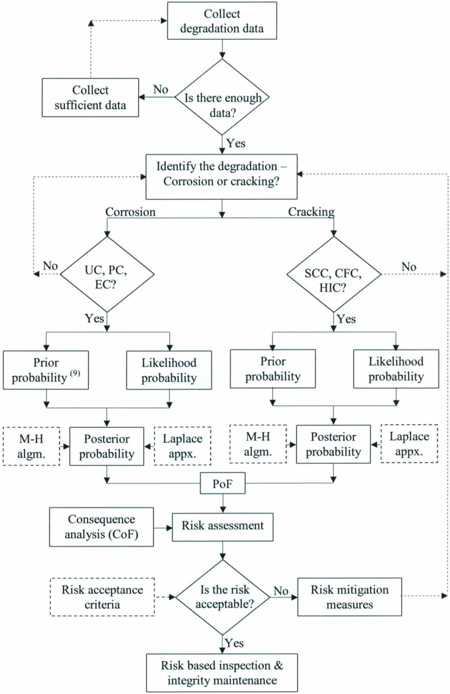

Fig. 5.1. Framework for Risk based Integrity Modeling

(CFC) and hydrogen induced cracking (HIC). Corrosion is the loss of material as a result of destructive chemical reaction between a metal or metal alloy and its environment (Jones, 1996).

Uniform corrosion is the uniform and regular removal of metals from the surface, which results in thinning of wall thickness leading to leaks and breakage. The localized attack of corrosive environment on an otherwise resistant surface produces pitting corrosion (Jones, 1996). The combination of a corrosive fluid and a high flow velocity results in material wear-out, leading to erosion type corrosion. The brittle fracture of a normally ductile alloy in the presence of an environment or cyclic loading is known as environmentally-induced cracking (Jones, 1996). The stress corrosion cracking occurs in metals or alloys with static tensile stress in the presence of specific corrosive environmental condition. The corrosion fatigue cracking occurs under cyclic stresses in a corrosive environment. Hydrogen induced cracking is caused by hydrogen diffusing into the alloy lattice when the hydrogen evolution reaction produces atomic hydrogen at the surface during corrosion, electroplating, cleaning and cathodic protection (Jones, 1996).

5.4 BAYES' THEOREM

Bayes theorem is one of the best suitable methods for logical and consistent reasoning. Probability is a degree of belief, that is, how much one thinks that something is true based on the evidence at hand. In the face of uncertainty in degradations, one can make the best inference based on the inspection data and any prior knowledge that one might have, reserving the right to revise the present knowledge if new information comes to light. Bayes theorem encapsulates this process of learning as more evidence becomes available.

Bayes' theorem states how to update the prior probability distribution, $p(\theta)$ with a likelihood function, $p(y/\theta)$ mathematically, to obtain the posterior distribution as:

$$p(\theta / y) = \frac{p(\theta)p(y/\theta)}{\int p(\theta)p(y/\theta)d\theta} \tag{1}$$

The posterior density $p(\theta / y)$ summarizes the total information, after viewing the data and provides a basis for inference regarding the parameter, θ (Leonard and Hsu, 1999). Denominator of (1), i.e., $\int p(\theta)p(y/\theta)d\theta$ is known as the normalizing factor, the estimation of which is a daunting task in Bayesian analysis.

5.5 PRIOR PROBABILITY MODELING

A prior probability refers to the initial belief of something to be true. In the case of asset degradation, the prior refers to the initial knowledge about each type of degradation mechanisms. Although the choice of a prior is often subjective, a rational agreement can be achieved by analyzing historic data from the same or other similar installations. [9] To develop the prior probability models for different corrosion and cracking degradations, several probability distributions have been tested using the data extracted from the relevant literature. Details of the literature and statistical test for estimating the priors are presented elsewhere. [9] A set of sample prior models, which are the initial knowledge based on judgmental studies, used to describe corrosion and cracking degradations are presented in Table 5.1.

5.6 LIKELIHOOD PROBABILITY MODELING

The inspection data obtained from an ageing offshore process facility has been used to estimate the likelihood probability of different types of corrosion degradation. The facility has different systems: a Gas Condensate system (GC), a Gas Export system (GE), and a high pressure

Table 5.1. Sample Prior Probability Models and the Estimated Parameters

Structural Degradation	Prior Probability Models and their Parameters				Sources of Data (12-17)
	Type of Model	Shape	Scale	Location	
UC	3P Weibull	1.7860	0.1062	0.0079	Anghel and Lazar (2005)
	3P Lognormal	-1.6500	0.2722	-0.0965	
PC	Type 1 Ext. Value	2.086	0.6821	-	Melchers (2005)
	3P Lognormal	6.3010	0.0016	-543.40	
EC	3P Weibull	4.5970	0.0545	-0.0075	Vinod et al. (2003)
	Type 1 Ext. Value	0.0482	0.0109	-	
SCC	Weibull	2.7070	2.6790	-	Shibata (2007)
	Type 1 Ext. Value	2.8520	0.8260	-	
CFC	Weibull	2.2550	2.5080	-	Robert and Harlow (2005)
	Lognormal	0.6192	0.7663	-	
HIC	Weibull	1.8750	18.130	-	Dell (1973)
	Lognormal	2.4830	1.2330	-	

Drilling Mud system (DM). Each system exhibited a different degradation mechanism. The Gas Condensate system exhibited uniform corrosion degradation. The Gas Export system exhibited localized or pitting corrosion. The Drilling Mud system suffered erosion corrosion degradation. The data collected from each of these systems were used to update the relevant model. The data includes the minimum and average wall thicknesses acquired during the period 1997-2003. Since no such data has been available for cracking, data from literature has been used instead.

5.6.1 Estimation of Corrosion Rate

The inspection data, which consists of wall loss measurements, has been divided into two groups, namely; straight pipes and features (both corrosion coated). The features include bends, tees, reducers, flanges and valves. [18] Three major components: straight pipes, bends and tees were considered in the analysis. The data is first analyzed to identify uniform or localized degradation. A time dependent regression analysis was used to analyze uniform degradation data, while the extreme value analysis was used to analyze localized degradation data.

Mathematical details of the analysis may be obtained from elsewhere (Thodi et al., 2009; Khan and Howard, 2007).

5.6.2 Probabilistic Model Testing

The system corrosion rate data has been tested with same probability distribution models as in the case of prior modeling. A goodness of fit test has been performed using the probability plot and Anderson-Darling (A-D) test, details of the testing and plots may be obtained from elsewhere (Thodi et al., 2009). A set of sample likelihood probability models and its parameters for each type of corrosion and cracking are reported in Table 5.2.

Table 5.2 Sample Likelihood Probability Models and the Estimated Parameters

Structural Degradation	Likelihood Probability Models and their Parameters				Sources of Data [19-21]
	Model	Shape	Scale	Location	
UC	3P Weibull	0.6863	0.2401	0.0062	GC system-Pipe's
	3P Lognormal	-1.937	1.2450	-0.0103	
PC	Type 1 Ext. Value	0.6604	0.5730	-	GE system-Bend's
	3P Lognormal	-1.672	1.1750	-0.0061	
EC	3P Weibull	0.9551	1.3400	-0.1281	DM system-Tee's
	Type 1 Ext. Value	2.0990	1.7760	-	
SCC	Weibull	0.8288	9.9507	-	Engelhardt et al. (2003)
	Type 1 Ext. Value	0.8331	0.0806	-	
CFC	Weibull	0.0015	0.2907	-	Sankaran et al. (2001)
	Lognormal	-8.2964	3.6164	-	
HIC	Weibull	0.0087	0.9359	-	Woodtli & Kieselbach (2000)
	Lognormal	-5.2798	1.0654	-	

The statistical reliability tests have been performed for the estimation of priors and likelihoods of different corrosion and cracking degradation mechanisms. From Table 5.1 and 5.2, it has been observed that the priors and likelihoods are identical distributions; therefore, one can say that the likelihood supports the prior and that makes the estimation of posteriors of degradation easy. Furthermore, it supports the assumption that the posteriors yield the same form of distributions as that of priors and likelihoods.

5.7 POSTERIOR PROBABILITY MODEL DEVELOPMENT

There are four methods for computing the posterior distributions using the known prior and likelihood functions. They include (Ghosh et al., 2006): analytical approximations, such as numerical integration techniques and Laplace approximations; data augmentation methods; Monte Carlo direct sampling and McMC (Markov chain Monte Carlo) methods, such as M-H algorithm and Gibb's sampling. If the problem under consideration does not involve a conjugate prior-likelihood pair, the posterior parameter estimation can not be performed in closed form; analytical approximation or Monte Carlo methods are needed (Tierney and Kadane, 1986). In the present study, the developed prior and likelihood for degradations, like Weibull, Lognormal (with two and three parameters) and Type 1 Extreme Value do not lend themselves easily to Bayesian updating. The main problem is that there is no distribution class on the parameters that is preserved under Bayesian updating (Bedford and Cooke, 2001). This means that simulation methods are the best ways to determine the posterior distributions of such prior models. The use of M-H algorithm in conjunction with a particular choice of prior has been suggested (Bedford and Cooke, 2001; Robert and Casella, 1999). In the present study, the M-H algorithm has been studied. In order to compare the results of the M-H algorithm, an analytical Laplace approximation method has also been used. By comparing the results of both the estimations against the values obtained from known conjugate pairs, the best suitable posterior development method has been concluded.

5.7.1 Metropolis – Hastings (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 (Metropolis et al., 1953; Hastings, 1970). This sequence is used in McMC simulations to approximate a distribution or to compute an integral. In Bayesian applications, the normalizing factor is often extremely difficult to compute, so the ability to generate the posterior samples without actually knowing this constant of proportionality is a major virtue of this algorithm (Berg, 2004). The McMC methods are extensively used in statistics to simulate complex, non-standard multivariate posterior distributions (Chib and Greenberg, 1995).

The algorithm generates a Markov chain in which each state x^{t+1} depends only on the previous sample state x^t. The algorithm uses a proposal density $q(x',x^t)$, which depends on the current state x^t, to generate the new proposed sample x'. The proposal is accepted as the next value $(x^{t+1} = x')$ if $\alpha(x',x^t)$ drawn from a uniform distribution, $u(0,1)$ is:

$$\alpha(x',x^t) < \frac{p(x').q(x^t,x')}{p(x^t).q(x',x^t)} \qquad (2)$$

If the proposal is not accepted, then the current value of x is retained; i.e., $x^{t+1} = x^t$. The proposal density may be a multivariate Gaussian distribution centered around the current state x^t; $q(x',x^t) \sim N(x^t,\sigma^2)$, where, $q(x',x^t)$ is the probability density function for x' given the previous value x^t. This proposed density would generate samples centered around the current state with variance, σ^2. The acceptance of such generated samples will be based on equation (2). Theoretical background of the M-H algorithm (Chib and Greenberg, 1995) has been summarized in the next section.

Theory behind the M-H Algorithm

A proposal density $q(x',x^t)$ is assumed, where $\int q(x',x^t)dx^t = 1$. It is assumed that the density is to be depending only on the current state of process, since dealing with Markov chains. This value is to be interpreted as saying that when a process is at the point x^t, the density generates a value x' from $q(x',x^t)$. For that to happen, $q(x',x^t)$ should satisfy reversibility condition (Chib and Greenberg, 1995). But mostly, it will not; one might find for example, that for some (x',x^t):

$$p(x^t).q(x',x^t) > p(x').q(x^t,x') \tag{3}$$

In this case, the process moves from x^t to x' too often and from x' to x^t too rarely. A convenient way to correct this condition is to reduce the number of moves from x^t to x' by introducing a probability $\alpha(x',x^t) < 1$, that the move is made. The $\alpha(x',x^t)$ is known as the probability of move. If the move is not made, the process again returns x^t as a value from the target distribution. Thus, the transition from x^t to x' are made according to $p_{MH}(x',x^t) = q(x',x^t)\alpha(x',x^t), \qquad x' \neq x^t$, where the probability of move, $\alpha(x',x^t)$ is yet to be determined. From (3), it is obvious that the movement from x' to x^t is not made often. One should therefore, define $\alpha(x^t,x')$ to be as large as possible and, since it is a probability its upper limit is 1. But now, the probability of move $\alpha(x',x^t)$ is determined by requiring that $p_{MH}(x',x^t)$ satisfies the reversibility condition, because then (Chib and Greenberg, 1995):

$$\begin{aligned} p(x^t)q(x',x^t)\alpha(x',x^t) &= p(x')q(x^t,x')\alpha(x^t,x') \\ &= p(x')q(x^t,x') \end{aligned} \tag{4}$$

Therefore, $\alpha(x',x^t) = \dfrac{p(x')q(x^t,x')}{p(x^t)q(x',x^t)}$ (5)

where, $\alpha(x^t,x')$ is set as 1 (the upper limit). If the inequality in (3) is reversed, we set $\alpha(x',x^t)=1$, and derive the $\alpha(x^t,x')$ as above. The probabilities $\alpha(x',x^t)$ and $\alpha(x^t,x')$ are introduced to ensure that the two sides of (3) are in balance or, in other words, $p_{MH}(x',x^t)$ satisfies the reversibility. Thus, in order for $p_{MH}(x',x^t)$ to be reversible, the probability of move must be set to:

$$\begin{aligned}\alpha(x',x^t) &= \min\left[\frac{p(x')q(x^t,x')}{p(x^t)q(x',x^t)},1\right], \quad p(x^t)q(x',x^t)>0 \\ &=1 \qquad\qquad\qquad\qquad\qquad \text{otherwise.}\end{aligned} \tag{6}$$

The M-H algorithm is specified by its proposal density, $q(x',x^t)$ (Chib and Greenberg, 1995). If a candidate value is rejected, the current value is taken as the next item in the sampling sequence. The calculation of $\alpha(x',x^t)$ does not require the knowledge of normalizing constant of $p(.)$ because it appears both in numerator and denominator. If the proposal density is symmetric, i. e., $q(x',x^t)=q(x^t,x')$, then the probability of move $\alpha(x',x^t)$ reduces to $p(x')/p(x^t)$, hence, if $p(x')>p(x^t)$, the chain moves to x'; otherwise it moves with probability given by $p(x')/p(x^t)$. In this study, the M-H algorithm has been implemented in Matlab software. The algorithm implementation details can be obtained from elsewhere (Makowski and Wallach, 2007; Makowski et al., 2002; Robert and Casella, 1999; Chib and Greenberg, 1995; Tierney, 1994).

5.7.2 Laplace Approximation

Laplace method (Laplace, 1986) is used for approximating the parameters of the posterior densities that is useful in Bayesian applications when direct estimations are difficult. The Laplace approximation is very handy tool when a normal approximation posterior is reasonable and can be especially useful in higher dimensions when other methods fail (Gill, 2002). The basic idea is to carry out a Taylor series expansion around the maximum likelihood estimate value (i.e., mode), ignore the negligible terms, and normalize. The derivation of the approximation in one dimension is simple and it starts with a posterior density of interest calculated by the likelihood times the specified prior:

$$p(\theta / y) \text{ is proportional to } p(\theta)L(y/\theta) \tag{7}$$

where, $p(\theta)$ is the prior, $L(y/\theta)$ is the conditional likelihood function and, $p(\theta / y)$ is the posterior. It is assumed that this distributional form is nonnegative, integrable, and single peaked about the distribution mode θ. The standard reference for approximating the Bayesian posteriors with Laplace method (Tierney and Kadane, 1986) and theoretical details on the accuracy of the approximation has been reported (Wong and Li, 1992; Kass, 1992). Furthermore, it was showed that how the Laplace approximation can be a handy tool for calculating the parameters of the Bayesian posteriors (Ghosh et al., 2006; Tanner, 1996; Kass, 1993; Tierney et al., 1989 a and b; Tierney and Kadane, 1986).

Theory behind the Laplace Approximation

A computable approximation for the posterior mean and variance of a smooth function of the parameter that is nonzero on the interior of the parameter space is introduced (Tierney and Kadane, 1986). Let $g(\theta)$ be a smooth, positive function on the parameter space, with a maximum at $\hat{\theta}$. The posterior mean of $g(\theta)$ can be written as: [23]

$$\bar{\mu} = E[g(\theta)/y] = \frac{\int g(\theta).e^{-nh(\theta)}d\theta}{\int e^{-nh(\theta)}d\theta} \tag{8}$$

where, $e^{-nh(\theta)} = p(\theta).L(y/\theta)$. It is a common practice to approximate the denominator integral by an approximating normal curve centered at the posterior mode and having variance equal to minus the inverse of the second derivative of the log posterior density at its mode. It will produce reasonable results as long as the posterior is dominated by a single mode (Tierney and Kadane, 1986; Tanner, 1996). Bayesian posterior analysis requires the evaluation of integrals of the form, as shown in (8):

$$I = \int g(\theta).e^{-nh(\theta)}d\theta \tag{9}$$

where, g and $-h$ are smooth functions of θ, with $-h$ having a unique maximum at $\hat{\theta}$. In Bayesian applications, $-nh(\theta)$ may be the log-likelihood function or logarithm of the un-normalized posterior density $p(\theta).L(y/\theta)$ and $\hat{\theta}$ may be the maximum likelihood estimate. If $g(\theta)$ has a unique sharp maximum at $\hat{\theta}$, then most contribution to the integral I comes from the integral over a small neighborhood $(\hat{\theta}-\delta, \hat{\theta}+\delta)$ of $\hat{\theta}$ (Ghosh et al., 2006).

As $n \to \infty$, we have, $I \approx I_1 = \int_{\hat{\theta}-\delta}^{\hat{\theta}+\delta} g(\theta).e^{-nh(\theta)}d\theta$ (10)

Laplace method involves Taylor series expansion of g and h about $\hat{\theta}$, which gives, [22]

$$I_1 \sim \int_{\hat\theta-\delta}^{\hat\theta+\delta} \left[g(\hat\theta) + (\theta-\hat\theta)g'(\hat\theta) + \frac{1}{2}(\theta-\hat\theta)^2 g''(\hat\theta) + smaller\ terms \right] \times$$
$$\ldots.\exp\left[-\{nh(\hat\theta) + n(\theta-\hat\theta).h'(\hat\theta) + \frac{n}{2}(\theta-\hat\theta)^2.h''(\hat\theta) + smaller\ terms\} \right]$$

$$I_1 \sim e^{-nh(\hat\theta)} g(\hat\theta) \int_{\hat\theta-\delta}^{\hat\theta+\delta} \left[1 + (\theta-\hat\theta)g'(\hat\theta)/g(\hat\theta) + \frac{1}{2}(\theta-\hat\theta)^2.g''(\hat\theta)/g(\hat\theta) \right] \tag{11}$$
$$\times \exp\left[-\frac{n}{2}(\theta-\hat\theta)^2 h''(\hat\theta) \right] d\theta$$

Assuming that $c = h''(\hat\theta)$ is positive and, using a change of variable, $t = \sqrt{nc}(\theta-\hat\theta)$, [22]

$$I \sim e^{-nh(\hat\theta)} g(\hat\theta) \frac{1}{\sqrt{nc}} \int_{-\delta\sqrt{nc}}^{+\delta\sqrt{nc}} \left[1 + \frac{t}{\sqrt{nc}} g'(\hat\theta)/g(\hat\theta) + \frac{1}{2}\frac{t}{nc}^2 .g''(\hat\theta)/g(\hat\theta) \right] \times \exp\left[-\frac{t}{2}^2 \right] dt$$

$$I \sim e^{-nh(\hat\theta)} \frac{\sqrt{2\pi}}{\sqrt{nc}} g(\hat\theta) \left[1 + \frac{g''(\hat\theta)}{2ncg(\hat\theta)} \right]$$
$$= e^{-nh(\hat\theta)} \frac{\sqrt{2\pi}}{\sqrt{nc}} g(\hat\theta)[1 + O(n^{-1})] \tag{12}$$

There is an approximation for estimating the mean, $E[g(\theta)/y]$ (Tierney and Kadane, 1986):

First apply the Laplace method to the numerator of (8) with $g(\theta)$ positive, and,

$$-nh^*(\theta) = -nh(\theta) + \log(g(\theta)) \tag{13}$$

where θ^* is the mode of $-nh^*(\theta)$ and, $\sigma^{*2} = \left[\frac{\partial^2 - nh^*(\theta)}{\partial\theta^2} |_{\theta^*} \right]^{-1/2}$

Next, apply the Laplace method to the denominator of (8) with, $g(\theta) = 1$.

$$-nh(\hat\theta) = \log L(y/\theta) + \log(p(\theta)) \tag{14}$$

where $\hat\theta$ is the mode of $-nh(\theta)$ and, $\hat\sigma^2 = \left[\frac{\partial^2 - nh(\theta)}{\partial\theta^2} |_{\hat\theta} \right]^{-1/2}$.

Taking the ratio, the approximate mean may be obtained as (Tierney and Kadane, 1986; Tanner, 1996):

$$E[g(\theta)] = \bar{\mu} = \frac{\sigma *}{\sigma}\{\exp[-nh*(\theta*)]\}/\{\exp[-nh(\hat{\theta})]\} \tag{15}$$

The simplest way to obtain such an approximation for posterior variance is to set: [23]

$$V[g(\theta)] = \bar{\sigma}^2 = E[g(\theta)^2] - E[g(\theta)]^2 \tag{16}$$

One can use (15) to approximate the posterior means of $g(\theta)$ and $g(\theta)^2$ and then insert these values into a standard computational formula for variance (16). Further, it has been showed that the mean and variance has a relative error of (Tierney and Kadane, 1986):

$$E[g(\theta)/y] = E(\hat{g})[1 + O(n^{-1})] \text{ and} \tag{17}$$

$$V[g(\theta)/y] = V(\hat{g})[1 + O(n^{-2})]. \tag{18}$$

Computational requirements of this approach are minimal; one just needs to evaluate the first and second derivative and maximize both the integrands. Still, the resulting approximations are quite accurate. An intuitive explanation for this is given (Tierney and Kadane, 1986); if the function is bounded away from zero near the posterior mode, then the two integrands will be similar in shape. Thus, by applying the same approximation technique to the numerator and the denominator one will be making similar errors, and in taking ratio some portion of these errors will be cancelled. Detailed mathematical derivation of the Laplace approximation for estimating parameters of the posterior distributions of known conjugate pairs, such as normal-normal, gamma-gamma, gamma-normal and gamma-poison are included in Appendix 5.1.

5.7.3 Comparison with Conjugate Pairs

Both the M-H algorithm and Laplace approximation are coded in Matlab and used for developing the posteriors of the aforementioned degradation priors. The known conjugate prior-posterior values are used to validate the code. Inputs to the Matlab codes are the sampling size, the respective prior and likelihood parameters and the outputs are the estimated posterior parameters using the both methods. The natural conjugate pair of exponential family is extracted from literature (Robert and Casella, 1999) and presented in Table 5.3. The sample prior, likelihood and conjugate posterior parameters considered are shown in Table 5.4a and the corresponding parameters estimated by the M-H algorithm and the Laplace approximation methods are presented in Table 5.4b. It has been observed that the M-H algorithm produced better results ($Error < 12\%$) compared with Laplace approximations ($Error < 28\%$). The error in Laplace estimation has been found to increase while estimating variances using higher order terms.

Table 5.3. Natural Conjugate Pair of Exponential Family (Robert and Casella, 1999)

Likelihood, $l(x/\theta)$	Prior, $p(\theta)$	Posterior distribution, $p(\theta/x)$
Normal, $N(\theta,\sigma^2)$	Normal, $N(\mu,\tau^2)$	$N(\rho(\sigma^2\mu+\tau^2x),\rho\sigma^2\tau^2)$ $\rho^{-1}=\sigma^2+\tau^2$
Poisson, $P(\theta)$	Gamma, $G(\alpha,\beta)$	$G(\alpha+x,\beta+1)$
Gamma, $G(\nu,\theta)$	Gamma, $G(\alpha,\beta)$	$G(\alpha+\upsilon,\beta+x)$
Normal, $N(\mu,1/\theta)$	Gamma, $Ga(\alpha,\beta)$	$G(\alpha+0.5,\beta+(\mu-x)^2/2$

Table 5.4a. Parameters of Prior, Likelihood and Conjugate Pair Posterior Distributions

Prior distribution			Likelihood distribution			Posteriors by conjugate pairs		
Type	Par1	Par2	Type	Par1	Par2	Type	Par1	Par2
Normal	5.00	2.000	Normal	9.00	1.00	Normal	8.2000	0.8000
Gamma	0.10	0.025	Gamma	2.00	1.00	Gamma	2.1000	1.0250
Gamma	0.10	0.025	Normal	2.00	1.00	Gamma	1.5000	0.7500
Gamma	0.10	0.025	Poisson	1.00	-	Gamma	1.1000	1.0250

Notes: Par1 denotes parameter 1, which refers to the mean in normal and shape parameter in Gamma
Par2 denotes parameter 2, which refers to the std. deviation in normal and scale parameter in Gamma

Table 5.4b. Comparison of Posteriors by M-H Algorithm and Laplace Approximations

Posterior	M-H algorithm		Percentage error		Laplace appx.		Percentage error	
Type	Par1	Par2	Par1	Par2	Par1	Par2	Par1	Par2
Normal	8.2286	0.7498	-0.35	6.28	8.2008	0.7476	-0.01	6.55
Gamma	2.3557	1.0362	-12.18	-1.09	2.0110	1.2084	4.24	-17.89
Gamma	1.5616	0.7444	-4.11	0.75	1.4331	0.7915	4.46	-5.53
Gamma	1.1986	1.0756	-8.96	-4.94	1.2213	0.7338	-11.03	28.41

5.8 RESULTS AND DISCUSSIONS

The prior-posterior analysis results obtained using the M-H algorithm for corrosion and cracking are summarized in Table 5.5, and are shown graphically in Figures 5.2 to 5.7. The prior and likelihood parameters were taken from Tables 5.1 and 5.2, respectively. The M-H algorithm coded in Matlab has been used to simulate the posterior samples and to estimate their parameters. Input to the code includes the prior and likelihood parameters, and required sample size. The posterior estimation based on M-H algorithm converges to results with around 10000 samples. First half of the simulated samples were ignored. These samples describe the transient state. The remaining samples which describe a steady state condition were used. The acceptance rate was above 65%. Being computationally intensive, the Laplace approximation was not very useful while using distributions with more than two parameters. The error in Laplace estimation has been found to increase as a result of computing the variance using second order terms.

Table 5.5. Summary of the Estimated Posterior Probability Models and its Parameters

Structural Degradations	Posterior Probability Models and its Parameters			
	Type of Model	Shape	Scale	Location
UC	3P Weibull	1.2660	0.1017	0.0079
	3P Lognormal	0.1202	0.2810	-0.0939
PC	Type 1 Ext. Value	1.7280	1.1070	-
	3P Lognormal	1.7370	1.0750	-543.50
EC	3P Weibull	2.7070	0.0421	-0.0065
	Type 1 Ext. Value	0.0447	0.0164	-
SCC	Weibull	1.6590	1.9500	-
	Type 1 Extreme Value	2.4450	1.3410	-
CFC	Weibull	1.4560	2.0650	-
	Lognormal	2.7700	2.6410	-
HIC	Weibull	1.0970	10.560	-
	Lognormal	14.190	10.050	-

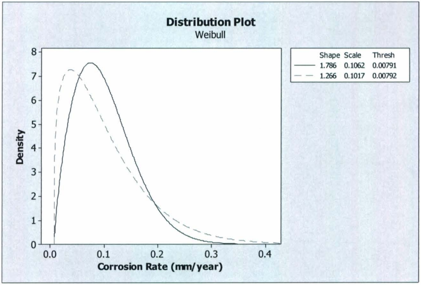

Fig.5.2. Sample Prior-Posterior (Weibull) Analysis Result for UC (M-H algorithm)

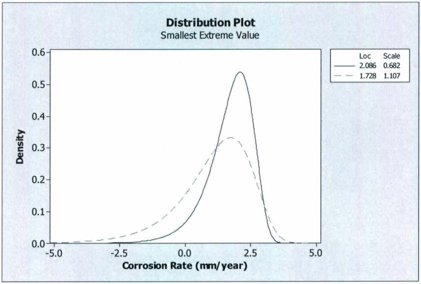

Fig. 5.3. Sample Prior-Posterior (Extreme Value) Analysis Result for PC (M-H algorithm)

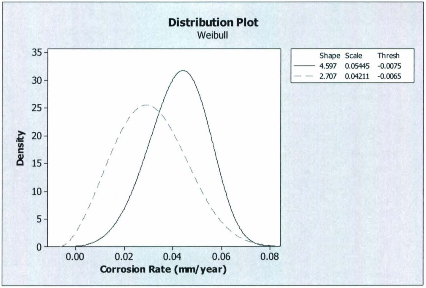

Fig. 5.4. Sample Prior-Posterior (Weibull) Analysis Result for EC (M-H algorithm)

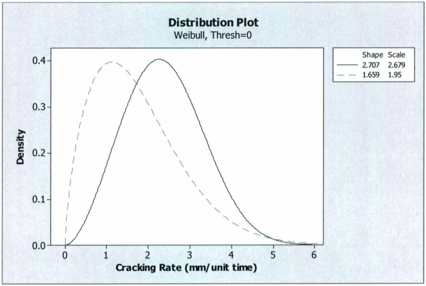

Fig. 5.5. Sample Prior-Posterior (Weibull) Analysis Result for SCC (M-H algorithm)

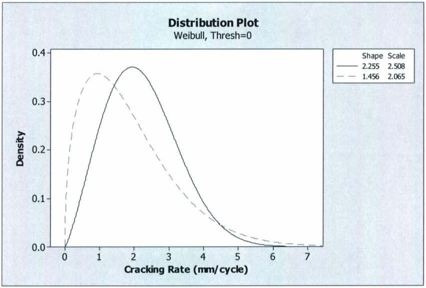

Fig. 5.6. Sample Prior-Posterior (Weibull) Analysis Result for CFC (M-H algorithm)

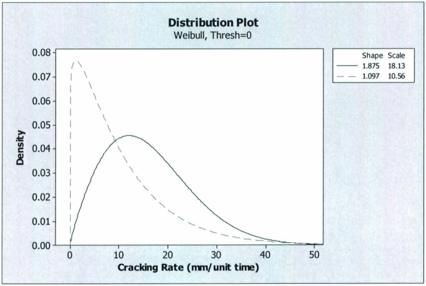

Fig. 5.7. Sample Prior-Posterior (Weibull) Analysis Result for HIC (M-H algorithm)

5.9 SUMMARY AND CONCLUSIONS

This paper presents a framework for risk based integrity modeling and the development of stochastic models for asset degradation mechanisms in process plants. The proposed framework takes into account the uncertainty and variability in degradations. The life threatening asset degradation mechanisms are identified as different types of corrosion and cracking. The earlier developed prior models of corrosion and cracking are revised to obtain posterior distributions using simulation based M-H algorithm and analytical Laplace approximation methods. Since these posterior models are based on real life NDT data, they provide more reliable and accurate predictions for the future degradations of assets.

The use of a simulation method is necessitated because; none of the prior models falls into the natural conjugate pair of the exponential family. The two Matlab programs, one using the M-H algorithm and another using the Laplace approximations, have been developed and used to compute the posterior distributions. The code is calibrated using known conjugate pairs. The programs work well for Weibull, Lognormal and Type 1 Extreme Value distributions. Further, it has been observed that, for posterior estimation, the rejection sampling based M-H algorithm is the best suitable method compared with the Laplace approximation method. For corrosion, the prior distribution is based on historic failure database, and likelihood is based on field NDT data of an ageing asset in operation, hence the posteriors converge based on their parameters. Since there was no field inspection data available in the case of different cracking; data from literature is used instead.

The posterior estimation based on the M-H algorithm converges to satisfactory results within 10000 steady state samples. The acceptance rate was above 65% which satisfies the statistical requirements. But, the Laplace approximation results were not encouraging, especially when working with three-parameter distributions. The error accumulates in the variance estimation due to the second order terms. Laplace approximation diverges as the parameter is either too small or too large due to numerical instability resulting from the use of higher order terms in the estimate. Therefore, for developing the posteriors of structural degradations in process plants, the Laplace approximation would not be recommended. While using the M-H algorithm, the change in location parameter from priors to posteriors was found insignificant. Therefore, instead of using three-parameter models, one may use the two-parameter models to develop the posteriors and subsequently the location parameter can be added.

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APPENDIX 5.1

1. NORMAL (PRIOR, (μ_p, σ_p)) + NORMAL (LIKELIHOOD, (μ_l, σ_l)) $\Rightarrow$ NORMAL (POSTERIOR, $(\bar{\mu}, \bar{\sigma})$)

Prior, $p(\theta) = \dfrac{1}{\sqrt{2\pi}\sigma_p} e^{-\frac{1}{2}\left(\frac{\theta-\mu_p}{\sigma_p}\right)^2}$, where (μ_p, σ_p) are the first two moments (i. e., mean and standard deviation) of the prior distribution.

Likelihood, $L(\theta/y_1,\ldots,y_n) = L(\theta / y) = \dfrac{1}{\sqrt{2\pi}\sigma_l} e^{-\frac{1}{2}\left(\frac{\theta-\mu_l}{\sigma_l}\right)^2}$, where (μ_l, σ_l) are the mean and standard deviation of the likelihood function.

1.1 Estimation of Posterior Mean

$$-nh(\theta) = \log p(\theta) + \log L(\theta / y)$$

$$= \log[(\sigma_p \sqrt{2\pi})^{-1} . e^{-\frac{1}{2\sigma_p^2}(\theta-\mu_p)^2}] + \log[(\sigma_l \sqrt{2\pi})^{-1} . e^{-\frac{1}{2\sigma_l^2}(\theta-\mu_l)^2}] \tag{1}$$

$$= -\frac{1}{2\sigma_p^2}(\theta-\mu_p)^2 - \frac{1}{2\sigma_l^2}(\theta-\mu_l)^2$$

where, the constant terms are ignored as it will cancel out while we take the differences.

Now, for estimating the posterior mode $\hat{\theta}$, $\dfrac{\partial(-nh(\theta))}{\partial\theta} = 0$, this implies,

$$i.e., -\frac{(\theta-\mu_p)}{\sigma_p^2} + -\frac{(\theta-\mu_l)}{\sigma_l^2} = 0$$

$$i.e., \left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right)\theta = \left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right) \tag{2}$$

$$\theta = \hat{\theta} = \frac{\mu_p \sigma_l^2 + \mu_l \sigma_p^2}{\sigma_l^2 + \sigma_p^2}$$

In order to estimate the standard deviation, $\hat{\sigma}$, $\hat{\sigma}^2 = \dfrac{-1}{\left(\dfrac{\partial^2(-nh(\theta))}{\partial\theta^2}\bigg|_{\hat{\theta}}\right)}$,

Now, $\dfrac{\partial^2(-nh(\theta))}{\partial\theta^2} = -\left(\dfrac{1}{\sigma_p{}^2} + \dfrac{1}{\sigma_l{}^2}\right)$

$$i.e., \hat{\sigma}^2 = -\frac{1}{-\left(\dfrac{1}{\sigma_p{}^2} + \dfrac{1}{\sigma_l{}^2}\right)} = \frac{1}{\left(\dfrac{1}{\sigma_p{}^2} + \dfrac{1}{\sigma_l{}^2}\right)} = \left(\frac{\sigma_l{}^2\sigma_p{}^2}{\sigma_l{}^2 + \sigma_p{}^2}\right)$$

$$\hat{\sigma} = \sqrt{\left(\frac{\sigma_l{}^2\sigma_p{}^2}{\sigma_l{}^2 + \sigma_p{}^2}\right)} = \frac{\sigma_l\sigma_p}{\sqrt{\sigma_l{}^2 + \sigma_p{}^2}} \tag{3}$$

$$\begin{aligned} -nh^*(\theta) &= -nh(\theta) + \log p(\theta) \\ &= -nh(\theta) + \log(\theta) \qquad (4) \\ &= -\frac{1}{2\sigma_p{}^2}(\theta - \mu_p)^2 - \frac{1}{2\sigma_l{}^2}(\theta - \mu_l)^2 + \log(\theta) \end{aligned}$$

Now, for estimating θ^*, lets find the first derivative and equate to zero, i.e., $\dfrac{\partial(-nh^*(\theta))}{\partial\theta} = 0$,

which implies,

$$i.e., -\frac{(\theta - \mu_p)}{\sigma_p{}^2} - \frac{(\theta - \mu_l)}{\sigma_l{}^2} + \frac{1}{\theta} = 0$$

$$i.e., -\left(\frac{1}{\sigma_p{}^2} + \frac{1}{\sigma_l{}^2}\right)\theta + \left(\frac{\mu_p}{\sigma_p{}^2} + \frac{\mu_l}{\sigma_l{}^2}\right) + \frac{1}{\theta} = 0$$

Multiplying through out by θ,

$$-\left(\frac{1}{\sigma_p{}^2} + \frac{1}{\sigma_l{}^2}\right)\theta^2 + \left(\frac{\mu_p}{\sigma_p{}^2} + \frac{\mu_l}{\sigma_l{}^2}\right)\theta + 1 = 0$$

$$\theta = \theta^* = \frac{-\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right) \pm \sqrt{\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)^2 - 4 \times -\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right) \times 1}}{2 \times -\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right)} \tag{5}$$

In order to estimate the standard deviation, σ^*, $\sigma^{*2} = \frac{-1}{\left(\left.\frac{\partial^2(-nh^*(\theta))}{\partial\theta^2}\right|_{\theta^*}\right)}$, this implies,

$$\frac{\partial^2(-nh^*(\theta))}{\partial\theta^2} = -\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right) - \frac{1}{\theta^2}$$

$$\sigma^{*2} = -\frac{1}{-\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right) - \frac{1}{\theta^2}} = \frac{1}{\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right) + \frac{1}{\theta^2}}$$

$$\sigma^* = \sqrt{\frac{1}{\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right) + \frac{1}{\theta^{*2}}}} \tag{6}$$

And then, we can compute the $E[g(\theta)]$ using equation (7), as outlined in (Tierney and Kadane, 1986; Tanner, 196) below:

$$E[g(\theta)] = \bar{\mu} = \frac{\sigma^*}{\hat{\sigma}} \exp[-nh^*(\theta^*)] / \exp[-nh(\hat{\theta})] \tag{7}$$

1.2 Estimation of Posterior Variance

Prior, $p(\theta^2) = \frac{1}{\sigma_p\sqrt{2\pi}} . e^{-\frac{1}{2\sigma_p^2}(\theta^2 - \mu_p)^2}$

Likelihood, $L(\theta^2 / y) = \dfrac{1}{\sigma_l \sqrt{2\pi}} .e^{-\frac{1}{2\sigma_l^2}(\theta^2 - \mu_l)^2}$

$$
\begin{aligned}
-nh(\theta^2) &= \log p(\theta^2) + \log L(\theta^2 / y) \\
&= \log[(\sigma_p \sqrt{2\pi})^{-1} .e^{-\frac{1}{2\sigma_p^2}(\theta^2 - \mu_p)^2}] + \log[(\sigma_l \sqrt{2\pi})^{-1} .e^{-\frac{1}{2\sigma_l^2}(\theta^2 - \mu_l)^2}] \\
&= -\frac{1}{2\sigma_p^2}(\theta^2 - \mu_p)^2 - \frac{1}{2\sigma_l^2}(\theta^2 - \mu_l)^2
\end{aligned}
\tag{8}
$$

where, the constant terms are ignored as it will cancel out while we take the differences.

Now, for estimating the posterior mode $\hat{\theta}$, $\dfrac{\partial(-nh(\theta^2))}{\partial\theta} = 0$, this implies,

$$
\begin{aligned}
&i.e., -\frac{2(\theta^3 - \mu_p \theta)}{\sigma_p^2} + -\frac{2(\theta^3 - \mu_l \theta)}{\sigma_l^2} = 0 \\
&i.e., \left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right)\theta^3 = \left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)\theta \\
&\theta^2 = \hat{\theta} = \frac{\mu_p \sigma_l^2 + \mu_l \sigma_p^2}{\sigma_l^2 + \sigma_p^2}
\end{aligned}
\tag{9}
$$

For estimating $\hat{\sigma}$, calculate as, $\hat{\sigma}^2 = \dfrac{-1}{\left(\left.\dfrac{\partial^2(-nh(\theta))}{\partial\theta^2}\right|_{\hat{\theta}}\right)}$,

Now, $\dfrac{\partial^2(-nh(\theta))}{\partial\theta^2} = -6\left(\dfrac{1}{\sigma_p^2} + \dfrac{1}{\sigma_l^2}\right)\theta^2 + 2\left(\dfrac{\mu_p}{\sigma_p^2} + \dfrac{\mu_l}{\sigma_l^2}\right)$

$$
i.e., \hat{\sigma}^2 = -\frac{1}{-6\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right)\theta^2 + 2\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)} = \frac{1}{6\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right)\theta^2 - 2\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)}
$$

$$\hat{\sigma} = \sqrt{\frac{1}{6\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right)\hat{\theta}^2 - 2\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)}} \qquad (10)$$

$$\begin{aligned} -nh^*(\theta^2) &= -nh(\theta^2) + \log p(\theta^2) \\ &= -nh(\theta^2) + \log(\theta^2) \\ &= -\frac{1}{2\sigma_p^2}(\theta^2 - \mu_p)^2 - \frac{1}{2\sigma_l^2}(\theta^2 - \mu_l)^2 + 2\log(\theta) \end{aligned} \qquad (11)$$

Now, for computing θ^*, $\frac{\partial(-nh^*(\theta^2))}{\partial\theta} = 0$, this implies,

$$i.e., -\frac{2(\theta^2 - \mu_p)\theta}{\sigma_p^2} + -\frac{2(\theta^2 - \mu_l)\theta}{\sigma_l^2} + \frac{2}{\theta} = 0$$

$$i.e., -2\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_p^2}\right)\theta^3 + 2\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)\theta + \frac{2}{\theta} = 0$$

Multiplying through out by θ,

$$-2\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_p^2}\right)\theta^4 + 2\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)\theta^2 + 2 = 0$$

$$\theta^2 = \theta^* = \frac{-2\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right) \pm \sqrt{4\left(\frac{\mu_p}{\sigma_p^2} + \frac{\mu_l}{\sigma_l^2}\right)^2 - 4 \times -2\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right) \times 2}}{2 \times -2\left(\frac{1}{\sigma_p^2} + \frac{1}{\sigma_l^2}\right)} \qquad (12)$$

Now, for estimating, σ^*, $\sigma^{*2} = \frac{-1}{\left(\left.\frac{\partial^2(-nh^*(\theta))}{\partial\theta^2}\right|_{\theta^*}\right)}$, this implies,

$$\frac{\partial^2(-nh^*(\theta))}{\partial\theta^2} = -6\left(\frac{1}{\sigma_p{}^2}+\frac{1}{\sigma_l{}^2}\right)\theta^2 - \frac{2}{\theta^2} + 2\left(\frac{\mu_p}{\sigma_p{}^2}+\frac{\mu_l}{\sigma_l{}^2}\right)$$

$$\sigma^2{*} = -\frac{1}{-6\left(\frac{1}{\sigma_p{}^2}+\frac{1}{\sigma_l{}^2}\right)\theta^2 - \frac{2}{\theta^2} + 2\left(\frac{\mu_p}{\sigma_p{}^2}+\frac{\mu_l}{\sigma_l{}^2}\right)} = \frac{1}{6\left(\frac{1}{\sigma_p{}^2}+\frac{1}{\sigma_l{}^2}\right)\theta^2 + \frac{2}{\theta^2} - 2\left(\frac{\mu_p}{\sigma_p{}^2}+\frac{\mu_l}{\sigma_l{}^2}\right)}$$

$$\sigma^* = \sqrt{\frac{1}{6\left(\frac{1}{\sigma_p{}^2}+\frac{1}{\sigma_l{}^2}\right)\theta^{*2} + \frac{2}{\theta^{*2}} - 2\left(\frac{\mu_p}{\sigma_p{}^2}+\frac{\mu_l}{\sigma_l{}^2}\right)}} \tag{13}$$

Then we can compute the $E[g(\theta)^2]$ (Tierney and Kadane, 1986; Tanner, 196):

$$E[g(\theta)^2] = \frac{\sigma^*\big|_{\theta^*}}{\hat{\sigma}\big|_{\hat{\theta}}} \exp[-nh^*(\theta^{*2})] / \exp[-nh(\hat{\theta}^2)] \tag{14}$$

Once the posterior mean, for θ, i.e., $E[g(\theta)]$ and the posterior mean, for θ^2, i. e., $E[g(\theta^2)]$ are known, we can compute the posterior variance using the equation (15);

$$V[g(\theta)] = \bar{\sigma}^2 = E[g(\theta^2)] - E[g(\theta)]^2 \tag{15}$$

2. GAMMA (PRIOR, (α_p, β_p)) + GAMMA (LIKELIHOOD, (α_l, β_l)) $\Rightarrow$ GAMMA (POSTERIOR, $(\bar{\alpha}, \bar{\beta})$)

Prior, $p(\theta) = \theta^{\alpha_p - 1} e^{-\beta_p \theta}$, where, (α_p, β_p) are the parameters of the prior distribution.

Likelihood, $L(\theta / y) = \theta^{\alpha_l - 1} e^{-\beta_l \theta}$, where (α_l, β_l) are the parameters of the likelihood.

2.1. Posterior Gamma Mean

$$\begin{aligned} -nh(\theta) &= \log p(\theta) + \log L(\theta / y) \\ &= \log\left(\theta^{\alpha_p - 1} e^{-\beta_p \theta}\right) + \log\left(\theta^{\alpha_l - 1} e^{-\beta_l \theta}\right) \\ &= [\alpha_p + \alpha_l - 2]\log\theta - [\beta_p + \beta_l]\theta \end{aligned} \tag{16}$$

For estimating the posterior mode $\hat{\theta}$, $\frac{\partial - nh(\theta)}{\partial\theta} = 0$, which implies,

$$[\alpha_p + \alpha_l - 2]\frac{1}{\theta} - [\beta_p + \beta_l] = 0$$

$$\theta = \hat{\theta} = \frac{[\alpha_p + \alpha_l - 2]}{[\beta_p + \beta_l]} \tag{17}$$

For estimating $\hat{\sigma}$, $\frac{\partial^2 - nh(\theta)}{\partial\theta^2} = -[\alpha_p + \alpha_l - 2]\frac{1}{\theta^2}$

$$\hat{\sigma}^2 = \frac{-1}{\frac{\partial^2 - nh(\theta)}{\partial\theta^2}} = \frac{1}{[\alpha_p + \alpha_l - 2]\frac{1}{\theta^2}} = \frac{\theta^2}{[\alpha_p + \alpha_l - 2]}$$

$$or, \hat{\sigma} = \sqrt{\frac{\theta^2}{[\alpha_p + \alpha_l - 2]}} = \frac{\hat{\theta}}{\sqrt{[\alpha_p + \alpha_l - 2]}} \tag{18}$$

$$\begin{aligned} - nh^*(\theta) &= -nh(\theta) + \log\theta \\ - nh^*(\theta) &= [\alpha_p + \alpha_l - 2]\log\theta - [\beta_p + \beta_l]\theta + \log\theta \end{aligned} \tag{19}$$

For estimating the posterior mode θ^*, $\frac{\partial - nh^*(\theta)}{\partial\theta} = 0$, which implies,

$$[\alpha_p + \alpha_l - 2]\frac{1}{\theta} - [\beta_p + \beta_l] + \frac{1}{\theta} = 0$$

$$\frac{1}{\theta}[\alpha_p + \alpha_l - 1] = [\beta_p + \beta_l]$$

Therefore, $\theta = \theta^* = \frac{[\alpha_p + \alpha_l - 1]}{[\beta_p + \beta_l]}$ (20)

For estimating $\hat{\sigma}$, $\frac{\partial^2 - nh^*(\theta)}{\partial\theta^2} = -[\alpha_p + \alpha_l - 1]\frac{1}{\theta^2}$

$$\sigma^{*2} = \frac{-1}{\dfrac{\partial^2 - nh^*(\theta)}{\partial\theta^2}} = \frac{1}{[\alpha_p + \alpha_l - 1]\dfrac{1}{\theta^2}} = \frac{\theta^2}{[\alpha_p + \alpha_l - 1]}$$

$$\text{or, } \sigma^* = \sqrt{\frac{\theta^2}{[\alpha_p + \alpha_l - 1]}} = \frac{\theta^*}{\sqrt{[\alpha_p + \alpha_l - 1]}} \tag{21}$$

$$\text{Therefore, posterior mean, } E[g(\theta)] = \bar{\mu} = \frac{\sigma^*}{\hat{\sigma}} \exp[-nh^*(\theta^*)]/\exp[-nh(\hat{\theta})] \tag{22}$$

2.2. Posterior Gamma Variance

Prior, $p(\theta^2) = \theta^{2(\alpha_p - 1)} e^{-\beta_p \theta^2}$

Likelihood, $L(\theta^2 / y) = \theta^{2(\alpha_l - 1)} e^{-\beta_l \theta^2}$

$$\begin{aligned} -nh(\theta^2) &= \log p(\theta^2) + \log L(\theta^2 / y) \\ &= \log\left(\theta^{2(\alpha_p - 1)} e^{-\beta_p \theta^2}\right) + \log\left(\theta^{2(\alpha_l - 1)} e^{-\beta_l \theta^2}\right) \\ &= 2[\alpha_p + \alpha_l - 2]\log\theta - [\beta_p + \beta_l]\theta^2 \end{aligned} \tag{23}$$

For estimating the posterior mode of $g(\theta^2)$, $\hat{\theta}$, $\dfrac{\partial - nh(\theta^2)}{\partial\theta} = 0$, which implies,

$$[\alpha_p + \alpha_l - 2]\frac{1}{\theta} - 2[\beta_p + \beta_l] = 0$$

$$\theta^2 = \hat{\theta} = \frac{[\alpha_p + \alpha_l - 2]}{[\beta_p + \beta_l]} \tag{24}$$

For estimating $\hat{\sigma}$, $\dfrac{\partial^2 - nh(\theta^2)}{\partial\theta^2} = -2[\alpha_p + \alpha_l - 2]\dfrac{1}{\theta^2} - 2(\beta_p + \beta_l)$

$$\hat{\sigma}^2 = \frac{-1}{\dfrac{\partial^2 - nh(\theta^2)}{\partial\theta^2}} = \frac{1}{2[\alpha_p + \alpha_l - 2]\dfrac{1}{\theta^2} + 2(\beta_p + \beta_l)}$$

$$or, \hat{\sigma} = \sqrt{\frac{1}{\left(\frac{2[\alpha_p + \alpha_l - 2]}{\hat{\theta}^2} + 2(\beta_p + \beta_l)\right)}} \tag{25}$$

$$\begin{aligned} -nh^*(\theta^2) &= -nh(\theta^2) + \log\theta^2 \\ &= 2[\alpha_p + \alpha_l - 1]\log\theta - [\beta_p + \beta_l]\theta^2 \end{aligned} \tag{26}$$

For estimating the mode θ^*, $\frac{\partial - nh^*(\theta^2)}{\partial\theta} = 0$, which implies,

$$2[\alpha_p + \alpha_l - 1]\frac{1}{\theta} - 2[\beta_p + \beta_l]\theta = 0$$

$$\frac{1}{\theta}[\alpha_p + \alpha_l - 1] = [\beta_p + \beta_l]\theta$$

Therefore, $\theta^2 = \theta^* = \frac{[\alpha_p + \alpha_l - 1]}{[\beta_p + \beta_l]}$ (27)

For estimating σ^*, $\frac{\partial^2 - nh^*(\theta^2)}{\partial\theta^2} = -2[\alpha_p + \alpha_l - 1]\frac{1}{\theta^2} - 2[\beta_p + \beta_l]$

$$\sigma^{*2} = \frac{-1}{\frac{\partial^2 - nh^*(\theta^2)}{\partial\theta^2}} = \frac{1}{\left(\frac{2[\alpha_p + \alpha_l - 1]}{\theta^2} + 2[\beta_p + \beta_l]\right)}$$

$$\text{or, } \sigma^* = \sqrt{\frac{1}{\left(\frac{2[\alpha_p + \alpha_l - 1]}{\theta^{*2}} + 2[\beta_p + \beta_l]\right)}} \tag{28}$$

Now, we can estimate the posterior mean for $g(\theta^2)$ as, $E[g(\theta)^2]$(Tierney and Kadane, 1986; Tanner, 196):

Therefore, posterior mean, $E[g(\theta^2)] = \frac{\sigma^*|_{\theta*}}{\hat{\sigma}|_{\hat{\theta}}}\exp[-nh^*(\theta^{*2})]/\exp[-nh(\hat{\theta}^2)]$ (29)

Once the posterior mean, for θ, i.e., $E[g(\theta)]$ and the posterior mean, for θ^2, i. e., $E[g(\theta)^2]$ are known, we can compute the posterior variance using equation (30) below;

$$V[g(\theta)] = E[g(\theta)^2] - E[g(\theta)]^2 \tag{30}$$

Hence, the posterior standard deviation, $\overline{\sigma} = \sqrt{V[g(\theta)]}$. Now one can easily compute the parameters of posterior distributions, using mean and standard deviation as,

$$\overline{\alpha} = \left(\frac{\overline{\mu}}{\overline{\sigma}}\right)^2 \text{ and } \overline{\beta} = \left(\frac{\overline{\mu}}{\overline{\sigma}^2}\right) \tag{30.1}$$

3. GAMMA (PRIOR, (α,β)) + NORMAL (LIKELIHOOD, (μ,σ)) $\Rightarrow$ GAMMA (POSTERIOR, $(\overline{\alpha},\overline{\beta})$)

Prior, $p(\theta) = G(\alpha,\beta) = \theta^{(\alpha-1)}e^{-\theta\beta}$, where (α,β) are the parameters of the distribution.

Likelihood, $L(\theta/y_1,\ldots,y_n) = L(\theta/y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{\theta-\mu}{\sigma}\right)^2}$, where (μ,σ) are the mean and standard deviation parameters of the likelihood function.

3.1 Estimation of Posterior Mean

$$\begin{aligned} -nh(\theta) &= \log L(\theta/y) + \log p(\theta) \\ &= \log[(\sigma\sqrt{2\pi})^{-1}.e^{-\frac{1}{2\sigma^2}(\theta-\mu)^2}] + \log[\frac{\beta^\alpha}{\Gamma(\alpha)}\theta^{\alpha-1}e^{-\beta\theta}] \\ &= -\frac{1}{2\sigma^2}(\theta-\mu)^2 + (\alpha-1)\log\theta - \beta\theta \end{aligned} \tag{31}$$

where, the constant terms are ignored as it will cancel out while we take the differences.

Now, for estimating the posterior mode $\hat{\theta}$, $\frac{\partial(-nh(\theta))}{\partial\theta} = 0$, this implies,

$$i.e., -\frac{(\theta-\mu)}{\sigma^2}+\frac{\alpha-1}{\theta}-\beta=0$$

$$-\frac{\theta}{\sigma^2}+\frac{(\alpha-1)}{\theta}+\frac{\mu}{\sigma^2}-\beta=0$$

Multiplying throughout by θ,

$$-\left(\frac{1}{\sigma^2}\right)\theta^2+\left(\frac{\mu}{\sigma^2}-\beta\right)\theta+(\alpha-1)=0$$

$$\text{Therefore, } \theta=\hat{\theta}=\frac{-\left(\frac{\mu}{\sigma^2}-\beta\right)\pm\sqrt{\left(\frac{\mu}{\sigma^2}-\beta\right)^2-4\times-\left(\frac{1}{\sigma^2}\right)\times(\alpha-1)}}{2.\times-\left(\frac{1}{\sigma^2}\right)} \tag{32}$$

Now, for estimating $\hat{\sigma}$, $\hat{\sigma}^2=\dfrac{-1}{\left(\left.\dfrac{\partial^2(-nh(\theta))}{\partial\theta^2}\right|_{\hat{\theta}}\right)}$,

$$\frac{\partial^2(-nh(\theta))}{\partial\theta^2}=-\frac{1}{\sigma^2}-\frac{(\alpha-1)}{\theta^2}$$

$$i.e., \hat{\sigma}^2=-\frac{1}{[-\frac{1}{\sigma^2}-\frac{(\alpha-1)}{\theta^2}]}=\frac{1}{\left(\frac{1}{\sigma^2}+\frac{(\alpha-1)}{\theta^2}\right)}$$

$$\hat{\sigma}=\sqrt{\frac{1}{\left(\frac{1}{\sigma^2}+\frac{(\alpha-1)}{\hat{\theta}^2}\right)}} \tag{33}$$

$$\begin{aligned}-nh^*(\theta)&=-nh(\theta)+\log p(\theta)\\&=-nh(\theta)+\log(\theta)\\&=-\frac{1}{2\sigma^2}(\theta-\mu)^2+(\alpha-1)\log(\theta)-\beta\theta+\log(\theta)\end{aligned} \tag{34}$$

Now, for estimating θ^*, $\dfrac{\partial(-nh^*(\theta))}{\partial\theta}=0$, this implies,

$$i.e., -\frac{1}{\sigma^2}(\theta-\mu)+(\alpha-1)\frac{1}{\theta}-\beta+\frac{1}{\theta}=0$$

$$i.e., -\left(\frac{1}{\sigma^2}\right)\theta+\frac{(\alpha)}{\theta}+\frac{\mu}{\sigma^2}-\beta=0$$

Multiplying through out by θ,

$$-\left(\frac{1}{\sigma^2}\right)\theta^2+\left(\frac{\mu}{\sigma^2}-\beta\right)\theta+\alpha=0$$

$$\theta=\theta^*=\frac{-\left(\frac{\mu}{\sigma^2}-\beta\right)\pm\sqrt{\left(\frac{\mu}{\sigma^2}-\beta\right)^2-4\times-\left(\frac{1}{\sigma^2}\right)\alpha}}{2\times-\left(\frac{1}{\sigma^2}\right)} \tag{35}$$

Now, for estimating σ^*, $\sigma^{*2}=\frac{-1}{\left(\left.\frac{\partial^2(-nh^*(\theta))}{\partial\theta^2}\right|_{\theta^*}\right)}$, this implies,

$$\frac{\partial^2(-nh^*(\theta))}{\partial\theta^2}=-\frac{1}{\sigma^2}-\frac{\alpha}{\theta^2}$$

$$\sigma^2*=-\frac{1}{-\frac{1}{\sigma^2}-\frac{\alpha}{\theta^2}}=\frac{1}{\frac{1}{\sigma^2}+\frac{\alpha}{\theta^2}}$$

$$\sigma*=\sqrt{\frac{1}{\frac{1}{\sigma^2}+\frac{\alpha}{\theta^{*2}}}} \tag{36}$$

And now, we can compute the $E[g(\theta)]$; [23, 40]

$$E[g(\theta)]=\bar{\mu}=\frac{\sigma^*}{\hat{\sigma}}\exp[-nh^*(\theta^*)]/\exp[-nh(\hat{\theta})] \tag{37}$$

3.2 Estimation of Posterior Variance

$$
\begin{aligned}
-nh(\theta^2) &= \log L(\theta^2 / y) + \log p(\theta^2) \\
&= \log[(\sigma\sqrt{2\pi})^{-1}.e^{-\frac{1}{2\sigma^2}(\theta^2-\mu)^2}] + \log[\frac{\beta^\alpha}{\Gamma(\alpha)}\theta^{2(\alpha-1)}e^{-\beta\theta^2}] \\
&= -\frac{1}{2\sigma^2}(\theta^2-\mu)^2 + (\alpha-1)\log\theta^2 - \beta\theta^2
\end{aligned}
\tag{38}
$$

where, the constant terms are ignored as it will cancel out while we take the differences.

Now, for estimating the posterior mode $\hat{\theta}$, $\frac{\partial(-nh(\theta^2))}{\partial\theta} = 0$, this implies,

$$
i.e., -\frac{2(\theta^3-\mu\theta)}{\sigma^2} + \frac{2(\alpha-1)}{\theta} - 2\beta\theta = 0
$$

$$
-\frac{2\theta^3}{\sigma^2} + \frac{2(\alpha-1)}{\theta} + \frac{2\mu\theta}{\sigma^2} - 2\beta\theta = 0
$$

Multiplying throughout by θ,

$$
-\left(\frac{2}{\sigma^2}\right)\theta^4 + 2\left(\frac{\mu}{\sigma^2} - \beta\right)\theta^2 + 2(\alpha-1) = 0
$$

$$
\text{Therefore, } \theta^2 = \hat{\theta} = \frac{-\left(\frac{\mu}{\sigma^2}-\beta\right) \pm \sqrt{\left(\frac{\mu}{\sigma^2}-\beta\right)^2 - 4\times -\left(\frac{1}{\sigma^2}\right)\times(\alpha-1)}}{2.\times -\left(\frac{1}{\sigma^2}\right)} \tag{39}
$$

Now, for estimating $\hat{\sigma}$, $\hat{\sigma}^2 = \dfrac{-1}{\left(\left.\dfrac{\partial^2(-nh(\theta))}{\partial\theta^2}\right|_{\hat{\theta}}\right)}$,

$$
\frac{\partial^2(-nh(\theta^2))}{\partial\theta^2} = -\frac{2(\alpha-1)}{\theta^2} - \frac{6\theta^2}{\sigma^2} - 2\beta + \frac{2\mu}{\sigma^2}
$$

$$
i.e., \hat{\sigma}^2 = -\frac{1}{\left(-\frac{2(\alpha-1)}{\theta^2} - \frac{6\theta^2}{\sigma^2} - 2\beta + \frac{2\mu}{\sigma^2}\right)} = \frac{1}{\left(\frac{2(\alpha-1)}{\theta^2} + \frac{6\theta^2}{\sigma^2} + 2\beta - \frac{2\mu}{\sigma^2}\right)}
$$

$$\hat{\sigma} = \sqrt{\frac{1}{\left(\frac{2(\alpha-1)}{\hat{\theta}^2} + \frac{6\hat{\theta}^2}{\sigma^2} + 2\beta - \frac{2\mu}{\sigma^2}\right)}} \tag{40}$$

$$\begin{aligned} -nh^*(\theta^2) &= -nh(\theta^2) + \log p(\theta^2) \\ &= -nh(\theta^2) + \log(\theta^2) \\ &= -\frac{1}{2\sigma^2}(\theta^2-\mu)^2 + (\alpha)\log(\theta^2) - \beta\theta^2 \end{aligned} \tag{41}$$

Now, for estimating θ^*, $\frac{\partial(-nh^*(\theta^2))}{\partial\theta} = 0$, this implies,

$$i.e., -\frac{2}{\sigma^2}(\theta^3 - \mu\theta) + 2\alpha\frac{1}{\theta} - 2\beta\theta = 0$$

$$i.e., -\left(\frac{2}{\sigma^2}\right)\theta^3 + \frac{2\alpha}{\theta} + 2\left(\frac{\mu}{\sigma^2} - \beta\right)\theta = 0$$

Multiplying through out by θ,

$$-\left(\frac{1}{\sigma^2}\right)\theta^4 + \left(\frac{\mu}{\sigma^2} - \beta\right)\theta^2 + \alpha = 0$$

$$\theta^2 = \theta^* = \frac{-\left(\frac{\mu}{\sigma^2} - \beta\right) \pm \sqrt{\left(\frac{\mu}{\sigma^2} - \beta\right)^2 - 4\times -\left(\frac{1}{\sigma^2}\right)\alpha}}{2\times -\left(\frac{1}{\sigma^2}\right)} \tag{42}$$

Now, for estimating σ^*, $\sigma^{*2} = \frac{-1}{\left(\left.\frac{\partial^2(-nh(\theta^2))}{\partial\theta^2}\right|_{\theta^*}\right)}$, this implies,

$$\frac{\partial^2(-nh^*(\theta^2))}{\partial\theta^2} = -\left(\frac{6}{\sigma^2}\right)\theta^2 - \frac{2\alpha}{\theta^2} + 2\left(\frac{\mu}{\sigma^2} - \beta\right)$$

$$\sigma^{2}* = -\frac{1}{-\left(-\left(\frac{6}{\sigma^{2}}\right)\theta^{2} - \frac{2\alpha}{\theta^{2}} + 2\left(\frac{\mu}{\sigma^{2}} - \beta\right)\right)} = \frac{1}{\left(\frac{6}{\sigma^{2}}\right)\theta^{2} + \frac{2\alpha}{\theta^{2}} + 2\beta - 2\left(\frac{\mu}{\sigma^{2}}\right)}$$

$$\sigma^{*} = \sqrt{\frac{1}{\left(\frac{6}{\sigma^{2}}\right)\theta^{*2} + \frac{2\alpha}{\theta^{*2}} + 2\beta - 2\left(\frac{\mu}{\sigma^{2}}\right)}} \tag{43}$$

And now, we can compute the $E[g(\theta)]$; [23, 40]

$$E[g(\theta^{2})] = \frac{\sigma^{*}}{\hat{\sigma}} \exp[-nh^{*}(\theta^{*2})] / \exp[-nh(\hat{\theta}^{2})] \tag{44}$$

In order to find the posterior gamma variance, the following expression can be used.

$$V[g(\theta)] = E[g(\theta)^{2}] - E[g(\theta)]^{2} \tag{45}$$

Therefore, the posterior standard deviation, $\overline{\sigma} = \sqrt{V[g(\theta)]}$. Now one can easily compute the parameters of posterior distributions, using mean and standard deviation as,

$$\overline{\alpha} = \left(\frac{\overline{\mu}}{\overline{\sigma}}\right)^{2} \text{ and } \overline{\beta} = \left(\frac{\overline{\mu}}{\overline{\sigma}^{2}}\right) \tag{45.1}$$

4. GAMMA (PRIOR (α, β)) + POISON (LIKELIHOOD, (θ)) $\Rightarrow$ GAMMA (POSTERIOR, $(\overline{\alpha}, \overline{\beta})$)

Prior, $p(\theta) = G(\alpha, \beta) = \theta^{(\alpha-1)} e^{-\theta\beta}$, where (α, β) are the parameters of the distribution.

Likelihood, $L(\theta / y_1, \ldots, y_n) = P(\theta) = e^{-n\theta} \theta^{\sum y_i}$, where $(y_1, \ldots, y_n)$ are the observations.

4.1 Estimation of Posterior Expectation

$$\begin{aligned} -nh(\theta) &= \log L(\theta / y) + \log p(\theta) \\ &= \log\{e^{-n\theta} \theta^{\sum y_i}\} + \log\{\theta^{(\alpha-1)} e^{-\beta\theta}\} \\ &= -n\theta + \sum y_i . \log(\theta) + (\alpha - 1)\log(\theta) - \beta\theta \\ &= \log\theta(\overline{\alpha} - 1) - \theta\overline{\beta} \end{aligned} \tag{46}$$

where, $\overline{\alpha} = \alpha + \sum y_i$ and $\overline{\beta} = \beta + n$ are the parameters of conjugate posteriors.

Now, for estimating the posterior mode $\hat{\theta}$, $\dfrac{\partial(-nh(\theta))}{\partial\theta} = 0$, this implies,

$$(\overline{\alpha} - 1)\frac{1}{\theta} - \overline{\beta} = 0$$

$$\theta = \hat{\theta} = \frac{(\overline{\alpha} - 1)}{\overline{\beta}} \tag{47}$$

Now, for estimating $\hat{\sigma}$, $\hat{\sigma}^2 = \dfrac{-1}{\left(\dfrac{\partial^2(-nh(\theta))}{\partial\theta^2}\bigg|_{\hat{\theta}}\right)}$ this implies,

$$i.e., \hat{\sigma}^2 = -\frac{1}{[-(\overline{\alpha} - 1)\frac{1}{\theta^2}]} = \frac{\theta^2}{(\overline{\alpha} - 1)} = \frac{(\overline{\alpha} - 1)^2}{(\overline{\alpha} - 1)\overline{\beta}^2} = \frac{(\overline{\alpha} - 1)}{\overline{\beta}^2}$$

$$\hat{\sigma} = \frac{(\overline{\alpha} - 1)^{1/2}}{\overline{\beta}} \tag{48}$$

$$\begin{aligned} -nh^*(\theta) &= -nh(\theta) + \log g(\theta) \\ &= -nh(\theta) + \log(\theta) \\ &= \log\theta(\overline{\alpha} - 1) - \theta(\overline{\beta}) + \log(\theta) \\ &= \overline{\alpha}\log\theta - \theta\overline{\beta} \end{aligned} \tag{49}$$

Now, for estimating θ^*, $\dfrac{\partial(-nh^*(\theta))}{\partial\theta} = 0$, this implies,

$$\overline{\alpha}\frac{1}{\theta} - \overline{\beta} = 0$$

$$\theta^* = \frac{\overline{\alpha}}{\overline{\beta}} \tag{50}$$

Now, for estimating σ^*, $\sigma^{*2} = \dfrac{-1}{\left(\dfrac{\partial^2(-nh^*(\theta))}{\partial\theta^2}\bigg|_{\theta^*}\right)}$, this implies,

$$i.e., \sigma^{*2} = -\frac{1}{[-(\overline{\alpha})\frac{1}{\theta^2}]} = \frac{\theta^2}{(\overline{\alpha})} = \frac{(\overline{\alpha})^2}{(\overline{\alpha})\overline{\beta}^2} = \frac{\overline{\alpha}}{\overline{\beta}^2}$$

$$\sigma^* = \frac{(\overline{\alpha})^{1/2}}{\overline{\beta}} \tag{51}$$

Then we can compute the $E[g(\theta)]$ (Tierney and Kadane, 1986; Tanner, 196):

$$E[g(\theta)] = \overline{\mu} = \frac{\sigma^*}{\hat{\sigma}} \exp[-nh^*(\theta^*)] / \exp[-nh(\hat{\theta})] \tag{52}$$

4.2 Estimation of Posterior Variance

In order to find the posterior variance, the following expression can be used. [23, 40]

$$V[g(\theta)] = E[g(\theta)^2] - E[g(\theta)]^2 \tag{53}$$

In order to use equation (53), we need to use the equation (52) and further approximate the $E[g(\theta)^2]$. Following the same procedure;

$$\begin{aligned} -nh(\theta^2) &= \log L(\theta^2 / y) + \log p(\theta^2) \\ &= \log\{e^{-n\theta^2} \theta^{2\sum y_i}\} + \log\{\theta^{2(\alpha-1)} e^{-\beta\theta^2}\} \\ &= -n\theta^2 + 2\sum y_i . \log(\theta) + 2(\alpha - 1)\log(\theta) - \beta\theta^2 \\ &= 2\log\theta(\overline{\alpha} - 1) - \theta^2\overline{\beta} \end{aligned} \tag{54}$$

Now, for estimating $\hat{\theta}$, $\dfrac{\partial(-nh(\theta^2))}{\partial\theta} = 0$, this implies,

$$2(\overline{\alpha} - 1)\frac{1}{\theta} - 2\theta\overline{\beta} = 0$$

$$i.e., (\overline{\alpha}-1)\frac{1}{\theta}=\theta\overline{\beta} \quad \text{or} \quad \theta^2=\frac{(\overline{\alpha}-1)}{\overline{\beta}}$$

$$or \qquad \hat{\theta}=\theta^2=\frac{(\overline{\alpha}-1)}{\overline{\beta}} \tag{55}$$

Now, for estimating $\hat{\sigma}$, $\hat{\sigma}^2=\dfrac{-1}{\left(\dfrac{\partial^2(-nh(\theta^2))}{\partial\theta^2}\Bigg|_{\hat{\theta}}\right)}$ this implies,

$$i.e., \hat{\sigma}^2=-\frac{1}{[-(\overline{\alpha}-1)\frac{2}{\theta^2}-2\overline{\beta}]}=\frac{1}{\frac{2(\overline{\alpha}-1)}{\theta^2}+2\overline{\beta}}$$

$$\hat{\sigma}=\sqrt{\frac{1}{\frac{2(\overline{\alpha}-1)}{\hat{\theta}^2}+2\overline{\beta}}} \tag{56}$$

$$\begin{aligned}-nh^*(\theta^2)&=-nh(\theta^2)+\log(\theta^2)\\&=\log\{e^{-n\theta^2}\theta^{2\sum y_i})+\log\{\theta^{2(\alpha-1)}e^{-\beta\theta^2}\}\\&=-n\theta^2+2\sum y_i.\log(\theta)+2(\alpha-1)\log(\theta)-\beta\theta^2\\&=2\log\theta(\overline{\alpha}-1)-\theta^2\overline{\beta}+2\log(\theta)\end{aligned} \tag{57}$$

Now, for estimating $\hat{\theta}$, $\dfrac{\partial(-nh^*(\theta^2))}{\partial\theta}=0$, this implies,

$$i.e., 2(\overline{\alpha}-1)\frac{1}{\theta}-2\overline{\beta}\theta+\frac{2}{\theta}=0$$

$$i,e, \frac{2}{\theta}(\overline{\alpha})=2\overline{\beta}\theta$$

$$or, \qquad \theta^*=\theta^2=\frac{\overline{\alpha}}{\overline{\beta}} \tag{58}$$

$$\frac{\partial^2(-nh^*(\theta^2))}{\partial\theta^2} = -2(\overline{\alpha}-1)\frac{1}{\theta^2} - \frac{2}{\theta^2} - 2\beta$$

$$= -\frac{2}{\theta^2}(\overline{\alpha}-1+1) - 2\beta$$

$$= -\frac{2\overline{\alpha}}{\theta^2} - 2\beta$$

Now, for estimating σ^* $\sigma^{*2} = \dfrac{-1}{\left(\left.\dfrac{\partial^2(-nh(\theta^2))}{\partial\theta^2}\right|_{\theta^*}\right)}$ this implies,

$$\sigma^{*2} = \frac{-1}{-\dfrac{2\overline{\alpha}}{\theta^2} - 2\beta} = \frac{1}{2\left(\dfrac{\overline{\alpha}}{\theta^2} + \beta\right)}$$

Therefore, $\sigma^* = \sqrt{\dfrac{1}{2\left(\dfrac{\overline{\alpha}}{\theta^{*2}} + \beta\right)}}$ (59)

And then we can compute the $E[g(\theta)^2]$ as;[23, 40]

$$E[g(\theta)^2] = \frac{\sigma^*\big|_{\theta^{*2}}}{\hat{\sigma}\big|_{\hat{\theta}^2}} \exp[-nh^*(\theta^*)]/\exp[-nh(\hat{\theta})] \tag{60}$$

And, therefore, the posterior variance will become,

$V[g(\theta)] = E[g(\theta^2)] - E[g(\theta)]^2$

Since, the posterior standard deviation, $\overline{\sigma} = \sqrt{V[g(\theta)]}$, one can easily compute the parameters of posterior distributions, using mean and standard deviation as,

$\overline{\alpha} = \left(\dfrac{\overline{\mu}}{\overline{\sigma}}\right)^2$ and $\overline{\beta} = \left(\dfrac{\overline{\mu}}{\overline{\sigma}^2}\right)$ (60.1)

CHAPTER VI

RISK BASED INTEGRITY MODELING FOR THE OPTIMAL REPLACEMENT DECISIONS OF OFFSHORE PROCESS COMPONENTS SUFFERING STOCHASTIC DEGARADATION

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PREFACE

This chapter discusses the optimization of maintenance using the replacement strategy for offshore process components. The replacement strategy entails the replacement of degrading components rather than performing maintenance. The principal author explored the literature on economic service life and replacement analysis of engineering economics. Understanding the inherent limitations of the condition-based and reliability-centered maintenance, a risk based replacement strategy is developed by principal author in this chapter. The risk to life of component has been used as the criteria for decision making regarding the optimum time to replace the components. The accurate failure probability is developed in Chapter V using Bayesian analysis. In this chapter, the failure consequences due to various degradation processes have been assessed by the principal author independently, using the economic analysis. The co-authors provided support and directions to improve the model. The research on RBIM is planned as multidisciplinary, encompassing the areas of engineering, statistics, economics and MATLAB programming. This work is accepted for publication in the Journal of Quality in Maintenance Engineering (2011) after the peer review process.

To provide a consistent measure of risk, all consequence categories are presented in one units, i. e., dollar. The principal author planned and determined the consequences of failure in terms of failure, inspection and maintenance costs. The failure cost include the loss of commodity due to breakdown, the loss due to shutdown, the cost of environmental cleanup, the cost of nature damage and liability. Each of these costs is estimated by the principal author independently by following the first principle, based on literature and unit cost. The various inspection techniques and maintenance methods are analyzed by principal author to identify the best suitable ones for process components. The inspection cost depends on the type of inspection, access, surface preparation, personnel, material and logistic costs. Similarly, the maintenance costs are based on type of maintenance, access, surface preparation and logistics cost. The principal author contacted an inspection and maintenance company operating in the North Sea regarding the data on unit cost of each inspection/maintenance activity. The obtained data is used in this chapter. The posterior probability of failure estimated in Chapter V is combined with the annual equivalent cost to produce the operational risk to life of component. In the risk profile thus developed, the point at which risk is minimum is treated as the optimal replacement interval. The principal author programmed the entire consequence analysis using Monte Carlo simulation in MATLAB and used to develop the optimum replacement interval. The replacement interval varies with degradation processes; however, least of them are reported as the optimum interval considering independent and isolated components. The methodology is demonstrated by using the data of erosion corrosion and corrosion fatigue cracking processes.

ABSTRACT

Finding an optimal replacement strategy for ageing offshore process components is a challenging task. Inspection and maintenance are essential to maintain normal operation in the face of structural deterioration, and the subsequent loss of strength. Risk based integrity modeling is a methodology for minimizing the risk of failure of a process component. Risk is the product of the probability of failure and its consequence. The probability failure of a component may be modeled using the Bayesian prior-posterior analysis. The consequence of failure is modeled using an engineering economic analysis. The consequences are analyzed in terms of the cost incurred as a result of failure, inspection and maintenance. The cost of failure includes the loss due to breakdown, loss due to shutdown, cost of spill cleanup, cost of nature damage and liability. The cost of inspection and maintenance depends mainly on the types of inspection and maintenance, access, surface preparation, gauging defects, coating and restoration costs. The annual equivalent cost of operating and maintaining the component is combined with the posterior probability of failure to produce the operational life risk curve. Since, the risk curve is a convex function of component's service life; the optimal replacement strategy is the one corresponding to the global minimum of the risk curve. The asset deterioration caused by erosion corrosion and corrosion fatigue cracking in an offshore process piping is discussed to illustrate the model. This model takes into account the effects of the uncertainty and variability in the degradation processes and cost estimations using probabilistic simulation models.

Keywords: Risk, integrity, degradation, consequences, replacement.

6.1 INTRODUCTION

Maintaining the structural integrity of deteriorating process assets has been a subject of research for many years (Khan *et al.*, 2006; API, 2002; Montgomery and Serratella, 2002). In the operational stage, the deterioration of component is mainly caused by environmentally-induced defects, such as corrosion and cracking (Thodi, *et al.*, 2010; Straub, 2004). Thus, at some points in life-cycle, it will not be economical to operate the components due to deterioration and strength loss. The continuation of operation depends on the instantaneous condition and the cost of operation and maintenance. The failure to make an appropriate decision may result in a slow down or shutdown of the complete facility. Time to execute maintenance on an operating component is decided on the basis of either the fear of eminent failure or that it becomes too expensive to operate. The age-related structural degradations increase the probability and consequences of failure over a period of time that may necessitate the replacement of components. The main challenges encountered in considering the maintenance by replacement strategy of operating equipment is to determine what is the exact condition and financial information to be include in the model. The objective of this article is to develop an optimal replacement strategy for ageing offshore process components. A brief description of the risk based integrity modeling (RBIM) methodology is discussed at first. The aim of RBIM is to protect human life, financial investment and environment from the likelihood of failure. A stochastic degradation modeling for corrosion and cracking is followed. Further, the consequence analysis using the engineering economics is emphasized in this article. Thus, by combining the probability and consequences of failure, an optimum interval for the risk based replacement of components is developed in the article.

6.2 BACKGROUND

Maintenance is defined as the combination of all technical and administrative actions intended to restore an item to a state, where it can perform a required function (Solderholm *et al.*, 2007). The established maintenance methodologies, such as reliability centered maintenance (RCM), total productive maintenance (TPM) and condition based maintenance (CBM) are robust enough to reduce the business risks. However, they are based on the component's probability of failure only. The incorporation of consequences of failure, inspection, and maintenance is not a part of such maintenance strategies. The RCM, TPM and CBM strategies become more useful if they incorporate information about the failure detection, mechanism, repair, costs, maintenance strategy and management policies (Garg and Deshmukh, 2006). Recently, the risk based maintenance has been emerged as an optimal maintenance strategy. It is becoming a recognized tool because it uses life cycle risks in optimizing the maintenance activities. A risk based maintenance model for offshore oil and gas pipeline based on a semi-quantitative risk ranking method is presented by Dey *et al.* (2004). The choice of a risk analysis approach has a major impact on the identification of risk sources and in developing a realistic decision making in maintenance process (Backlund and Hannu, 2002). Careful requirement identification, a systematic approach with clear aims and goals are needed when performing risk analysis. Component failures involve various costs that are difficult to estimate. A classification of expected failure costs for pipelines involving factors such as loss of production, loss of commodity, loss of life and property, loss of reputation and environmental damage are presented by Dey (2001). However, factors such as when the failure happens, the impact of failure, cost associated with inspection and maintenance were not discussed. The total cost of combining corrective maintenance, preventive maintenance and condition based maintenance policies is reported by Silva *et al.* (2008). But, it has taken into account the actual repair costs only; while the associated failure, inspection and replacement costs are ignored. The approach presented by Anderson and Rasmussen (1999) for short term maintenance planning strategies doesn't consider the effect of the economic consequences of failure in decision making. This article presents a risk based integrity modeling for the optimal replacement, based on the component's likelihood and consequences of failure. In the RBIM methodology, an economic consequence model for failure, inspection and maintenance is emphasized here.

6.3 ECONOMIC SERVICE LIFE AND REPLACEMENT

Once the offshore process facility is operational the only way to avoid failure is through inspection and maintenance, as the design or manufacturing changes in the operational stage is cumbersome (Thodi, *et al.*, 2010). If the operation is following a well-established design procedure and the components receive proper inspection and maintenance, they can be kept operating for an extended period of time. If a component continues to operate for an indefinite period of time, failure will eventually occur as a result of the structural deterioration and strength loss, resulting in excessive corrective maintenance cost. Replacement is a maintenance strategy, which involve replacing the component instead of performing the maintenance (Duffuaa *et al.*, 1999). After each replacement, the system returns to its original condition. Economic service life is the period of time during which a piece of equipment can function safely and economically. Based on equipment's condition, if an appropriate life span is computed dynamically, the operator can schedule the replacement strategy to smooth out operation. The costs of operating a facility can be divided into two categories: failure costs and operating costs. The failure costs have two components: the failure recovery costs and the salvage value at the time of disposal. The operating costs include the inspection and maintenance costs, the labor wages, the material cost, coating, testing and alignment costs. Usually, it is the inspection and maintenance cost that increases annually, due to degradations and material loss.

6.4 RISK BASED INTEGRITY MODELING (RBIM)

The risk to component's operational life is defined as the multiplication of the probability of failure and its consequence. The RBIM is a methodology to quantify the risk to life posed by deteriorating components and to mitigate that in a cost-effective manner. The general framework for RBIM is illustrated in Fig. 6.1. The wall thickness of components deteriorates due to environmental effects, causing leaks and breakage. The potential process components integrity threats have been identified as various types of corrosion and cracking (Thodi, *et al.,* 2010; 2009). Since these deterioration mechanisms are stochastic processes, the inspection data are also random in nature. A probability distribution function obtained using a Bayesian prior-posterior analysis, can be used to model real life inspection data. An assumption is made is that the degradation processes are independent to each other. In an RBIM framework (Fig. 6.1), the consequence analysis focuses on estimating the cost incurred as a result of failure occurrence, inspection, and maintenance tasks (Thodi, *et al.,* 2010). Failure costs include loss of breakdown, loss due to shut down, loss due to spill cleanup, loss due to environmental damage and liability. The cost of inspection includes cost of gaining access to the component, cost of surface preparation, and cost of detecting and sizing of flaws using the non-destructive tests (NDT). Upon detection and sizing of flaws, the maintenance cost consists of cost of transportation of equipment, and cost of skilled personnel. To rule out likelihood of failure completely, the component needs to be replaced at the onset of deterioration. But, if replacement is performed prematurely, maintenance will be large, while late performance of replacement will result in large costs as a result of unplanned shutdown and costly breakdown maintenance. Hence, there is a need for an optimal policy which aims at minimizing total operating cost. This article presents an attempt to obtain an optimal replacement decision based on minimizing the operational risk.

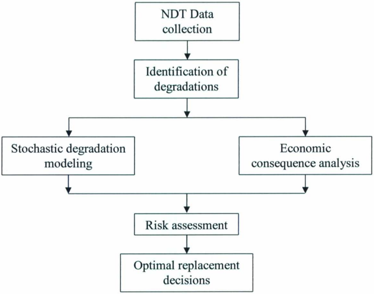

Fig. 6.1. Risk Based Integrity Modeling Framework

6.5 STOCHASTIC DEGRADATION MODELING

How to estimate the probability of structural deterioration-related-failure, based on the present condition of component is discussed in detail in Thodi *et al.* (2010, 2009). The failure rate estimation is based on the expert's prior knowledge and the NDT data acquired during inspection. The Bayesian prior-posterior analysis has been used to model such a dynamic system, where the prior knowledge of the system and field data are input. The prior probability is based on judgmental studies and analyzing generic database (Thodi *et al.,* 2009). The NDT data has been used to derive the likelihood probability. Since the prior-likelihood combinations were non-conjugate pairs, the simulation based Metropolis-Hastings algorithm and Laplace approximation methods are used to estimate the posterior models (Thodi *et al.,* 2010). The posterior model has been developed for corrosion: uniform, pitting, and erosion, and cracking: stress corrosion, corrosion fatigue, and hydrogen induced cracking. The Bayesian analysis methodology used for the said degradation mechanisms has been discussed in brief in Section 6.5.1.

6.5.1 Bayes' Theorem

Bayes theorem is one of the best suitable methods for logical and consistent reasoning. Basically, probability is a degree of belief, that is, how much one thinks that something is true based on the evidence at hand. Due to uncertainty in degradations, the prior knowledge of the condition of the component may be revised with field NDT data, reserving the right to revise the present knowledge as new information arrives. Bayes theorem encapsulates this process of learning as more data becomes available. That is, it states how to update the prior probability distribution, $p(\theta)$, with a likelihood function, $p(y/\theta)$, to obtain the posterior probability distribution as:

$$p(\theta / y) = \frac{p(\theta)p(y/\theta)}{\int p(\theta)p(y/\theta)d\theta} \tag{1}$$

This posterior density $p(\theta / y)$ summarizes the total information, after viewing the data and provides a basis for inference regarding degradation parameters. However, the denominator of (1) is the normalizing factor, the estimation of which is a daunting task in Bayesian analysis. The posterior models thus developed are robust and reliable enough to predict the future probability of failure of deteriorating components in process facilities.

Prior Probability Modeling

For component degradation, the prior probability refers to the initial knowledge about each type of degradation processes. Although the choice of a prior is subjective, a rational agreement can be achieved by analyzing historic data from the same or other similar components. To develop the prior models for different corrosion and cracking, several probability distributions have been tested using the data extracted from the relevant literature. Details of the literature and statistical test performed for estimating the priors are presented in Thodi *et al.* (2009). A set of sample prior models used to describe erosion corrosion (EC) and corrosion fatigue cracking (CFC) are presented in Table 6.1.

Table 6.1. Sample Prior Probability Models and the Estimated Parameters

Structural	Prior Probability Models and their Parameters			
Degradation	Type of Model	Shape	Scale	Location
EC	3P Weibull	4.5970	0.0545	-0.0075
CFC	Weibull	2.2550	2.5080	-

Likelihood Probability Modeling

The inspection data (NDT) obtained from an ageing process facility has been used to estimate the likelihood probabilities of various degradation processes. The facility has different subsystems exhibiting different degradation processes, for example, a gas condensate system exhibiting uniform corrosion and a high pressure drilling mud system exhibiting erosion corrosion. The data includes the minimum and average wall thicknesses acquired during the period 1997-2003. The data, which consists of wall loss measurements, has been divided into; straight pipes, bends, and tees. A time-dependent regression analysis was used to estimate the rates of EC and CFC. Then, these rate data has been tested with standard probability models and a goodness of fit test has been performed using the probability plot and Anderson-Darling (A-D) tests. Details of the likelihood modeling may be may be obtained from Thodi *at al.* (2010). A sample set of likelihood probability models for EC and CFC are presented in Table 6.2.

Table 6.2. Sample Likelihood Probability Models and the Parameters

Structural Degradation	Likelihood Probability Models and their Parameters			
	Model	Shape	Scale	Location
EC	3P Weibull	0.9551	1.3400	-0.1281
CFC	Weibull	0.0015	0.2907	-

From Table 6.1 and 6.2, it has been observed that the priors and likelihoods are identical distributions. Further, since the likelihoods are revising the priors, it indicates that the posteriors would yield the same form of distributions as that of priors and likelihoods.

Posterior Probability Modeling

The methods for computing the posterior distributions include; analytical approximations, data augmentation methods, Monte Carlo direct sampling and Markov chain Monte Carlo (McMC) simulations. If the prior-likelihood pair under consideration does not involve a conjugate pair, the posterior estimation cannot be performed in closed form; analytical or

Monte Carlo methods are needed (Bedford and Cooke, 2001). The prior-likelihood pairs for EC and CFC are Weibull (with two and three parameters), which do not lend themselves easily to Bayesian updating. This means that simulation methods are the ideal ways to compute the posterior distributions of EC and CFC. Thus, the Metropolis-Hastings algorithm, which is a McMC method, in conjunction with a particular choice of prior, has been used (Bedford and Cooke, 2001). Details of the posterior development methodology and models are presented in Thodi *et al.* (2010).

The Metropolis-Hastings (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. This sequence is used in McMC simulations to approximate the posterior distribution. In Bayesian applications, the normalizing factor is difficult to compute, so the ability to generate the samples without actually knowing this constant is a major virtue of this algorithm. The algorithm generates a Markov chain in which each state x^{t+1} depends only on the previous sample state x^{t}. The algorithm uses a proposal density $q(x', x^{t})$, which depends on the current state x^{t}, to generate the new proposed sample x'. The proposal is accepted as next value $(x^{t+1} = x')$ in the chain if $\alpha(x', x^{t})$, drawn from a uniform distribution, $u(0,1)$ is (Thodi *et al.,* 2010):

$$\alpha(x', x^{t}) < \frac{p(x').q(x^{t}, x')}{p(x^{t}).q(x', x^{t})} \tag{2}$$

If the proposal is not accepted, then the current value of x is retained; i.e., $x^{t+1} = x^{t}$. Thus, the simulation generates a Markov chain, the acceptance of samples, which are eligible for posterior probability model, will be based on equation (2).

6.6 CONSEQUENCE ANALYSIS

The purpose of risk-based integrity modeling is to maximize the profit from the operation of facility by minimizing the risk by preventing failures associated with deteriorations. By operating a dynamic system of life-time data accumulation and processing, the accuracy should be improved with time and experience. To provide a consistent measure of risk, all consequence categories should be in the same units. Otherwise, the overall risk from many contributing sources cannot be computed. A standard choice of unit to represent all consequence categories is dollar, because risk can be interpreted as the expected loss due to a certain event or groups of events (Jones, 1995). Therefore, the failure consequences are expressed in terms of dollar in this study. The overall frame work for economic consequence analysis is presented in Fig. 6.2.

6.6.1 Economic Consequences of Failure

Failure consequences are quantified in terms of the associated dollar value. Failure cost is the cost associated with the loss of a facility due to structural deteriorations. The failure cost may be classified into corrosion or cracking costs. Corrosion or cracking cost is the increase in operating and maintenance cost throughout the life of a facility due to various corrosion or cracking mechanisms (Verink, 2000). The total cost is given by the sum of corrosion or cracking costs associated with four main aspects of life of a facility: failure expenditures, operating expenditures, cost of lost production and the material residual value (Jackson, 2003). In the case of cracking, it is assumed that a component failure is followed by an immediate repair to prevent any system failure scenario with much higher consequences. Also, the component is assumed to be isolated and hence its failure will not contribute to any chain of reactions. The economic consequences of failure includes loss due to breakdown in terms of commodity loss, production loss due to shutdown, cost of spill cleanup, the legal fees and fines due to nature damage and liability (Fig. 6.2). Each of these cost components are discussed in brief in the following sections.

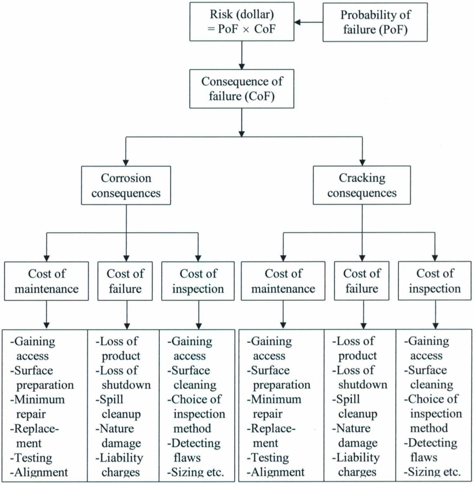

Fig. 6.2. The Framework for Economic Consequence Analysis

Loss due to Breakdown

Breakdown costs are the financial losses, which are associated with loosing commodity.

This cost depends upon what product is being carried or stored, the rate of leakage and its current market value when the failure occurs. The leak or rupture of component's wall thickness by corrosion and cracking is the main cause for breakdown. If a component failure results in a system failure, then the breakdown consequences can be in terms of lost material dollar value (Jones, 1995). The focus in this article is on a topside piping in the North Sea and the product being conveyed is assumed to be crude oil. The market value of crude oil is considered to be $ 70 per barrel in this article. To estimate the rate of leakage, the source model, i.e., the flow of liquid through a hole in pipe (Crowl and Louvar, 2002) is used. It provides a description of the rate of discharge, the total quantity discharged and the state of the discharge. The mass flow rate, Q_m resulting from a hole (in a typical pipe) of area A is given by (Crowl and Louvar, 2002):

$$Q_m = AC_0\sqrt{2\rho g_c P_g} \tag{3}$$

where, C_0 is the discharge coefficient, ρ is the fluid density (mass/volume), g_c is the gravitational constant (length mass/force time^2), P_g is the gauge pressure. The calculations to estimate the rate of release due to structural degradation based on equation (3) are presented in Appendix 6.1.1 and are summarized in Table 6.3.

Table 6.3. Rates of Release through Hole in a Pipe

Deterioration	Rate of release of fluid	
	(kg/sec)	(barrels/hr)
Corrosion	0.677	17.784
Cracking	0.413	10.849

The cost estimation associated with piping breakdown is discussed in the section below:

Cost of Breakdown due to Degradation

The method of calculating the loss due to breakdown varies for each operating company. The cost of lost commodity due to degradation is dependent on the operation. The following formula may be used to estimate the cost of breakdown (Jackson, 2003):

$$C_{flp} = E \times P \times D_{rp} \times Q_{pl} \times C_{dp} \tag{4}$$

where, C_{flp} = the cost of lost commodity in dollars, C_{dp} = cost of downtime calculated in dollars barrel, Q_{pl} = quantity of commodity loss per unit time (for e.g., barrels per hour), D_{rp} = duration of the commodity loss (hours), P = probability of loss of commodity (depending on the equipment redundancy levels)=1 (assuming there is no redundancy and the components are in series), E = average number of critical failures in life time. The sample calculation associated with the cost estimation of pipe corrosion is presented in Appendix 6.1.2 and are summarized in Table 6.4.

Loss of Production due to Shutdown

The main factor influencing the cost of failure is the facility's unavailability for production. Maintenance can be planned, whereas failures may lead to an unplanned, immediate shutdown of the facility. The cost of such a shutdown is highly dependent on the number of days of shutdown, the rate of loss of production and value of products at the time of failure. Typically, the loss of shutdown may be estimated using the unit cost of product, quantity of affected production and the maintenance delay time. The maintenance delay depends on the availability of skilled personnel and spare parts which are necessary to carry out the maintenance. The shutdown may be necessitated because of rupture and leakage due to corrosion and cracking processes.

Cost of Shutdown due to Degradation

The shutdown cost due to degradation is calculated by combining the unit cost of product, loss of affected production and maintenance delay time (Straub *et al.*, 2006) as:

$$C_{fsd} = Cu \times Q \times T_m \qquad (5)$$

where, C_{fsd} is the cost of shutdown (dollar), C_u is the unit cost of product (dollar/barrel), Q is the quantity of affected production (barrel/day) and T_m is the maintenance delay (days). A sample shutdown cost estimation associated with the pipe corrosion is presented in Appendix 6.1.3 and is summarized in Table 6.4.

Cost of Spill Cleanup

The cost of oil spill cleanup varies considerably from one incident to another, depending on a number of factors, such as, the type of oil, amount spilled and the rate of spillage, the characteristics of the affected area, weather and sea conditions, local and national laws, time of the year and the spill clean up strategy (White and Molloy, 2003; White, 2002; Etkin, 2000; 1999; Purnell, 1999). Predicting the per-unit cost of spill response is highly uncertain since the factors impacting the costs are quite complex (Etkin, 2000). The most important factors in determining the impact and response costs for an oil spill is the type of oil and geographic location. In this article, the type of oil is assumed to be crude oil and spillage is in offshore. Based on the location, the average per-unit offshore oil spill cleanup costs is \$ 6508 per tonne (Etkin, 2000). This unit cost represent only the cleanup costs and do not reflect third-party damage claims or natural resources damage costs which may be incurred in addition to cleanup costs, depending on regulations.

Cost of Spill Cleanup due to Degradation

The cost of environmental cleanup comprises of unit cost of spill cleanup and the total quantity released due to structural failures caused by degradations. Further, the total quantity released depends on the rate of spillage and duration of release. The following formula may be used to estimate the cost of spill cleanup:

$$C_{fsc} = Q_m \times D_{rp} \times C_{usc} \quad (6)$$

where, C_{usc} is the unit cost of spill cleanup (dollar/tonne), Q_m loss of product per unit time (tonne/hour) due to corrosion or cracking and, D_{rp} is the duration of spillage (hour). To demonstrate the calculations of spill cleanup cost, a sample calculation is provided in Appendix 6.1.4, where it is assumed that the pipe failure is caused by corrosion. The cleanup cost thus obtained is presented in Table 6.4.

Loss due to Nature Damage

The size of penalty that the company will incur as a result of damaging the environment is difficult to estimate, because costs increase with the scope of failure. The failure modes developed for each degradation-related failure could be graduated to more complex system failures leading to significant environmental damages. The cost due to loss of habitat and damage to natural resources are also difficult to estimate. Still, approximate assessments considering the quantity of release and unit rate are quite possible (Etkin, 2000; 1999). The nature damage due to oil spillage includes loss of marine as well as coastal habitat, soil pollution, damage to agriculture land and adverse health impact (Etkin, 2000; Purnell, 1999). The natural cleansing approach may be an attractive option from a cost perspective. However, the responsible decision makers need to take notice of the provincial and federal regulations, as well as respond to the values and needs of local communities and stake holders before choosing this option (Etkin, 2000). The per-unit cleanup cost of nature damage is $ 5086 per tonne of oil (for a shoreline length of 1 km), based on Etkin (2000). This cost includes the cleanup cost of damage happened to the coastal ecosystem, consisting of nearshore and shoreline response.

Cost of Nature Damage due to Degradation

The total cost of environmental damage comprises of unit cost of nature damage and the total quantity released. Again, the total quantity released from a facility depends on the rate of release and the duration of spillage. Thus, the total cost associated with damaging the natural recourses by structural failures may be estimated using the following formula:

$$C_{fnr} = Q_m \times D_{rp} \times C_{dnr} \tag{7}$$

where, C_{dnr} is the unit cost of nature damage (dollar/tonne), Q_m release of product per unit time (tonne/hour) due to corrosion and cracking, D_{rp} is the duration of release (hour). The pertaining sample calculation is presented in Appendix 6.1.5, and the nature damage cost due to corrosion degradation is reported in Table 6.4.

Cost of Liability

The injuries and deaths caused by a system failure have the most severe implications possible. The loss of life or pain of an injury is impossible to quantify, yet, the cost implied due to worker's compensation and corporate liabilities shall be taken into account (Jones, 1995). Apart from that, safety related system failures have other immediate implications, such as legal fines and penalties of professional negligence. The estimates of liability costs that result from motor vehicle accidents are routinely published by several public and private organizations. The US department of transportation published a technical note (Judycki, 1994) on comprehensive motor vehicle accident costs which is adopted as a baseline in this study. The components of the comprehensive costs includes medical costs, emergency services, vocational rehabilitation, lost earnings, administrative costs, legal consulting fees, pain and lost quality of life. The seven categories of liability costs (Judycki, 1994) and their descriptions are presented in Appendix 6.1.6. For typical process piping, liability cost is extracted from Appendix 6.1.6 and presented in Table 6.4. Liability cost associated with degradation-related failure is assumed to be similar to Category 2, moderate injury causing a liability of $ 40 000 in this article.

Total Cost of Degradation Failure

The total cost of failure is the summation of loss of breakdown, loss due to shutdown, the costs of spill cleanup, nature damage and the liability charges. Hence, the total cost associated with a structural failure due to degradation is given by:

$$C_F = C_{flp} + C_{fsd} + C_{fsc} + C_{fnr} + C_{fl} \tag{8}$$

The developed total cost is based on two assumptions; the component is isolated, and the component failure leads to a system failure with subsequent unavailability for production.

Table 6.4. Degradation Failure Cost for Piping (Pipeline segments) Components

Cost consequence	Cost divisions	Cost of corrosion (dollar)	Sources (Appendix)
Failure cost	Loss due to breakdown	14 939	Appendix 6.1.2
	Loss due to shutdown	149 384	Appendix 6.1.3
	Spill cleanup	190 336	Appendix 6.1.4
	Damage to nature	148 748	Appendix 6.1.5
	Liability charges	40 000	Appendix 6.1.6
	Total cost (C_F)	543 407	

The expected annual equivalent of the total cost of failure due to degradation, which is also called the failure recovery cost, over the service period of n years, with annual interest rate of $i\%$ can be calculated using the following equation (Park, 2007):

$$FR(i) = C_F (A/P, i, n) \tag{9}$$

where, $(A/P, i, n)$ is the recovery factor. The failure recovery factor (the A/P factor, which is also known as annuity factor, and indicates a series of future payments towards a fixed amount for a specified number of periods) can be estimated as:

$$(A/P, i, n) = \left[\frac{i(1+i)^n}{(1+i)^n - 1}\right] \tag{10}$$

6.6.2 Economic Consequences of Inspection

The integrity of process components has to be assessed for the facility's safe operation. The NDT techniques may be used for detection and quantification of unwanted discontinuities and separations in materials due to degradations. The NDT provides the qualitative as well as quantitative information by detecting, locating and sizing of flaws. Several types of defects exist in components, such as corrosion, cracking, inclusions, dents and holes. Defect quantification requires considerable skill and experience, use of more than one NDT method owing to the fact that each method is able to provide limited information on a particular type of defect. Based on literature (Roberge, 2007; Gros, 1997), the best suitable inspection methods for corrosion and cracking, and the corresponding costs are estimated. The sample inspection cost estimation for corrosion has been presented in Appendix 6.2. The per-unit cost for inspection, as obtained from an inspection and testing contracting company in North America has been used in this study.

Cost of Degradation Inspection

The purpose of inspection is to detect and quantify the extent of wall loss, pit depth, and surface crack as well as coating breakage. The routine inspection costs depend on how much area to inspect from a risk point of view. Thus, the inspection cost includes the cost for gaining access to the degraded component, the cost for surface preparation, personnel cost for inspection, the cost associated with technical assistance, the cost of consumables and chemicals, and the logistics cost (rent, storage and transportation etc.). For piping (pipeline segments, bends and tees), the suggested inspection methods are ultrasonic test (UT) thickness measurement and radiographic inspection (RI) for different corrosion, and the magnetic particle inspection (MPI) and UT defect sizing for quantification of different types of cracking degradations (Roberge, 2007; Gros, 1997).

Gaining Access for Inspection

Cost of gaining access, $C_{iga} = C_{li} \times t$ (11)

where, C_{li} = cost of inspection personnel per hour, and t = the duration of inspection (in hours). Sample calculation for corrosion inspection is presented in Appendix 6.2.1.

Surface Preparation (Washing, Purging and Coating Breakage)

Cost of surface preparation, $C_{isp} = C_{li} \times t$ (12)

where, C_{li} = cost of skilled labor per hour, and t = the duration of work (in hours). Sample calculation for corrosion inspection is presented in Appendix 6.2.2.

Inspection Personnel Cost

Cost of visual inspection of piping, $C_{iv} = C_{lvi} \times t$

Cost of UT-(piping) thickness measurements, $C_{iut} = C_{lut} \times t$

Cost of radiographic inspection of piping, $C_{ir} = C_{lri} \times t$ (13)

Cost of UT-(piping) defect sizing, $C_{ids} = C_{lds} \times t$

Cost of magnetic particle inspection of piping, $C_{imp} = C_{lmp} \times t$

where, C_{lvi} = personnel cost (dollar) of visual inspection per hour, C_{lut} = personnel cost for UT thickness measurements per hour, C_{lri} = personnel cost for radiographic inspection per hour, C_{lds} = personnel cost for UT defect sizing per hour, C_{lmp} = personnel cost of MPI (dollar per hour) and t=total duration of inspection activity in hours. Sample calculation for corrosion and cracking inspection is presented in Appendix 6.2.3.

Technical Assistance

Cost of technical expert's assistance, $C_{ita} = C_{ta} \times t$ (14)

where, C_{ta} = technical expert's consultancy fees per hour, and t = the duration of work in hours. Sample calculation for corrosion inspection is presented in Appendix 6.2.4.

Logistics Cost

Logistic cost includes the cost of consumable, equipment rent, storage and transportation.

Logistics cost, $C_{il} = C_c + C_r + C_{st}$ (15)

where, C_c = cost of consumables, C_r= cost of inspection equipment rent, and C_{st}= cost of storage and transportation. Sample calculation is presented in Appendix 6.2.5.

Thus, the total costs associated with piping degradation inspection can be estimated as;

$$C_I = C_{iga} + C_{isp} + C_{iut} + C_{ir} + C_{ita} + C_{il} \qquad (16)$$

This cost includes the inspection with respect to wall thickness as well as coating checks. The estimated costs of corrosion inspection cost are presented Table 6.5.

Table 6.5. Corrosion Inspection Cost for Piping (pipeline segment) Components

Degradation	Cost component	Cost ($)	Source (Appendix)
Corrosion	Gaining Access	240	Appendix 6.2.1
	Surface preparation	960	Appendix 6.2.2
	Inspection: UT	960	Appendix 6.2.3
	Inspection: RI	240	Appendix 6.2.3
	Technical assistance	240	Appendix 6.2.4
	Logistics	1200	Appendix 6.2.5
	Total cost (C_I)	3840	Appendix 6.2.6

The expected inspection costs tend to increase as a function of age of components due to strength degradations and subsequent wall loss. This increasing trend can be modeled using arithmetic gradient (Park, 2007). The cost of inspection involves periodic payments that increase by a constant amount (G) from period to period. The function to model the increasing trend of inspection cost is given by (Newnan, 1976):

$$CI(i) = C_I(A/G,i,n) \tag{17}$$

where, the gradient to equal-payment series conversion factor is given by:

$$(A/G,i,n) = G\left[\frac{(1+i)^n - in - 1}{i[(1+i)^n - 1]}\right] \tag{18}$$

6.6.3 Economic Consequences of Maintenance

This cost is associated with restoring or maintaining a process facility safely. To have a safe facility, the maintenance should be performed at very small time interval. However, it is impractical due to the huge costs, large maintenance-induced errors, and the facility's unavailability for production. To optimize the replacement economically, the cost of replacement should be greater after failure than before, and the component should be in the wear-out region. The maintenance can be either corrective or proactive depending on the condition of facility. The corrective maintenance is performed in response to an unplanned or unscheduled downtime of the component, usually as a result of a failure. This could be based on previous experience and an assessment of the risk of failure caused by deteriorations. In general, the costs of corrective maintenance will always be huge. The proactive maintenance is the advance maintenance and it can be either preventive or predictive. Preventive maintenance is a scheduled downtime, usually periodical, in which a set of well defined tasks are performed. The predictive maintenance estimates through diagnostic tools, such as NDT and probabilistic modeling, when a component is about to fail and should be repaired or replaced, thus, reducing the costly corrective maintenance. This article focuses on predicting the optimum interval for the economic replacement of process components.

Cost of Degradation Maintenance

Maintenance in practice may be either a minor patch repair work or the complete replacement of degraded component. In this study, it is assumed that the proposed inspection method is able to detect the presence of corrosion discontinuities and surface cracks. For all types of corrosion, minor patch repair work of the affected area is considered, and for any types of cracking, immediate component replacement with necessary repair work is considered. The maintenance work includes the access to degradation part, surface preparation, cutting and removal of pipes and plates, welding and restoration of protective coating. Thus, in addition to the cost of component to be replaced, the personnel cost, logistics cost related to transportation, storage and rents of facilities are also must be included. For a piping component, the maintenance costs are estimated below. The sample calculations are presented in Appendix 6.3.

Gaining Access to the Degraded Component

The cost of gaining access for maintenance, $C_{mga} = C_{lm} \times t$ (19)

where, C_{lm} is the cost of maintenance personnel per hour and t is the duration of work (hour). A sample calculation for cost of gaining access is presented in Appendix 6.3.1.

Surface Preparation (Coating Breakage, Cleaning, Purging with Gas)

Cost of surface preparation for maintenance, $C_{msp} = C_{lm} \times t$ (20)

where, C_{lm} is the cost of maintenance labor per hour and t is the duration of work (hour). A sample calculation for the cost of surface preparation is presented in Appendix 6.3.2.

Gauging Defects

Personnel cost, $C_{mp=}C_{lm} \times t$ (21)

Total cost of defects gauging for maintenance, $C_{mgd} = C_{mp} + C_{ml}$ (22)

where, C_{ml} is the logistics cost (equipment rent, transportation and storage). The sample calculation for the cost of defect gauging for maintenance is presented in Appendix 6.3.3.

Repair Work of Corroded Components

Repair cost (cutting, welding, fitting etc.), $C_{mcw} = C_{lcr} \times t$ (23)

where, C_{lcr} is cost of labor for minor repair in dollar per hour, t is total repair time.

Weld quality test and coating restoration, $C_{mwt} = C_{lwt} \times t$ (24)

where, C_{lwt} is the personnel cost for weld quality testing, t weld test duration.

Technical assistance, $C_{mta} = C_{lta} \times t$ (25)

where, C_{lta} = the cost of technical consultancy per hour, t is the total work hours.

The cost of minor repair, $C_{mmr} = C_{ms} + C_{mcw} + C_{mwt} + C_{mc} + C_{mta}$ (26)

where, C_{ms} is the spare or part's cost, and C_{mc} is the cost of consumables. The sample calculation for the cost of minor repair is presented in Appendix 6.3.4.

Thus, for minor patch repair of corroded component, the total costs are estimated by;

$$C_M = C_{mga} + C_{msp} + C_{mgd} + C_{mmr} \quad (27)$$

The final costs thus estimated are reported in Table 6.6.

Table 6.6. Corrosion Maintenance Cost for Piping Components

Degradation	Cost component	Cost ($)	Source (Appendix)
Corrosion	Gaining access	800	Appendix 6.3.1
	Surface preparation	1200	Appendix 6.3.2
	Gauging defects	1200	Appendix 6.3.3
	Minor repair work	6800	Appendix 6.3.4
	Total cost (C_M)	10000	

Similar to inspection, the expected maintenance cost also tends to increase as a function of age of components due to degradations and subsequent loss of wall thickness. This increasing trend can be modeled using arithmetic gradient. The cost of operation and maintenance involves periodic payments that increase by a constant amount (G) from period to period. In such a gradient series, $A_n = (n-1)G$, where $G > 0$. The cost function to model the increasing trend of annual maintenance cost is given by (Newnan, 1976):

$$CM(i) = C_M(A/G,i,n) \tag{28}$$

where, the gradient to equal-payment series conversion factor is same as in equation (18). Similar to corrosion, the estimated costs of pipe cracking are presented in Table 6.7.

Table 6.7. Estimated Cracking Costs for Piping Components

Degradation	Cost subdivisions	Cost (dollar)
Cracking	Total cost of failure	438 235
	Total cost of maintenance	15 000
	Total cost of inspection	4 400
	Salvage value	0

6.6.4 Annual Equivalent Cost (AEC) of Degradation

The AEC of operating and maintaining the ageing process component is the summation of the annual equivalent costs of failure recovery, inspection, and maintenance. Hence the AEC may be estimated as follows:

$$AEC(i) = FR(i) + CI(i) + CM(i) \tag{29}$$

where, FR is the failure recovery cost, CI is the inspection cost, CM is the maintenance cost and i represents the annual interest rate.

6.6.5 Tax Considerations

The corporate tax rate is applied to the taxable income of a corporation. Whether the existing component is kept, or replaced with a new one, the tax credits on operating expenses must be incorporated into the analysis. To apply the concepts of minimum risk to life, the tax effects (gains or losses) on failure, inspection and maintenance are incorporated. In analysis, the operating income is taxed at an annual rate of 35%.

6.6.6 Probabilistic Cost Analysis

The uncertainty and variability in the above cost models has been overcame through probabilistic cost analysis using the Monte Carlo simulations. In simulation, the total cost of component's failure, inspection and maintenance, as presented in Tables 6.4 to 6.6, is assumed to be a Gaussian distribution with the estimated mean value. A coefficient of variation of 2.5% has been assumed in the cost estimation.

6.6.7 Risk Assessment

The AEC has been combined with the cumulative density function (CDF) of the posterior probability to estimate the operational life risk curve as shown in equation (30). Thus, finding the optimal replacement period reduces to finding a value of n that minimizes the operational risk. At the optimal risk point, the risk will be reduced to as low as reasonably practicable (ALARP) level and at the same time, ensures the safety of operation.

$$R = F\left[p(\theta / y)\right] \times AEC \tag{30}$$

where, R is the risk of failure (in dollar) from a degradation, $F\left[p(\theta / y)\right]$ is the CDF of posterior probability of failure and AEC is the annual equivalent cost of consequences.

6.7 RESULTS AND DISCUSSIONS

6.7.1 Stochastic Degradation Modeling

The Bayesian analysis results obtained using the M-H algorithm for EC and CFC are summarized in Table 6.8, and are shown graphically in Figures 6.3 and 6.4 (Thodi *et al.*, 2010). The M-H algorithm coded in MATLAB has been used to simulate the posterior samples and to estimate their parameters. Input to the code includes the prior and likelihood parameters, and required sample size. The posterior estimation based on M-H algorithm converges to satisfactory results with 10000 samples. First half of the simulated samples, which were in a transient state, were ignored. The remaining samples which describe a steady state condition were used to produce the posterior models.

Table 6.8. The Estimated Posterior Probability Models and its Parameters

Structural	Posterior Probability Models and its Parameters			
Degradations	Type of Model	Shape	Scale	Location
EC	3P Weibull	2.7070	0.0421	-0.0065
CFC	Weibull	1.4560	2.0650	-

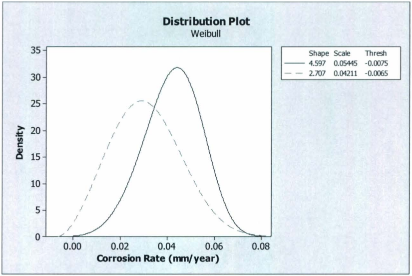

Fig. 6.3. Sample Prior-Posterior (Weibull) Analysis Result for Erosion Corrosion

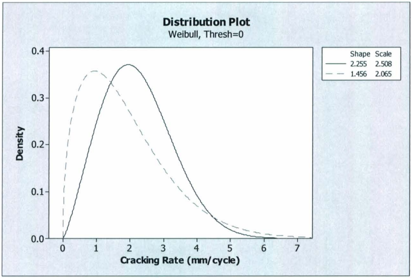

Fig. 6.4. Sample Prior-Posterior Analysis Result for Corrosion Fatigue Cracking

6.7.2 Economic Consequence Analysis

The economic consequence analysis has been performed for the cost of failure, inspection and maintenance. The mean and standard deviation of estimated costs are summarized in Table 6.9. The results for estimated annual equivalent costs due to EC and CFC are presented in Figs. 6.5 and 6.6. The failure recovery cost over the service life of component is estimated by considering a fixed rate of annual interest of 8%. The cost of inspection and maintenance is estimated using the present worth factor approach, assuming the same rate of interest. The annual equivalent of failure cost is observed to be a decreasing function, where as the inspection and maintenance costs are increasing functions of service life. Increase in the inspection and maintenance costs are expected due to the loss of material and strength. The computed AEC is observed to be a convex function of service life.

Table 6.9. Corrosion and Cracking Costs Estimated in the Consequence Analysis

Degradation	Cost divisions	Corrosion cost ($)		Cracking cost ($)	
		Mean	Std. dev	Mean	Std. dev
Corrosion/ Cracking	Total cost of failure	543 407	13585	438 235	10956
	Total cost of maintenance	10 000	250	15 000	375
	Total cost of inspection	3840	96	4 400	110
	Salvage value	0	0	0	0
	Annual interest rate	8 %		8%	

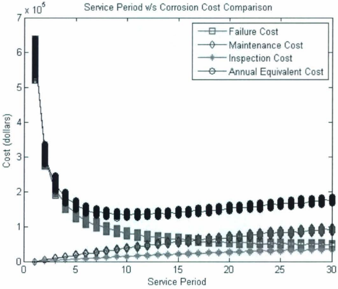

Fig. 6.5. Sample Economic Consequence Analysis Results for Erosion Corrosion

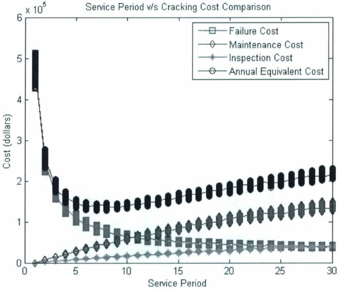

Fig. 6.6. Sample Economic Consequence Results for Corrosion Fatigue Cracking

6.7.3 Optimum Replacement Interval

Results of the risk analysis are presented in Figures 6.7 and 6.8 for sample EC and CFC. A clear trend is obtained for the operational life risk in the form of a convex curve using 10000 iterations. The intervals for the optimal replacement of components are obtained from Figure 6.7 and 6.8 are summarized in Table 6.10. Ideally, it is the optimum interval with minimum risk, to replace the component rather than performing maintenance. Also, after each optimal replacement, the component returns to as good as new condition.

Table 6.10. Optimum Replacement Interval for Deteriorating Components

Assets	**Deterioration**	**Source**	**Optimum maintenance interval**
Piping	EC	Figures 6.7	10 yrs
Piping	CFC	Figures 6.8	08 yrs

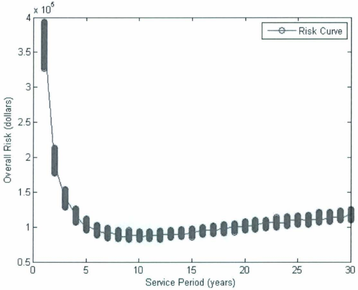

Fig. 6.7. The Operational Life Risk Curve due to Erosion Corrosion

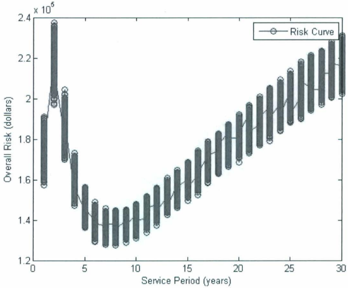

Fig. 6.8. The Operational Life Risk Curve due to Corrosion Fatigue Cracking

6.8 SUMMARY AND CONCLUSIONS

An RBIM strategy for optimal replacement decisions of offshore process components has been discussed in this article. Replacement strategies are designed to remedy the effects of physical deterioration, strength loss and obsolescence of process components. Physical deterioration leads to reduction in the efficiency of operation, wall thickness and material strength. Obsolescence occurs as a result of continuous developments of new components. In the first part of this article, an integrity modeling framework is discussed, followed by a brief discussion of the stochastic degradation modeling using the Bayesian prior-posterior analysis. An economic consequence analysis model based on component replacement concepts is discussed further in detail. The annual equivalent cost is calculated by combining the failure, inspection and maintenance costs. The posterior probability of failure is then combined with the annual equivalent cost of consequences to produce the operational life risk curve. The optimal replacement interval is the interval corresponding to minimum risk. By performing replacement at this interval, the risk of operation will be reduced to the ALARP level. In this study, a case study of a pipeline segment was presented. The optimum replacement intervals for a pipeline segment were found to be 10 years for EC and 8 years for CFC. The smaller of these two values has been selected as the optimum replacement interval for the ageing pipeline segment. The replacement strategy entails the economic replacement of components rather than performing maintenance. This model takes into account the effects of taxes, the uncertainty and variability in the degradation process and the consequence parameters using the Bayesian Monte Carlo simulations.

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Appendix 6.1

6.1.1 Flow of Liquid through a Hole in a Pipe

$$Q_m = AC_0\sqrt{2\rho g_c p_g}$$

Assume the hole diameter = 5mm = 0.005m

$$\therefore A = \frac{\pi}{4}d^2 = \frac{\pi}{4}(0.005^2) = 1.9635\times10^{-5}\,m^2$$

ρ = density of crude oil = 862 kg/m^3 (32.6^0, API, www.simetric.co.uk/siliquids.htm)

g_c = gravitational constant (length mass/force time^2), i. e., $g_c = 1\dfrac{kg.m}{N.s^2}$

$p_g = 100\,psi = 689475.7\,N/m^2$

For corrosion, assume $C_0 = 1$ (Crowl and Louvar, 2002)

$$Q_m = AC_0\sqrt{2\rho g_c p_g}$$
$$Q_m = 1.9635\times10^{-5}\times1\sqrt{2\times862\times1\times689475.7}$$
$$Q_m = 0.677\,kg/s = 17.784 \text{ barrels/hr}$$

For cracking, assume $C_0 = 0.61$ (Crowl and Louvar, 2002)

$$Q_m = AC_0\sqrt{2\rho g_c p_g}$$
$$Q_m = 1.9635\times10^{-5}\times0.61\sqrt{2\times862\times1\times689475.7}$$
$$Q_m = 0.413\,kg/s = 10.849 \text{ barrels/hr}$$

6.1.2 Loss of Breakdown by Corrosion Degradation

For corrosion, $C_{flp} = E\times P\times D_{rp}\times Q_{pl}\times C_{dp}$

where, C_{flp} = present cost of lost commodity in dollars

C_{dp} = cost of downtime calculated in dollars per barrel = \$ 70 per barrel

D_{rp} = duration of the loss of commodity (hour) = ½ day =12hr

P = probability of equipment breakdown (depending on equipment redundancy levels)=1 (assume there is no redundancy and components are in series).

E = average number of critical failures in life time=1 failure

Q_{pl} = quantity of commodity loss per unit time (barrels per hour)

Cost of a pipe breakdown due to corrosion mechanism:

The present cost: $C_{flp} = 1 \times 1 \times 12hr \times \dfrac{17.784bl}{hr} \times \dfrac{\$70}{bl} = \$14939$

6.1.3 Shutdown Cost due to Corrosion Degradation

The present worth, on an annual basis, $C_{fsd} = Cu \times Q \times T_m$

Unit cost of product, C_u = \$ 70 per barrel

Maintenance delay, T_m = 5 days (Including time to access, minor patchwork, testing etc.)

Cost of shutdown due to the corrosion failure of pipeline segments:

Quantity of affected production, Q = 17.784 barrel /hour = 426.816 barrels/day

Total loss due to shutdown, $C_{fsd} = \dfrac{\$70}{barrel} \times \dfrac{426.816barrel}{day} \times 5days = \$149384$

6.1.4 Spill Cleanup Cost due to Corrosion Degradation

Total cost of spill clean up, $C_{fsc} = Q_m \times D_{rp} \times C_{usc}$

Unit cost of spill clean up, $C_{usc} = \ \$6508/tonne$

Leakage through hole in a pipe due to corrosion failure:

Rate of spillage, $Q_m = 0.677kg/s = 2.437tonnes/hr$

Therefore, $C_{fsc} = \dfrac{2.437tonnes}{hr} \times 12hr \times \dfrac{\$6508}{tonnes} = \$190336$

6.1.5 Nature Damage Cost due to Corrosion Degradation

The total loss of nature damage, $C_{fnr} = Q_m \times D_{rp} \times C_{dnr}$

Unit cost of spill clean up, $C_{dnr} = \$5086 / tonne$

Leakage through hole in a pipe due to corrosion failure:

Rate of spillage, $Q_m = 0.677 kg/s = 2.437 tonnes/hr$

Therefore, $C_{fsc} = \dfrac{2.437 tonnes}{hr} \times 12 hr \times \dfrac{\$5086}{tonnes} = \$148748$

6.1.6 Comprehensive Liability Cost

Severity	Descriptor	Cost per Injury (dollars)*
Category 1	Minor	5,000
Category 2	Moderate	40,000
Category 3	Serious	150,000
Category 4	Severe	490,000
Category 5	Critical	1,980,000
Category 6	Fatal	2,600,000

* Technical advisory, Motor Vehicle Accident Costs (Judycki, 1994), US Department of Transportation, Federal Highway Administration.

Appendix 6.2 Inspection Cost Associated with Pipe Corrosion

6.2.1 Gaining Access

Cost of inspection labor per hour, $C_{li} = \$80/hr$

Duration of work, $t = 3hr$

Gaining access cost, $C_{iga} = 3hr \times \$80/hr = \$240$

6.2.2 Surface Preparation (Washing, Purging and Coating Breakage)

Cost of inspection labor per hour, $C_{li} = \$80/hr$

Duration of work, $t = 12hr$

Surface preparation cost, $C_{isp} = 12hr \times \$80/hr = \$960$

6.2.3 Inspection Cost

Cost of UT thickness measurements, $C_{iut} = 12hrs@\$80/hr = \$960$

Cost of radiographic inspection of piping, $C_{ir} = 3hrs@\$80/hr = \$240$

Cost of piping UT defect sizing, $C_{ids} = 10hrs@\$80/hr = \$800$

Cost of piping magnetic particle inspection, $C_{imp} = 12hrs@\$80/hr = \$960$

6.2.4 Technical Assistance

Cost of technical assistance, $C_{ita} = 3hrs@80 = \$240$

6.2.5 Logistics Cost

Logistic cost includes the cost of consumable, equipment rent, storage and transportation.

Logistics cost, $C_{il} = \mathrm{C_c} + \mathrm{C_r} + \mathrm{C_{st}}$

$\mathrm{C}_c = \$400$, $C_r = \$400$, $C_{st} = \$400$, $\therefore C_{il} = \$1200$ (from an inspection company)

6.2.6 Total Cost of Inspection

Thus, for piping corrosion inspection, the associated total costs can be estimated by;

$C_I = C_{iga} + C_{isp} + C_{iut} + C_{ir} + C_{ita} + C_{il} = \$3840$

Appendix 6.3 Maintenance Cost Associated with Pipe Corrosion

6.3.1 Gaining Access

Cost of gaining access for maintenance, $C_{mga} = 10hrs \times \$80/hr = \$800$

6.3.2 Surface Preparation (Coating Breakage, Cleaning, Purging with Gas)

Cost of surface preparation for maintenance, $C_{msp} = 15hrs @ \$80/hr = \$1200$

6.3.3 Gauging Defects

Personnel cost, $C_{mp} = 10hrs @ \$80/hr = \$800$

Logistics cost, $C_{ml} = \$400$

Total cost of gauging for maintenance, $C_{mgd} = C_{mp} + C_{ml} = \$1200$

6.3.4 Minor Patch Repair Work

Spare/part's cost, $C_{ms} = \$2200$

Cutting, welding, fitting, $C_{mcw} = 30hrs @ \$80/hr = \$2400$

Weld quality test and alignment, $C_{mwt} = 10hrs @ \$80/hr = \$800$

Cost of consumables, $C_{mc} = \$1000$ (from an inspection company)

Technical assistance, $C_{mta} = 5hrs @ \$80/hr = \$400$

Total cost of minor patch repair, $C_{mmr} = C_{ms} + C_{mcw} + C_{mwt} + C_{mc} + C_{mta} = \$6800$

Thus, for minor patch repair of concerned piping, the total costs are approximated by;

$C_M = C_{mga} + C_{msp} + C_{mgd} + C_{mmr} = \$10,000$

CHAPTER VII

RISK BASED INTEGRITY MODELING FOR THE OPTIMAL INSPECTION AND MAINTENANCE DECISIONS OF OFFSHORE PROCESS COMPONENTS

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PREFACE

This chapter discusses the optimization of inspection and maintenance strategy for offshore process components under deteriorating conditions. The decision making regarding the inspection and maintenance under uncertainty is a challenging task. Structural degradation is a stochastic process, thus the probabilistic models are developed to optimize the inspection and maintenance. The aim of RBIM is to minimize the risk of failure associated with degradations and at the same time, maximize the inspection and maintenance intervals to avoid unnecessary maintenance. To apply this model, the cost of corrective maintenance should be high compared to the predictive maintenance and the component should be in the wear-out region. Both these conditions are prevailing in the ageing offshore process components. This manuscript is reviewed internally by co-authors and submitted for review to the Journal of Risk Analysis (March 2011).

An independent literature review on risk based inspection and maintenance has been conducted by the principal author. The stochastic degradation model developed in Chapter V and the economic consequence model developed in Chapter VI are integrated in this chapter by the principal author. The failure consequences are analyzed in terms of cost incurred as a result of failure, inspection and maintenance. The cost of failure is estimated under five headings; the loss of breakdown, the loss due to shutdown, the cost of environmental cleanup, the cost of nature damage and liability. The inspection and maintenance costs are estimated considering the: access, surface preparation, gauging defects, inspection and maintenance, logistic and technical assistance costs. The RBIM methodology has been integrated and implemented by the principal author to achieve the target of optimal inspection and maintenance strategy.

The rates of failure, inspection and maintenance costs are developed to produce the annual equivalent cost consequences. The estimated risk is plotted against the inspection and maintenance interval. In the risk curve, the point at which the inspection and maintenance interval is maximum (and where the risk is minimum) has been found out. The risk to life from UC, PC, EC, SCC, CFC and HIC are developed and compared by the principal author. The inspection and maintenance interval corresponding to the minimum of them are designated as optimum interval. This quantitative model takes into account the prior knowledge and NDT data using Bayes theorem, it is dynamic and it performs well even though the degradation process follows non-conjugate pairs. The principal author prepared the first draft of this manuscript, which was later consecutively revised and improved based on comments from the co-authors.

ABSTRACT

Degradation of components of offshore process facilities poses a major threat to the integrity of the facility and may lead to its complete failure. Failure of such facilities may have catastrophic effects on human life, the environment, and financial investment. A robust inspection and maintenance strategy mitigates the effects of structural degradations and reduces the threats of failure. Such a strategy needs to take into account the stochastic nature of failure caused by structural degradations. Risk-based integrity modeling (RBIM) is a newly-developed methodology that aims to protect human life, financial investment, and the environment against the consequences of failure. RBIM quantifies the risk associated with individual components and uses this as a basis for the design of an inspection and maintenance strategy. The major structural degradations dealt with are corrosion: uniform, pitting, erosion; and cracking: stress corrosion, corrosion fatigue, and hydrogen induced cracking. The component's degradation processes are modeled using Bayesian prior-posterior analysis. Field non-destructive test data is used in the analysis to update the prior knowledge of degradation. The consequences of failure are modeled considering the costs of failure, inspection and maintenance. The cost of failure includes breakdown loss, shutdown loss, the cost of spill cleanup, loss caused by environmental damage and liability. The total annual equivalent cost (AEC) of operating and maintaining the facility is the summation of annual equivalent costs of failure, inspection and maintenance. Further, the operational risk to the life of components is computed by combining the posterior probability and the AEC. As the overall risk curve is a convex function of the maintenance interval, the optimum maintenance interval is the global minimum point. In this article, the operational risk is reduced to as low as

practicable level and at the same time the inspection and maintenance intervals are maximized to avoid unnecessary maintenance. This model performs well even though the degradation processes follow non-conjugate pairs. Bayesian Monte Carlo simulations are used to model the uncertainty in the risk analysis.

Keywords: Risk, integrity, degradation, probability, consequence, optimal maintenance

7.1 INTRODUCTION AND BACKGROUND

In recent years, the optimization of maintenance planning using stochastic models is gaining predominance due to the inherent limitations of breakdown maintenance. A large number of articles have been published on the subject of maintenance optimization using mathematical models [1-9]. Most of them [1-6] are based on lifetime distribution, the Markov process and qualitative risk ranking. The main drawbacks of such models are: subjective being qualitative or semi-quantitative, lack of enough data for estimating the parameters of distribution, lack of a dynamic updating mechanism, lack of information on failure consequences, and hence the lack of true risk estimation associated with its operation. Risk based maintenance is the latest development in asset integrity management. It takes into account the probability and consequences of a failure, as risk minimization is the maintenance objective, as opposed to condition monitoring or cost minimization. Some of the literature [7-8] has used Bayesian analysis in maintenance management; however, this literature conveniently assumes there are conjugate pairs for degradation process, for easy computation of posteriors, which is not the case in real life. This introduces significant uncertainty in the analysis, and thus proposes sub-optimal strategy. The prior and likelihood are often non-conjugate pairs in real-life degradation processes, but, their modeling has not been reported so far in literature. Thus, there is a need for a quantitative, risk based maintenance model based on the time-dependent degradation of components and consequences of failure caused by degradations.

Maintaining the integrity of process components has been a subject of research for many years [1-9]. The age-dependent structural degradation of components is a major threat to the integrity of offshore process facilities. Asset integrity management is the means of ensuring that the people, systems, process and resources that deliver integrity are in place, in use and will perform when required over the whole life cycle of the asset [10]. From the historic database it was observed that the major causes of process component failures in offshore facilities are the environmentally induced defects, such as different types of corrosion and cracking [11]. For components in the operational stage, the design changes or modifications are often cumbersome; thus, inspection and maintenance are the only feasible measures for risk reduction [2]. However, the extent of inspection and maintenance is unknown due to the large uncertainty and variability in degradation processes and failure consequences. The failure caused by structural degradations is a stochastic process. Failure consequences include the failure, inspection and maintenance consequences. Failure consequences would include the loss of commodity due to breakdown, production loss due to shutdown, cost of spill cleanup and the legal fees and penalties due to environmental damage and liability. All these parameters are stochastic and required to be taken into account in the designing of an optimal inspection and maintenance strategy. Risk-based integrity modeling (RBIM) is a newly-developed methodology that aims at the protection of human life, financial investment and the environment against the consequences of failure [11]. The RBIM quantifies the level of risk to which the individual components are subjected and uses this as a criterion for developing the optimal inspection and maintenance strategy.

Leaks and ruptures are the principal cause of hydrocarbon release, blowout, fire and explosions in offshore process facilities. The accident statistics reported for offshore systems on the UK continental shelf reported from the period 1990 to 2007 are: 836 hydrocarbon releases (with frequency 0.590), 17 blowouts (with frequency 0.012), 245 fire events (with frequency 0.173), 14 explosions (with frequency 0.010), 20 leakages (with frequency 0.014) and 24 structural failures (10). The offshore hydrocarbon release report (12) indicates that 25% of the total releases are due to corrosion, 9% of the total releases are due to erosion, 24% of them are due to fatigue and 13% are due to mechanical wear. In Canada, environmentally induced defects, such as metal corrosion, stress corrosion cracking, hydrogen induced cracking etc. have caused 40% of the natural gas pipeline failures and 38% of hazardous liquid releases (9).

The cost of corrosion in the USA is observed to be 3.4 percent of the Gross National Product (GNP). The direct cost of corrosion in industrialized countries in billions of USD is reported (13): USA (303.76), Japan (59.02), former USSR (55.01), Germany (49.26), UK (8.51), Australia (7.32) and Canada (3.38). These figures show that material degradation of assets is an economic problem, which needs to be addressed on a priority basis (13).

This paper presents a methodology and models for risk based maintenance optimization. The age-based asset integrity threats are identified and modeled. In order to model uncertainty and variability in the degradation processes, stochastic Bayesian prior-posterior analysis has been used. The consequences of failure are modeled using economic consequence analysis. The risk to operational life is used as a criterion for decision making regarding the inspection and maintenance interval. The increasing rate of failure cost and decreasing rates of inspection and maintenance costs with respect to inspection and maintenance intervals are used to minimize the risk. This quantitative risk model accounts for uncertainty in asset integrity with Bayesian Monte Carlo analysis.

7.2 ASSET INTEGRITY THREATS IN PROCESS COMPONENTS

Asset integrity is defined as the ability of an asset to perform its required function effectively and efficiently whilst protecting health, safety and the environment [10]. Past studies indicate that the major asset integrity threats in pipelines are [9] third party damage, environmentally induced defects, material and fabrication defects and operational errors. Most of these degradations may be reduced by implementing better design procedures, effective quality assurance and quality control programs, better programs for personnel training and by imposing stringent policies and regulations. However, a major share of process components and pipelines in offshore fail primarily due to environmentally-induced (age-based) defects, such as different types of corrosion and cracking [1-2, 11, 14]. In reality, the time-based structural degradation processes are stochastic in nature. This makes its precise modeling with predictive capability a challenging task. This is addressed in this article.

Corrosion is the result of a chemical reaction between a metal or alloy and its environment which causes loss of the properties of the metal or alloy, most importantly its strength. [15] The extent of deterioration per unit time is expressed in terms of corrosion rate. Corrosion may be either uniform, pitting or erosion types. Uniform corrosion (UC) is characterized by the corrosive attack proceeding evenly over the entire surface area, resulting in thinning of wall thickness until failure. The localized attack of a corrosive environment on an otherwise resistant surface produces pitting corrosion (PC). It is confined to a point or small surface area that takes the form of a cavity. A joint action involving the corrosive environment and erosion in the presence of a moving corrosive fluid is known as erosion corrosion (EC). It leads to the accelerated loss of material. The brittle fracture of a normally ductile alloy, in the presence of a corrosive environment or cyclic loading, is known as cracking [15]. The amount of cracking per unit of time either in length or depth is expressed as the cracking rate. Cracking may be either stress corrosion, corrosion fatigue, or hydrogen induced types. Stress corrosion cracking (SCC) is the cracking induced from the combined influence of static tensile stress and a corrosive environment. The tensile stresses may be in the form of directly applied stresses or in the form of residual stresses. The process in which a metal fractures prematurely under conditions of simultaneous corrosion and repeated cyclic loading at lower stress levels or fewer cycles is known as corrosion fatigue cracking (CFC). Hydrogen induced cracking (HIC) refers to the severe loss of ductility caused by the presence of hydrogen in the metal. Hydrogen absorption may occur during electroplating, welding, pickling or other processes that favor the production of nascent hydrogen. Different types of structural degradation processes were depicted in Figures 1.1 and 1.2.

7.3 RISK-BASED INTEGRITY MODELING

The risk to life of a component is a function of the combination of its Probability of Failure (PoF) and Consequence of Failure (CoF). Thus, the main steps in an RBIM program are the estimation of the probability of degradation-related-failures and the likely consequences of such failures. In RBIM, the probability of failure is estimated using stochastic modeling of all identified degradations. Bayesian analysis is used for generating a dynamic model, which facilitates the system-learning process with the arrival of new data over a period of time. Field non-destructive test data is used in the model. Consequence analysis estimates the economic consequences of failure. Consequence analysis is based on the dollar cost incurred as a result of failure. The RBIM is a quantitative, risk-based maintenance model that takes into account the stochastic nature of the structural degradation processes and failure consequences. An effective RBIM strategy should reduce the risk of operating the component to as low as reasonably practicable (ALARP) level. An overall framework for the RBIM is presented in Figure 7.1. The framework consists of the following tasks (Figure 7.1): data collection to identify the potential degradation mechanisms, stochastic degradation modeling to develop the best suitable prior, likelihood and posterior probability models, consequence analysis to estimate the failure consequences, determination of inspection and maintenance intervals, which optimize the operational risk, and testing and validation.

7.3.1 Data Collection

There are various testing techniques available for collecting integrity data. Two of these techniques are destructive testing and non-destructive testing (NDT). NDT is useful to collect the data from large and expensive process components. The commonly used NDT techniques are [16] visual inspection, liquid penetrant inspection, magnetic particle inspection, eddy current testing, ultrasonic testing and radiography. In this article, component, the service (sweet or sour), the product being used or transported and ultrasonic testing (UT) is used for detecting and quantifying the unwanted discontinuities and separations in the wall thickness of offshore process components.

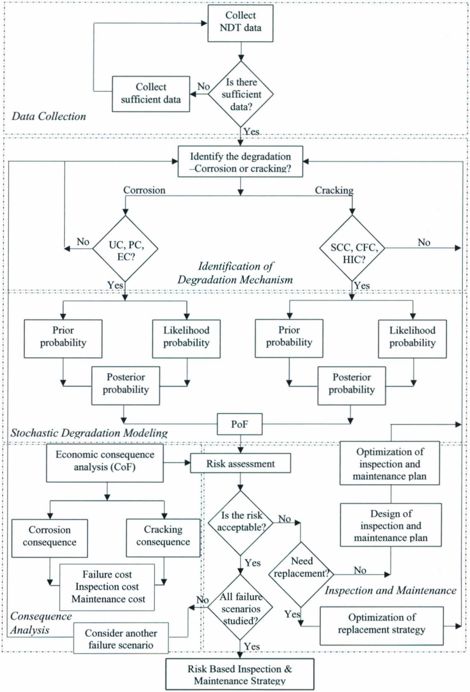

Fig.7.1. Framework for Risk based Integrity Modeling

7.3.2 Identification of Degradation Mechanisms

The functional details of the system, subsystem and components are analyzed to study the potential degradation mechanisms. The data to be analyzed includes the material of the environmental conditions, such as pressure, temperature and humidity. Furthermore, the wall thickness data obtained from NDT is used to identify the degradations. If the degradation is a uniform loss of material, regression analysis has been used; and if it is localized attack, extreme value analysis has been used to develop the rates of degradation [1, 14].

7.3.3 Stochastic Degradation Modeling

Degradation modeling is performed based on Bayesian analysis. Statistical Bayes' theorem is used to learn about the system more precisely with the arrival of new inspection data. Since the structural degradation is a random process, the NDT data indicates large uncertainty and variability. This uncertainty and variability may be best modeled by stochastic models. The uncertainty in degradations can be best minimized by inferring prior knowledge about the system, and revising the present knowledge with new information (NDT data). Bayes' theorem states how to update the prior probability, $p(\theta)$, with a likelihood probability, $p(y/\theta)$, to obtain the posterior probability as:

$$p(\theta / y) = \frac{p(\theta)p(y/\theta)}{\int p(\theta)p(y/\theta)d\theta} \tag{1}$$

The posterior probability density $p(\theta / y)$ provides the latest information, after viewing the data. It provides a basis for the inference on the degradation parameter θ [11]. The prior probability, which is the initial information about the degradation, is developed first [14]. Further, these prior models are combined with NDT data as the likelihood function to develop posterior probability. The posterior model is a system-learned model to predict the future failure probability of degrading components. Stochastic degradation modeling for potential corrosion and cracking processes is discussed in Section 7.4.

7.3.4 Economic Consequence Analysis

The failure consequences are analyzed in terms of operational-life cost incurred as a result of the failure, inspection and maintenance. The consequences of failure include the loss of a commodity due to breakdown, loss due to shutdown, the cost of spill cleanup, the cost of nature damage and liability [(17)]. The inspection cost depends on the method of NDT inspection, type of component, cost of gaining access, surface preparation and logistics costs. The maintenance cost depends mainly on the type of repair; i.e., minimal repair or component replacement, along with the cost of gaining access, surface preparation, gauging and coating restoration. Further, the total cost, also known as annual equivalent cost (AEC) of operating and maintaining the component is computed. The AEC is a summation of expected annual equivalent costs of failure, inspection and maintenance. Details of consequence analysis are presented in Section 7.5.

7.3.5 Optimization of Inspection and Maintenance

In the proposed risk-based model, the estimated posterior probability of failure and the economic consequences are combined to produce the operational risk in the service life. The cumulative probability density of structural degradations is combined with the AEC of operating and maintaining the component, to plot the operational risk curve. From the risk curve, optimal inspection and maintenance strategy is obtained by minimizing the overall risk. The optimum inspection and maintenance interval thus obtained satisfies the two necessary criteria of maintenance: first, the risk is reduced to ALARP level; and second, the maintenance interval is maximized, thus avoiding unwanted maintenance and its associated costs. The developed inspection and maintenance risks are compared with the company's operating budget, as risk acceptance criteria. Details of the inspection and maintenance interval optimization are presented in Section 7.6.

7.3.6 Testing and Validation

To demonstrate the applicability of developed RBIM, a practical case study is presented. The probabilities of piping component (pipes, bends, tees etc.) failure are modeled using the field NDT data, associated with an ageing process facility operating in the North Sea. The consequence of failure models are tested using the unit cost data of failure, inspection and maintenance, obtained from an inspection and maintenance company operating in the North Sea. Results of testing and validation are presented in Section 7.7.

7.4 STOCHASTIC DEGRADATION MODELING

As reported in Section 7.3.3, the life-threatening structural degradation processes are modeled using Bayesian analysis. Statistical Bayes' theorem provides a formal and structured approach that can be used to update the prior knowledge of degradation processes based on data obtained through field NDT inspections.

7.4.1 Prior Probability Modeling

In the context of degradations, the prior probability refers to the initial understanding of each type of degradation mechanism. Although the choice of prior is often subjective, a rational consensus may be achieved by analyzing historic data from the same or similar installations. To develop the prior probability models for each type of corrosion and cracking degradations, several probability distributions have been tested using the data extracted from relevant literature. Details of the literature and statistical tests performed for developing the degradation prior models are presented elsewhere [14].

The prior probability models are developed for degradation process, such as, UC, PC, EC, SCC, CFC and HIC. It is observed that, for UC, the 3P Weibull; for PC, the Type 1 Extreme Value; for EC, the 3P Weibull; and for SCC, the 3P Weibull or Type 1 Extreme Value; for CFC and HIC, the Lognormal and Weibull are observed to be the ideal candidates [14]. The goodness of this fit is tested using probability plots and Anderson-Darling (A-D) tests. Then, the model parameters are estimated using the methods of least square (LS) and maximum likelihood estimates (MLE) [14].

7.4.2 Likelihood Probability Modeling

The integrity inspection data from an ageing offshore process facility has been used to develop the likelihood probability models for different types of corrosion mechanisms. The facility has different systems; a gas condensate system exhibiting UC, a gas export system exhibiting PC, and a high pressure drilling mud system exhibiting erosion type corrosion. Inspection data includes the minimum and average wall thickness acquired during the period 1997 to 2003. The nominal diameters of the facility's components varied from 19.05 to 508.0 mm. The inspection was carried out using the ultrasonic testing (UT) technique. A typical sample isometric drawing related to the gas export system is presented in Figure 7.2. Since no such data were available for cracking, such as SCC, CFC and HIC, the data from literature is used in the analysis.

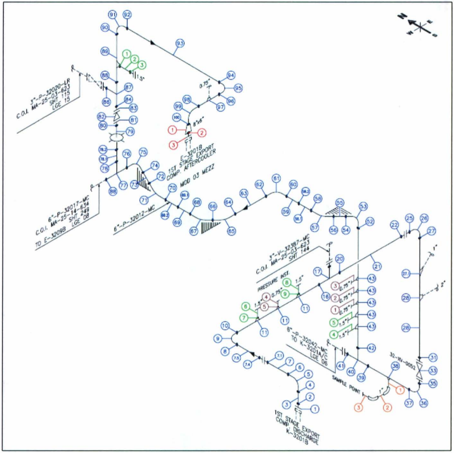

Fig. 7.2. Sample Gas Export System Piping Isometric Drawing

The inspection data (NDT) is first analyzed to estimate the degradation rates. Then, these degradation rates are tested with standard probability distributions to develop the likelihood probability models. The method outlined in article [(1)] has been used to compute the corrosion rates from the available wall loss data. The collected data is first analyzed to identify uniform or localized degradation. In the case of uniform degradation, a time dependent regression analysis, and in the case of localized degradation, an extreme value analysis has been carried out for estimating the rates. Details of corrosion rate estimation and the probability testing may be obtained from article [14]. Similar to priors, the likelihood probability has also been observed to be of the same form. That is, for UC, 3P Weibull; for PC, Type 1 Extreme Value; for EC, 3P Weibull or Type 1 Extreme Value; for SCC, 3P Weibull; and for CFC and HIC, the Lognormal and Weibull distributions are observed to be more suitable likelihood models.

7.4.3 Posterior Probability Modeling

The methods for computing posterior models are [18]: analytical approximations, data augmentation methods, Monte Carlo direct sampling and Markov chain Monte Carlo (McMC) methods. The degradation priors and likelihoods, such as Weibull, Type 1 Extreme Value and Lognormal distributions with two and three parameters do not have conjugate prior-likelihood pairs; therefore, the posterior probability estimation cannot be performed in closed form. In such cases, the McMC simulation or analytical approximation methods are the best ways to determine the posterior distributions [19-20]. In this study, the simulation based Metropolis-Hastings (M-H) algorithm, which is a McMC method; and Laplace approximation, which is an analytical method, are used for this purpose. Fundamentals of the M-H algorithm and Laplace approximation are presented in below section. The derivation and implementation details are reported elsewhere [11, 21-22].

Metropolis-Hastings Algorithm

The M-H algorithm is a rejection-sampling algorithm used to generate a sequence of posterior samples following a probability distribution that is difficult to sample directly [23-24]. This sequence is used in McMC simulations to approximate a distribution or to compute an integral. In Bayesian applications, the normalization factor (denominator of equation 1) is difficult to compute, so the ability to generate posterior samples without knowing this constant of proportionality is a major virtue of this algorithm [25]. The algorithm generates a Markov chain in which each state x^{t+1} depends only on the previous sample state x^t. The algorithm uses a proposal density $q(x', x^t)$, which depends on the current state x^t, to generate the new proposed sample x'. The proposal is accepted as the next value ($x^{t+1} = x'$) if $\alpha(x', x^t)$ drawn from the uniform distribution $u(0,1)$ is:

$$\alpha(x', x^t) < \frac{p(x').q(x^t / x')}{p(x^t).q(x' / x^t)} \tag{2}$$

If the proposal is not accepted, then the current value of x is retained; i.e., $x^{t+1} = x^t$. The proposal density could be a multivariate normal distribution centered on the current state x^t; $q(x', x^t) \sim N(x^t, \sigma^2)$, where, $q(x', x^t)$ is the probability density function for x' given the previous value x^t. This proposal density generates samples centered around the current state with variance σ^2. The acceptance of generated samples will be based on equation (2). Algorithm implementation details can be obtained from articles [11, 21, 25-26].

Laplace Approximation Method

When direct estimations are difficult, the Laplace Approximation (LA) is a useful tool for estimating the posterior parameters. It is based on a Taylor series expansion around the maximum likelihood estimate value, ignoring the negligible terms and normalizing. The best references for approximating the Bayesian posteriors with the Laplace method [27] are articles [22, 28]. The implementation details of LA method may be obtained from the article [11]. A computable approximation for the posterior mean and variance of smooth function of the parameter that is nonzero on the interior of the parameter space has been introduced [22]. Let $-h(\theta)$ be a smooth, positive function on the parameter space, with a maximum at its mode, $\hat{\theta}$. The posterior mean of any function $g(\theta)$ can be written as [22]:

$$\bar{\mu} = E[g(\theta)/y] = \frac{\int g(\theta).e^{-nh(\theta)}d\theta}{\int e^{-nh(\theta)}d\theta}, \text{ where, } e^{-nh(\theta)} = l(y/\theta).p(\theta) \tag{3}$$

The LA method is to approximate the numerator and denominator of the above integral by approximating normal curves centered at the posterior mode and having variance equal to minus the inverse of the second derivative of the log posterior density at its mode. It produces reasonable results as long as the posterior is dominated by a single mode [22]. By Laplace approximation, the mean and variance may be obtained as [11, 22]:

$$E(g(\theta)) = \frac{\sigma *}{\sigma}\{\exp[-nh*(\theta*)]\}/\{\exp[-nh(\hat{\theta})]\} \tag{4}$$

$$V(g) = \bar{\sigma}^2 = E[g(\theta)^2] - E[g(\theta)]^2 \tag{5}$$

where, $\sigma *$ is the mode of $-nh*(\theta*)$ and σ is the mode of $-nh(\hat{\theta})$ [11].

Both the M-H algorithm and the Laplace approximation method are coded in Matlab and used for developing the posteriors of the aforementioned degradation priors. In order to calibrate the codes, the known conjugate pair parameters are used as true estimates. The following conjugate pairs are used for the purpose of testing: Normal-Normal, Gamma-Gamma, Gamma-Normal and Gamma-Poisson [11]. It is observed that the M-H algorithm produced better results compared to the Laplace approximation [11]. The estimated sample posterior parameters using the M-H algorithm are presented in Table 7.1.

Table 7.1. Degradation Posterior Probability Models and their Parameters

Structural Degradations	Posterior Probability Models and their Parameters			
	Types of Model	Shape	Scale	Location
UC	3P Weibull	1.2660	0.1017	0.0079
PC	Type 1 Extreme Value	1.7280	1.1070	-
EC	3P Weibull	2.7070	0.0421	-0.0065
SCC	2P Weibull	1.6590	1.9500	-
CFC	Lognormal	2.7700	2.6410	-
HIC	Lognormal	14.190	10.050	-

7.5 ECONOMIC CONSEQUENCE ANALYSIS

The purpose of RBIM is to minimize the risk associated with degradation-related failures. To provide a consistent measure of risk, all consequences are represented in dollars. That is, risk is interpreted as the expected loss due to a certain event or groups of events [29]. To minimize the likelihood of failure, components need to be inspected and maintained at every possible interval. However, if the inspection and maintenance is performed too frequently, it will involve large costs and if it is performed too rarely, it will result in failure followed by an unplanned shutdown and costly corrective maintenance. Therefore, the aim here is to find an optimal maintenance strategy, which takes into account the component's condition and actual risk. Typically, the failure consequences include the economic consequences of failure, inspection and maintenance.

7.5.1 Economic Consequences of Failure

The operating and maintenance costs increase throughout the life of a facility due to various degradation processes. Failure cost is the cost associated with the loss of a facility due to deterioration failures. The failure cost may be divided into corrosion and cracking costs. It is equal to the sum of the failure costs, operating costs, and the cost of lost production, together with the material salvage value. It is assumed that a component failure is followed by an immediate repair to prevent any system failure scenario with much higher consequences. Degradation-related failures may lead to increased risk of loss of the entire unit through a chain of reactions. In such cases event tree analysis will be required to assess the system-level consequences. In this study, the component is assumed to be independent and isolated. Further, the economic consequences of a component failure include loss of commodity due to breakdown, production loss due to shutdown, cost of spill cleanup, legal fees and penalties due to environmental damage and liability [17].

Loss due to Breakdown

The leak or rupture of the component's wall thickness by degradation is a main cause for breakdown. Thus, breakdown costs are financial losses, which are associated with losing the commodity. This cost depends upon what product is being processed, the rate of leakage and its current market value when the failure occurs. The focus in this article is on a topside process piping in the North Sea and the product is crude oil. The market value of crude oil is assumed to be $ 70 per barrel in this article. To estimate the rate of leakage, the source model, that is, the flow of liquid through a hole in a pipe, is used [17]. The following formula may be used to estimate the cost of breakdown [17, 30]:

$$C_{flp} = E \times P \times D_{rp} \times Q_{pl} \times C_{dp} \quad (6)$$

where, C_{flp} = the cost of the lost commodity in dollars, C_{dp} = cost of downtime calculated in dollars per barrel, Q_{pl} = quantity of commodity loss per unit of time (for e.g., barrels per hour), D_{rp} = duration of the commodity loss (hours), P = probability of loss of the commodity (depending on the equipment redundancy levels)=1 (assuming there is no redundancy and the components are in series), E = average number of critical failures in the lifetime. Estimated cost of piping degradation is presented in Table 7.2.

Loss of Production due to Shutdown

The main factor influencing the cost of failure is the facility's unavailability for production. Inspection and maintenance can be planned, whereas failures may lead to an unplanned, immediate shutdown of the facility. The cost of such a shutdown is dependent on the number of days of shutdown, the rate of loss of production and the value of products at the time of failure. Thus, the shutdown cost is calculated by combining the unit cost of the product, loss of affected production and maintenance delay time as [17, 31]:

$$C_{fsd} = Cu \times Q \times T_m \quad (7)$$

where, C_{fsd} is the cost of shutdown (dollars), C_u is the unit cost of product (dollars/barrel), Q is the quantity of affected production (barrels/day) and T_m is the maintenance delay (days). The estimated cost of piping degradation is presented in Table 7.2.

Cost of Spill Cleanup

The cost of an oil spill cleanup depends on a number of factors, such as, the type of oil, the amount spilled and rate of spillage, the characteristics of the affected area, weather and sea conditions, local and national laws, time of the year and the spill cleanup strategy [32-33]. Predicting the unit cost of spill response is highly uncertain since the factors impacting the cost are complex. In the present article, crude oil spillage in offshore is considered. Based on the location, the average per-unit offshore oil spill cleanup cost is \$6508 per tonne [33]. The cost of environmental cleanup comprises the unit cost of spill cleanup and the total quantity released due to failures caused by degradations. Further, the total quantity released depends on the rate of spillage and the duration of the release. The following formula may be used to estimate the cost of spill cleanup:

$$C_{fsc} = Q_m \times D_{rp} \times C_{usc} \tag{8}$$

where, C_{usc} is the unit cost of spill cleanup (dollars/tonne), Q_m loss of product per unit time (tonne/hour) due to corrosion or cracking, and D_{rp} is the duration of spillage (hour). The cleanup cost thus estimated is presented in Table 7.2.

Loss due to Environmental Damage

The size of penalty as a result of damaging the environment is difficult to estimate, because costs increase with the scope of failure. The failure modes developed could escalate to more complex system failures leading to significant environmental damages. However, approximate assessments considering the quantity released and the unit penalty rate are possible [33]. The environment damage due to oil spillage includes loss of marine as well as coastal habitat, soil pollution, damage to agriculture land and adverse health impacts [33-34]. The per-unit cleanup cost of environmental damage is \$ 5086 per tonne of oil [33]. This cost includes the cleanup cost of damage to the coastal ecosystem, consisting of near shore and shoreline response. The cost of environmental damage comprises the unit cost of nature damage and the total quantity released. The total quantity released depends on the rate of release and the duration of spillage. Thus, the total cost associated with damaging natural resources by failures may be estimated using the formula:

$$C_{fnr} = Q_m \times D_{rp} \times C_{dnr} \tag{9}$$

where, C_{dnr} is the unit cost of nature damage (dollars/tonne), Q_m is the release of product per unit time (tonnes/hour) due to corrosion and cracking, and D_{rp} is the duration of the release (hour). The nature damage cost due to degradation is presented in Table 7.2.

Cost of Liability

The injuries and deaths caused by process component failure have the most severe implications possible. The loss of life or pain of an injury is impossible to quantify, yet, the cost incurred due to workers compensation and corporate liabilities shall be taken into account [(29)]. Apart from that, safety-related system failures have other immediate implications, such as legal fines and penalties for professional negligence. The estimates of liability costs that result from motor vehicle accidents are routinely published by several public and private organizations. The US Department of Transportation published a technical note [(35)] on comprehensive motor vehicle accident costs which is adopted as a baseline in this article. The comprehensive liability cost includes medical costs, emergency services, vocational rehabilitation, lost earnings, administrative costs, legal consulting fees, pain and lost quality of life. For a typical piping failure, the liability is assumed to be a moderate injury, causing a lump sum payout of \$ 40 000 in this article.

Total Cost of Failure

The total cost of failure (C_F) is the summation of loss of breakdown, loss due to shutdown, cost of spill cleanup and costs of environmental damage and liability, as:

$$C_F = C_{flp} + C_{fsd} + C_{fsc} + C_{fnr} + C_{fl} \tag{10}$$

This total cost is based on two assumptions: the component is isolated, and the component failure leads to a system failure with subsequent unavailability. The estimated values for failure cost are presented Table 7.2. The rate of failure cost due to degradations, over the service life of n years, with varying inspection and maintenance intervals may be calculated using the following equation:

$$FC(j) = C_F \frac{j}{n} \tag{11}$$

where, j is the inspection and maintenance interval, which varies from 1 to n years.

7.5.2 Economic Consequences of Inspection

The NDT techniques are used for the detection and quantification of unwanted discontinuities and separations in materials due to degradations. This quantitative information is achieved by detecting, locating and sizing of any detected flaws. Several types of defects exist in components, such as corrosion, cracking, inclusions, dents and holes. Defect quantification requires considerable skill and experience, and the use of more than one NDT technique. Based on literature [16, 36], the best suitable inspection methods for corrosion and cracking are identified, and their corresponding dollar costs are estimated. The unit costs of the NDT techniques obtained from an inspection contracting company have been used in the analysis.

Cost of Degradation Inspection

The NDT technique is used to detect and quantify the extent of wall loss, pit depth and surface cracks as well as coating breakage. The inspection costs depend on how much area to inspect from a risk perspective. The inspection cost includes the cost for gaining access to the degraded component, the cost for surface preparation, personnel cost for inspection, the cost associated with technical assistance, the cost of consumables and chemicals, and the logistics cost. In this article, it is assumed that the proposed inspection method is able to detect the presence of corrosion discontinuities, and surface or subsurface cracks. For piping (pipeline segments, bends and tees), the suggested inspection methods are UT thickness measurement and radiographic inspection (RI) for corrosion, and magnetic particle inspection (MPI) and UT defect sizing for cracking [16, 36]. The cost of each inspection activity is estimated using the per-unit personnel cost, and the total duration of inspection [17]. Cost associated with piping inspection (C_I) is [17]:

$$C_I = C_{iga} + C_{isp} + C_{iut} + C_{ir} + C_{ita} + C_{il} \tag{12}$$

where, C_{iga} = cost of gaining access, C_{isp} = cost of surface preparation, C_{iut} = cost of UT defect sizing, C_{ir} = cost of radiographic inspection, C_{ita} = cost of technical assistance and C_{il} = cost of logistics (equipment storage, rent and transportation). The cost of UT thickness measurements, $C_{iut} = C_{lut} \times t$, whereas C_{lut} = personnel cost for UT thickness measurements per hour, and t=total duration of inspection in hours. The estimated costs for corrosion and cracking are presented in Table 7.2. On an annual basis, the rate of inspection costs tends to decrease with the increase in inspection and maintenance intervals. This decreasing trend may be modeled using the following equation:

$$IC(j) = C_I \frac{n}{j} \tag{13}$$

where, j is the inspection interval, $IC(j)$ is the inspection cost in the j^{th} interval, and n is the component service life in years.

7.5.3 Economic Consequences of Maintenance

This is the cost associated with restoring the components. To ensure safe operation, maintenance needs to be performed at very small intervals. However, it is impractical to have frequent maintenance due to large costs, the possibility of maintenance-induced errors, and the associated plant unavailability. To optimize maintenance, the following necessary conditions must be satisfied: the cost of maintenance should be greater after failure than before, and the hazard rate of the component should be increasing, i.e., the component should be in the wear-out region. This article focuses on predictive maintenance of process components. Predictive maintenance estimates through diagnostic tools, such as NDT techniques and probabilistic models, when a component or part is about to fail and should be repaired or replaced; thus reducing costly corrective maintenance. It covers the cost of necessary minimal repair, replacement, and material costs associated with inspection and maintenance. Risk-based predictive maintenance is possible only because the degradation-induced failures can be predicted with a certain probability.

Cost of Degradation Maintenance

Maintenance may be either a minor patch repair task or the complete replacement of a degraded component. For all types of corrosion, minor patch repair work of the affected area is considered, and for any types of cracking, immediate component replacement with necessary repair is considered. Maintenance task includes access to the degraded part, surface preparation, cutting and removal of parts, assembling, welding, testing and restoring the protective coating. Thus, in addition to the cost of repair and replacement, the personnel and logistics cost related to transportation, storage and rent of facilities also should be included. The cost of each maintenance activity is estimated using the unit cost of maintenance personnel and the total duration of maintenance. Details of the estimation have been presented elsewhere [17]. The total cost associated with piping maintenance for degradation may be estimated as:

$$C_M = C_{mga} + C_{msp} + C_{mgd} + C_{mmr} \tag{14}$$

where, C_{mga} = cost of gaining access to the degraded component, C_{msp} = cost of surface preparation, C_{mgd} = cost of gouging defects, and C_{mmr} = cost of minimal repair or replacement. Where, the repair (cutting, welding and fitting) cost, $C_{mcw} = C_{lcr} \times t$, whereas the C_{lcr} is cost of labor for repair in dollars per hour, t is the total repair time in hours. The rate of maintenance costs decreases with the increase in maintenance intervals over the service life. This decreasing trend may be modeled using the following equation:

$$MC(j) = C_M \frac{n}{j} \tag{15}$$

where, j is the inspection interval, $MC(j)$ is the maintenance cost for the j^{th} interval, and n is the service life in years. The cost estimates associated with piping degradation (corrosion and cracking) is presented in Table 7.2.

7.5.4 Annual Equivalent Cost of Degradations

The annual equivalent cost (AEC) of operating and maintaining the component is the summation of the rate costs of failure, inspection and maintenance, and is estimated as:

$$AEC(j) = FC(j) + IC(j) + MC(j) \tag{16}$$

Due to the increasing trend of rate of failure cost and the decreasing trends of rate of inspection and maintenance costs, the AEC v/s maintenance interval will be a convex function.

7.5.5 Probabilistic Cost Analysis

Uncertainty and variability in consequence analysis are modeled with probabilistic analysis using Monte Carlo simulations. For simulation, the total cost of component failure, inspection and maintenance is considered to be a Gaussian distribution with the estimated mean. The coefficients of variation of costs are assumed to be 2.5%. The estimated mean and standard deviation values of the piping degradation costs are reported in Table 7.2.

Table 7.2. Probabilistic Piping Degradation Costs used in the Economic Analysis

Structural degradation	Cost divisions	Corrosion cost ($)		Cracking cost ($)	
		Mean	Std. dev	Mean	Std. dev
Corrosion (UC, PC, EC) & Cracking (SCC, CFC, HIC)	Total cost of failure	543 407	13585	438 235	10956
	Total cost of maintenance	10 000	250	15 000	375
	Total cost of inspection	3840	96	4 400	110
	Salvage value	0	0	0	0
	Annual rate of interest	8 %			
	Service period	30 years			

7.6 OPTIMIZATION OF INSPECTION AND MAINTENANCE

The AEC has been combined with the cumulative density function (CDF) of the posterior probability to estimate the operational life risk as shown in equation (17). Thus, finding the optimal inspection and maintenance interval is reduced to finding the value of inspection and maintenance intervals that minimizes the operational risk. At the optimal risk point, the risk will be reduced to as low as reasonably practicable (ALARP) level, which at the same time ensures the safety of the facility's operation.

$$R(j) = F[p(\theta / y, j)] \times AEC(j) \tag{17}$$

where, $R(j)$ is the risk of failure due to degradation (in dollars) in the j^{th} interval, $F[p(\theta / y), j]$ is the CDF of posterior probability of failure and AEC is the annual equivalent cost, corresponding to the inspection and maintenance interval, j.

The operational risk curve is observed to be a convex function of the component's service life. A search is conducted to identify the minimum risk point, and the interval of this minimum risk is considered as the optimal inspection and maintenance interval. The optimum inspection and maintenance interval thus obtained satisfies the two necessary criteria of optimal maintenance: one, the risk is reduced to ALARP level; and two, the maintenance interval is maximized, thus avoiding unwanted maintenance and its associated costs. The inspection and maintenance risk in dollars is compared with the company's operating budget, as risk acceptance criteria. The results of estimated risk due to UC, PC, EC, SCC, CFC, and HIC of process components are discussed in section 7.7.

7.7 RESULTS AND DISCUSSIONS

Results of analysis are discussed under three headings: stochastic degradation modeling, economic consequence analysis and optimization of inspection and maintenance.

7.7.1 Stochastic Degradation Modeling

Sample results of the stochastic degradation modeling are presented in Figures 7.3 to 7.8 [11]. The prior and likelihood models for the identified degradations, such as UC, PC, EC, SCC, CFC and HIC, are observed to be of the same type. Since these likelihoods are revising priors, the posteriors also converge to the same type of distribution. The posterior estimation based on the M-H algorithm converged to satisfactory results. The first half of the simulated samples is ignored, as these samples describe a transient state. The remaining samples which describe a steady state condition are used in the analysis. Laplace approximation is computationally intensive; it is not effective when using distributions with more than two parameters. The error accumulates in the variance estimation due to the second order terms in the computation. Laplace approximation diverges as the parameter size is either too small or too large due to numerical instability resulting from the use of higher order terms in the estimation. Therefore, for developing the posteriors of structural degradations in process components, the Laplace approximation method is not recommended. Further, the M-H algorithm produced better results compared with Laplace approximation, and hence it was used for the posterior development of degradation priors [11]. While using the M-H algorithm, the change in the value of the location parameter from the prior to the posterior was observed to be insignificant. Thus, instead of using a three-parameter model, a two-parameter model may be used to develop posteriors and the location parameter may be added subsequently.

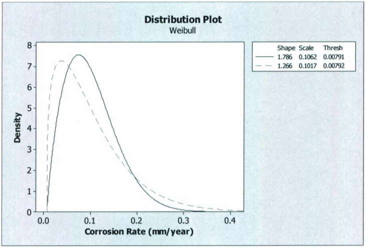

Fig. 7.3. Sample Prior and Posterior Distributions for Uniform Corrosion

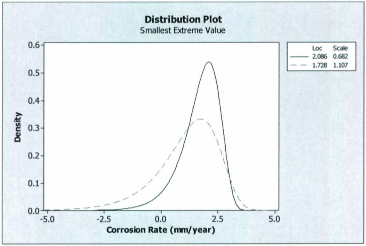

Fig. 7.4. Sample Prior and Posterior Distributions for Pitting Corrosion

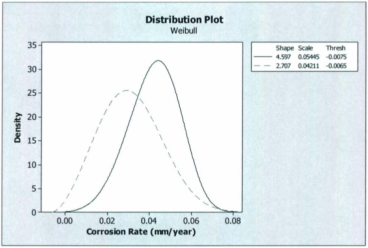

Fig. 7.5. Sample Prior and Posterior Distributions for Erosion Corrosion

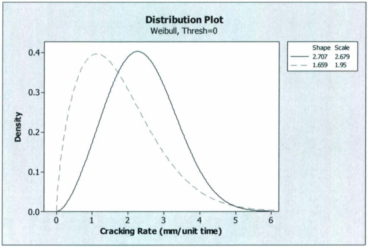

Fig. 7.6. Sample Prior and Posterior Distributions for Stress Corrosion Cracking

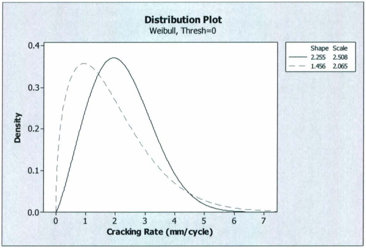

Fig. 7.7. Sample Prior and Posterior Distributions for Corrosion Fatigue Cracking

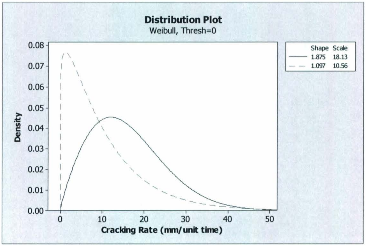

Fig. 7.8. Sample Prior and Posterior Distributions for Hydrogen Induced Cracking

7.7.2 Economic Consequence Analysis

Sample results of the economic consequence analysis are presented in Figures 7.9 to 7.14. The rate of failure cost is observed to be an increasing function of the inspection and maintenance interval. The rate of inspection and maintenance costs is found to be a decreasing function of inspection and maintenance intervals. Further, the expected AEC of operating and maintaining the component are computed using simulations. The AEC is found to be a convex function of inspection and maintenance interval. The operational risk curve is produced by combining the CDF and AEC to minimize the risk.

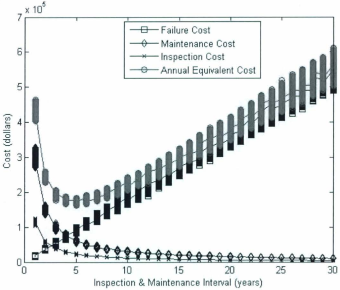

Fig. 7.9. Economic Consequence Results for Uniform Corrosion

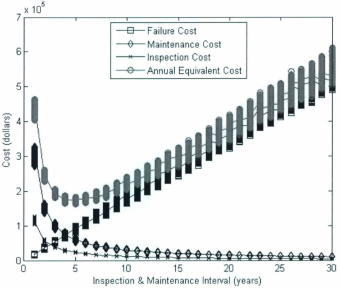

Fig. 7.10. Economic Consequence Results for Pitting Corrosion

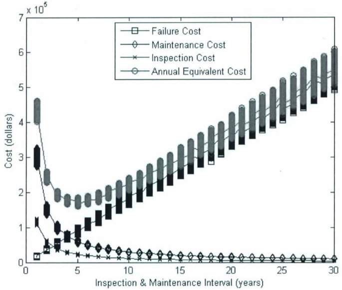

Fig. 7.11. Economic Consequence Results for Erosion Corrosion

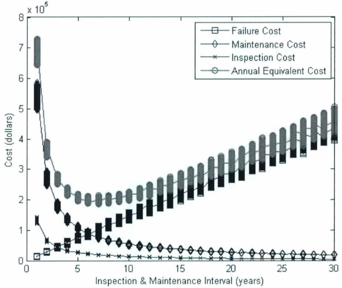

Fig. 7.12. Economic Consequence Results for Stress Corrosion Cracking

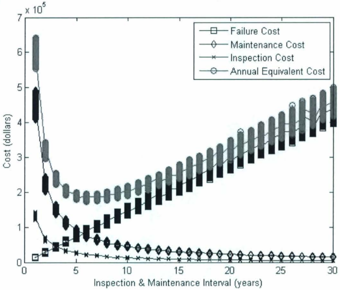

Fig. 7.13. Economic Consequence Results for Corrosion Fatigue Cracking

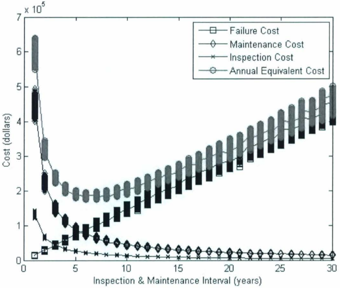

Fig. 7.14. Economic Consequence Results for Hydrogen Induced Cracking

7.7.3 Optimization of Inspection and Maintenance Interval

The sample results of operational life risks due to corrosion and cracking are presented in Figures 7.15 to 7.20. These Figures show overall risk in dollars due to various structural degradations, such as UC, PC, EC, SCC, CFC and HIC, plotted against the inspection and maintenance interval. On the risk curve thus developed, the point where the risk is minimal is defined as the optimum maintenance interval for the component with respect to that particular degradation process. The degradation processes are assumed to be independent of each other and isolated. Also, it is assumed that the minimal repair for corrosion leaves the system in a state similar to its state just before its failure, whereas the replacement for cracking brings the system back to an as good as new condition. With respect to the considered piping degradations, the computed optimal inspection and maintenance intervals are reported in Table 7.3. The optimum maintenance interval is the time to the next inspection and maintenance starting from now onwards. Around 10 000 iterations are used to produce operational risk curves, shown in Figures 7.15 to 7.20.

Table 7.3. Optimum Inspection and Maintenance Interval for the Components

Process Component	Deterioration Process	Source of Result	Optimum Maintenance Interval (years)
Piping (straight pipe, bends, tees)	UC	Figure 7.15	5
	PC	Figure 7.16	4
	EC	Figure 7.17	5
	SCC	Figure 7.18	6
	CFC	Figure 7.19	4
	HIC	Figure 7.20	5

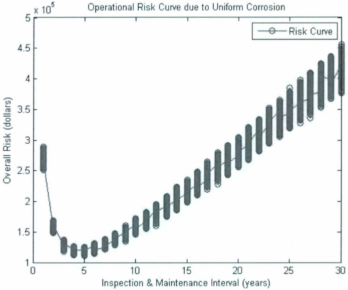

Fig. 7.15. Operational Life Risk Curve due to Uniform Corrosion

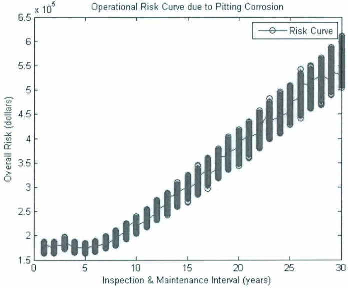

Fig. 7.16. Operational Life Risk Curve due to Pitting Corrosion

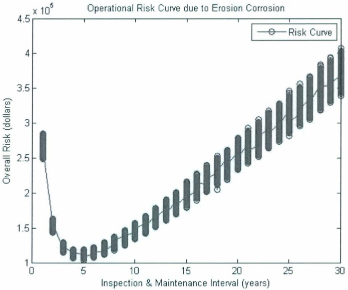

Fig. 7.17. Operational Life Risk Curve due to Erosion Corrosion

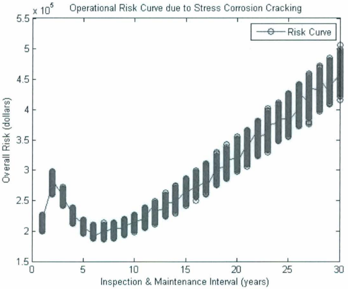

Fig. 7.18. Operational Life Risk Curve due to Stress Corrosion Cracking

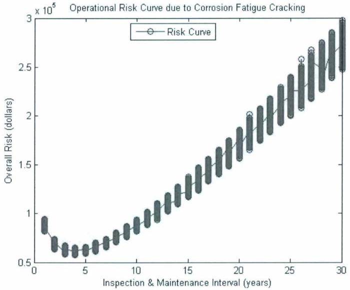

Fig. 7.19. Operational Life Risk Curve due to Corrosion Fatigue Cracking

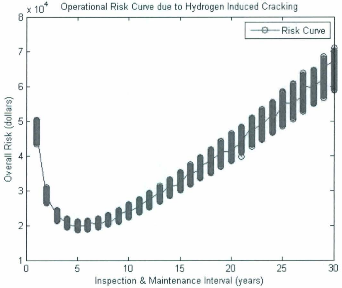

Fig. 7.20. Operational Life Risk Curve due to Hydrogen Induced Cracking

7.8 SUMMARY AND CONCLUSIONS

This article presents methodology and models using the risk based integrity modeling framework capable of making optimal maintenance decisions for offshore process components. Structural degradations are random processes and thus, probabilistic models are developed to accurately predict failure mechanisms. The life threatening component degradation processes are identified as different types of corrosion and cracking. The degradation processes include UC, PC, EC, SCC, CFC and HIC. These structural degradations are modeled using prior distributions, which are subsequently updated using NDT data to posterior distributions through the use of Bayes' theorem. The simulation based M-H algorithm and analytical Laplace approximation methods are used to develop the posteriors. Since these posterior models are based on real life NDT data, they provide more reliable and accurate predictions for the future degradations of components.

The first part of this article discussed the development of an RBIM framework using the potential degradation mechanisms. The prior distributions for various degradation processes are developed based on the data extracted from literature. The relative accuracy of the prior model is tested using probability plots and A-D tests, and the parameters are estimated using the methods of least square and maximum likelihood estimates. The model was applied to a real life case study, using field NDT data from an ageing offshore process facility. Literature data is used for estimating the likelihoods of cracking.

The posterior probability models are then developed. The use of a simulation method is necessitated because none of the prior-likelihood models fall into the natural conjugate pairs of the exponential family. Two MATLAB codes, one using the M-H algorithm and the other using the Laplace approximations, have been developed and used to compute the posterior distributions. These codes are calibrated using known conjugate pair estimates. The MATLAB codes performed well for Weibull, Lognormal and Type 1 Extreme Value distributions with two and three parameters. The posterior probability thus developed is useful in assessing the potential risk to the life of component. Further, it has been observed that the rejection sampling based M-H algorithm is the more suitable method compared with the Laplace approximation for posterior estimation of components. Using the M-H algorithm, it is observed that the posterior probability model that can be used to estimate the future failure probability due to the UC is 3P Weibull; the PC is Type1 Extreme Value, and the EC is by 3P Weibull. Similarly, the SCC degradation can be best modeled by Weibull; the CFC and HIC by Lognormal and Weibull distributions.

An economic consequence analysis model based on the component's minimal repair and replacement concept is discussed. The consequences of failure are estimated by developing the cost of failure, inspection and maintenance. The cost of failure includes the loss due to breakdown, loss due to shutdown, the cost of a cleanup strategy, loss of nature damage and liability. Then, the CDF of posterior probability and AEC are combined to produce the operational risk curve.

The optimal inspection and maintenance interval is determined from the operational risk curve at the point corresponding to the minimum risk. In this article, the optimum inspection and maintenance interval is observed to vary from 4 to 6 years for different corrosion and cracking processes. The smaller value (4 years) should be considered the optimum maintenance interval. This interval should be revised as new NDT data is obtained. The developed model may be applied to the optimization of inspection and maintenance even though component degradations follow non-conjugate pairs. This model could be refined further by incorporating the actual costs and rates of interest based on the market value at the time of analysis.

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CHAPTER VIII

SUMMARY, CONCLUSIONS AND NOVELITIES

8.1 GENERAL

The development of an optimal maintenance strategy taking into consideration of the uncertainty surrounding the age-based degradation processes is critical to the safe operation of offshore process facilities. During the operational life of the facility, the only way to prevent component failure is through optimal maintenance as the design modifications are cumbersome. The maintenance strategy can be inspection and repair, component replacement, or both. The inspection, repair and replacement may involve costs, shutdown and the possibility of maintenance induced errors. Any human intervention has to be limited from the safety and cost perspectives. If the interval between subsequent inspections and maintenance tasks is prolonged irrationally, it may cause the premature failure of components. On the other hand reducing the interval between subsequent maintenance increases the operating, and maintenance cost as well as the probability of maintenance induced errors. Hence, finding an optimal strategy taking into consideration the uncertainty which accompany the degradation process is a challenging task. The age-dependent degradation processes are one of the main asset integrity threats in offshore process components. The degradation is a stochastic process and hence the probability distributions are ideal to model them. However, experience and system field data play a crucial role in the modeling of the degradation processes. If the model to have some merit, it should represent the system in terms of data and experience and reduce the uncertainty. It is argued that Bayesian analysis is an ideal choice in such situations as it is good for logical and consistent reasoning under uncertainty. The expertise may be utilized in the form of prior information and the system integrity data from NDT may be utilized to obtain a likelihood function to predict the latest degradation of components in terms of posterior probability. Since, the posterior probability is based on field data; it provides a suitable model for the degradation process and may be used successfully to predict the likelihood of future failures.

Existing maintenance strategies, like the reliability centered maintenance and condition based maintenance, are based on the component probability of failure only. However, it is not difficult to visualize a situation where an event having a low probability of failure will have drastic consequences on the facility, safety, and the environment. The failure consequences include the loss of breakdown due to commodity loss, the loss due to facility shutdown, the loss of environmental cleanup, the loss of nature damage, and liability. The different inspection and maintenance tasks have economic consequences themselves, such as the type of inspection and maintenance, the cost of personnel, cost of gaining access to the degraded component, the cost of surface preparation, the logistics, the cost of consumable and transportation of parts and spares. If one keep in mind the importance of probability of failure and its consequence, the risk based maintenance strategy developed in this thesis provides a rational choice for the decision making process regarding the inspection and maintenance.

In this work, the reduction of risk to as low as reasonably practicable levels and at the same time ensuring the safety of operation through the optimal utilization of resources has been achieved by developing an RBIM strategy which has been presented. The maintenance may be either minimal repair or component replacement; hence models for their optimization are developed in this thesis. The optimization is a trade off between the cost of maintenance resources and the benefits of risk reduction achieved by the optimal maintenance in terms of increased safety and reliability. This chapter presents a summary and conclusion of the thesis, along with the novelties and the scope for future work.

8.2 SUMMARY

Maintenance optimization using mathematical modeling of stochastic degradation processes is a burgeoning area of research. A critical review of literature shows that there is a need for a robust risk based integrity model to help make informed decision on maintenance strategies in the face of uncertainty in the degradation processes. The aim of such an RBIM is to protect human life, financial investment, and the environment. Based on these requirements an RBIM methodology is developed in this thesis. This methodology takes into account the uncertainty and variability in structural degradation processes by using stochastic degradation modeling, and the consequences of failure in terms of costs in dollars associated with it. By combining the stochastic degradation modeling and economic consequences analysis, an optimal strategy is designed for the inspection and maintenance, and replacement of ageing components.

The life threatening structural degradation processes are caused by various types of age-dependent corrosion and cracking phenomena. The critical corrosion mechanisms observed in process components are uniform, pitting and erosion corrosion. Similarly, the critical cracking processes observed are stress corrosion cracking, corrosion fatigue cracking and hydrogen induced cracking. Degradation processes are identified by analyzing historic data bases, the functional, service (sweet or sour), product and environmental conditions, such as pressure, temperature, humidity and the presence of corrosive media, like H_2S, CO_2, Cl^- and H_2O. The wall loss data obtained by NDT has also been used to identify the degradation processes. The identified degradations are observed to be random processes, which prompted their stochastic modeling.

8.2.1 RBIM Framework Development

The RBIM framework is based on optimizing the maintenance strategy, considering the age-dependent stochastic degradation processes. Essentially, it is comprised of identification of potential degradation processes and its precise modeling, the estimation of consequences analysis, the optimization of risk based inspection and maintenance and finally, testing and validation. A brief outline of the various asset integrity threats and the philosophical background of Bayes theorem are discussed in the following sections.

8.2.2 Asset Integrity Threats

The potential degradation processes, threatening the integrity of offshore process components are observed to be caused by several environmentally induced corrosion and cracking. This thesis models three major corrosion processes and three major cracking processes. These are uniform, pitting and erosion corrosion; and stress corrosion, corrosion fatigue and hydrogen induced cracking. Statistical Bayesian analysis is applied for all these processes. However, the physics of failure is captured using a system learning process which is continually updated using new data.

8.2.3 Bayesian Analysis

Probability is a degree of analysts' belief, i. e., how much one thinks that something is true based on the evidence at hand. When dealing with random phenomena, the ideal option would be to make an inference based on the experimental data and any prior knowledge one might have, reserving the right to revise the position if new information comes to light. This is the rationale behind Bayes theorem.

Degradation process modeling is often viewed as an iterative process of integrating, accumulating and interpreting information. The analysts can assess the current state of knowledge regarding the degradation level, gather new data to address the question of future degradation, and then update and refine the current understanding to incorporate new data. Bayesian inference provides a logical and quantitative framework for this. Bayesian approach to degradation modeling starts with the formulation of a model that is expected to describe the degradation process accurately. The prior distributions of unknown parameters of the model may then be formulated, which is meant to capture the beliefs about the degradation before actually seeing the data. After observing data, the Bayes theorem may be applied to obtain the posterior distributions for those unknowns, which takes account of both the prior and system data. From these posterior distributions, predictive distributions for future observations may be computed.

8.2.4 Stochastic Degradation Modeling

Prior Probability Modeling

In RBIM, the uncertainty in the material degradation is modeled using prior distribution, which is subsequently updated to obtain a posterior distribution using Bayes theorem and actual inspection data. This updated distribution is useful in assessing the potential risk to facility. The development of prior models is inevitable in the integrity assessments. The priors are often subjective; however, subjectivity can be reduced by the use of generic databases, and consulting studies of similar installations. Several statistical tests were conducted based on data extracted from the literature to assess their suitability. How well the data fits is tested using the probability plots and an A-D test. The underlying parameters are estimated using the method of least squares and maximum likelihood estimates. Once the prior models for UC, PC, EC, SCC, CFC and HIC are identified, they are validated using a case study using the life inspection data associated with the operation of an ageing FPSO in the North Sea. For UC, the regression analysis and for localized PC and EC, the extreme value analysis has been used to estimate the rates of degradation. The rates of degradation are tested using standard probability models and the best fitting model for each of them was identified.

Likelihood Probability Modeling

In Bayesian analysis, the likelihood refers to the evidence obtained from field data that supports the prior's assessment. In this study the NDT data obtained from an ageing FPSO operating in the North Sea is used to model the likelihood probability function. The tested facility had different subsystems: a gas condensate system has been observed to follow uniform corrosion; a gas export system has been observed to follow pitting corrosion; and a high pressure drilling mud system has been observed to follow the erosion type corrosion. Regression analysis was used for UC and extreme value analysis was used for localized PC and EC. Similarly, the data from the literature is used for different cracking processes due to lack of field NDT data. The rates of degradation are tested using standard probability models and the best fitting models are identified. A-D based goodness of fit test is used for the same. Parameters of the best fitting models are estimated using the method of least squares and maximum likelihood estimates.

Posterior Probability Modeling

In statistics, there are different methods to estimate the posteriors from the known prior and likelihood function. These include analytical approximations, data augmentation methods, Monte Carlo direct sampling and Markov chain Monte Carlo simulations. In theory, a posterior distribution always exists. However, in reality the computation of posteriors is challenging if the prior and likelihood pair do not fall into the category of exponential conjugate pairs. After extensive analysis, the simulation based methods and analytical approximations have been found most suitable for use in developing posteriors of degradation of process components. Likewise, the developed prior models of corrosion and cracking are revised to obtain the posterior distributions using simulation based Metropolis-Hastings (M-H) algorithm and an analytical Laplace approximation method. Since, the posterior models are based on real life NDT data; they provide more reliable and accurate predictions for future degradation of components. The use of simulation and approximation methods was deemed necessary because none of the prior models (Weibull, extreme value and lognormal) falls into the natural conjugate pair of the exponential family. Matlab programs are developed using the M-H algorithm and the Laplace approximations to compute the posterior distributions. The code has been calibrated using known conjugate pairs, such as normal-normal, Gamma-Gamma, Gamma-Poisson and Gamma-normal. In order to test these combinations, the posterior functions are developed using Laplace approximations. The programs work satisfactorily for all time-dependent degradation process, such as Weibull, lognormal and extreme value distributions.

8.2.5 Economic Consequence Analysis

The consequence of component failure is expressed in terms of the cost incurred as a result of failure due to degradation processes. To provide a consistent measure of risk, all consequences categories should be in the same units, and then only the overall risk from many contributing factors may be computed. A standard choice of unit to represent all consequence categories is the dollar, because risk can be interpreted as the expected loss due to a certain event or a group of events. The failure consequences are analyzed in terms of the failure, inspection and maintenance consequences as summarized below.

Failure Consequences

Failure consequences are the financial losses due to loosing a facility upon failure due to degradations. It includes the corrosion and cracking consequences. In this thesis, the failure consequences are analyzed in terms of loss of commodity due to breakdown, the production loss due to shutdown, loss of spill cleanup, and legal fees and fines due to environmental damage and liability. Each of this cost components are estimated using the developed formula, using the unit cost, rate of release and the duration of release. The estimated costs are assumed to follow a Gaussian distribution with mean and variance.

Inspection Consequences

The NDT techniques are used to detect and quantify the unwanted discontinuity in materials due to degradations. Several types of discontinuities exist in components, such as holes, inclusions, corrosion and cracking. Different NDT techniques are required for the quantification of different corrosion and cracking. The best suitable methods for each corrosion and cracking are identified and their corresponding dollar costs are estimated. The purpose of inspection is to detect and quantify the extent of wall loss, pit depth and surface as well as subsurface cracks. The inspection cost models the cost of gaining access to the degraded component, cost of surface preparation, personnel cost for inspection, the cost associated with technical assistance, the cost of consumables and logistics. The ultrasonic testing and radiographic inspection are used for corrosion, and the magnetic particle inspection and ultrasonic testing for defect sizing are used for cracking. These costs are estimated based on the unit cost obtained from an inspection contracting company operating in the North Sea. It is expected that the NDT inspection is able to detect the degradation process with adequate reliability and accuracy.

Maintenance Consequences

The cost of restoring a process facility back to the operating condition after failure is the maintenance consequence. To have a safely operating facility, maintenance needs to be performed at very small intervals. However, frequent maintenance tasks cost more, increase the probability of the occurrence of maintenance-induced errors and reduce the availability of the facility. If maintenance is performed too rarely, it will result in costly breakdown maintenance. Thus, finding an optimum strategy based on the condition of a component is a challenging task. A predictive maintenance model is developed and discussed in this thesis. One can use predictive maintenance diagnostic tools, such as NDT and probabilistic modeling to estimate the time at which a component may fail, and it should be repaired or replaced, thus reducing the costly corrective maintenance.

Maintenance cost is obtained as the sum of the costs of access to the degraded component; surface preparation; cutting and removal of pipes and plates; welding and restoration of protective coating; component repair; component replacement; personnel; and logistics related to transportation; and storage and rent of facilities. It was found that on an annual basis, the inspection and maintenance cost increase due to degradation. This is due to the material and strength loss of components.

8.2.6 Optimization of Maintenance Strategy

Two types of maintenance strategy is presented in this thesis; one is finding the optimal inspection and maintenance interval, and second one is finding the optimal time to inspect and replace the component economically. The component need to be maintained or replaced depending on the condition of component as well the economic analysis.

Inspection and Maintenance

The inspection and maintenance strategy is used for repairable components. If the component can be brought back to a state similar to its state just before failure through minor repair, this strategy should be adopted. It consists of estimating the rate costs of failure, inspection and maintenance on an annual basis. Then, the annual equivalent cost (AEC) is estimated through the summation of various costs. This AEC is combined with the posterior probability cumulative density function (CDF) to profile the operational risk in dollars. From the operational risk curve one is able to determine the point of minimum; this point is taken as the optimal inspection and maintenance interval. This interval satisfies two necessary conditions of predictive maintenance: the risk of operating the facility is reduced to as low as reasonably practicable level and at the same time the inspection and maintenance interval is maximized to reduce unwanted maintenance. Risk at this interval may be compared with company's maintenance budget as acceptance criteria, which include the individual, societal and environmental aspects. It rationalizes the inspection and maintenance decision.

Replacement Strategy

Replacement is a maintenance strategy that entails the replacement of component rather than performing maintenance. This strategy is based on the economic service life of component. At some point in an asset's life cycle, it will not be economical to operate the component due to deterioration, strength loss and obsolescence. From the estimated failure cost, on annual basis, the failure recovery cost is estimated using a fixed rate of interest using the present worth factor approach. The inspection and maintenance cost tends to increase as a result of strength degradation and wall loss of components as it ages. This increasing trend is modeled using arithmetic gradient with a particular rate of interests, on an annual basis. Then, the annual equivalent cost is estimated by combining the annual costs of failure recovery, inspection and maintenance costs. This AEC is combined with the posterior probability CDF of failure to produce the operational life risk curve. The point of minimum risk on the operational risk curve is taken as the optimum interval for replacement. This interval also satisfies two necessary conditions of predictive replacement: the risk of operating the facility is reduced to as low as reasonably practicable level and at the same time, the replacement interval is maximized to reduce unwanted operating and maintenance cost. This rationalizes the replacement decision, safety and reliability of the components.

8.3 CONCLUSIONS

8.3.1 RBIM Frame work

Overcoming the limitations of existing models, a risk based integrity modeling framework is developed and used in this thesis. The framework is based on the identification of degradation processes threatening the integrity of components, stochastic degradation modeling, economic consequence analysis, and finally the testing and validation using a case study. The degradation is a random process and hence the inspection data includes large uncertainty and variability. This has taken into account in the model using stochastic Bayesian analysis. The field NDT data from an ageing offshore process facility is used in the analysis. The concepts from statistics, engineering failure analysis and economics are integrated in the developed framework.

8.3.2 Degradation Mechanisms

The environmentally induced degradation mechanisms threatening the integrity of process components are several types of corrosion and cracking. Amongst, the most critical processes identified are uniform, pitting and erosion corrosion, and stress corrosion, corrosion fatigue and hydrogen induced cracking. They belong to the age-dependent degradation processes due to the effects of chemical and mechanical stresses in corrosive environment in which the offshore component operates.

8.3.3 Bayesian Analysis

The statistical Bayesian analysis is suitable for modeling the stochastic degradation processes because it uses both experience and system data to model random processes.

The prior probability is the initial information or judgment, which is updated using field NDT data. This encapsulates a process of learning the system as the facility ages.

8.3.4 Stochastic Degradation Modeling

Stochastic degradation modeling has been performed using Bayesian analysis. Bayesian analysis essentially consists of computing three probabilities: a prior, a likelihood and a posterior, which best models the physics of a degradation process.

Prior Probability Modeling

Judgmental studies based on historic data may be used to develop prior probability models for degradation rates. Statistical goodness of fit tests using A-D tests are performed to identify the best prior model. It is concluded that the most appropriate prior models that can be used to describe uniform corrosion are the 3P Weibull and the 3P lognormal distributions; the pitting priors is best modeled using Type1 extreme value and 3P Weibull, and the erosion corrosion using 3P Weibull, 3P lognormal or Type 1 extreme value distributions. Similarly, the stress corrosion cracking can be best modeled using Weibull and Type 1 extreme value; the corrosion fatigue cracking using lognormal and Weibull, and the hydrogen induced cracking using Weibull and lognormal distributions. Once the ideal distributions are selected, the parameters are estimated using the method of least squares and maximum likelihood estimates. These parameters determine the characteristics of the degradation process and they account for the uncertainty.

Likelihood Probability Modeling

The field inspection data obtainable from operating facilities, such as offshore structures, subsea pipelines and process piping may be used to model the likelihood function. Initially, data may be categorized to system, subsystem and component level and then it needs to be processed for identifying the underlying degradation processes. The rates of degradation may then be estimated using statistical analysis. The rate of degradation is the most uncertain parameter. Regression analysis and extreme value analysis may be used to estimate the rates of degradation in cases of uniform degradation and localized effects, respectively. It is concluded that most appropriate likelihood models that can be used to describe uniform corrosion are the 3P Weibull and the 3P lognormal distributions; the likelihood for pitting is best modeled using Type1 extreme value and 3P Weibull, and the erosion corrosion using 3P Weibull and 3P lognormal distributions. Similarly, the likelihood of stress corrosion cracking can be best modeled using Weibull and Type 1 extreme value; the corrosion fatigue cracking and hydrogen induced cracking using the Weibull and lognormal distributions. The estimated rates of degradations may further be tested using probability plots and A-D test to obtain the underlying likelihood function. Once the likelihood distribution is identified, characteristic parameters may be estimated using the method of least squares and maximum likelihood estimates.

Posterior Probability Modeling

The simulation based M-H algorithm and analytical Laplace approximation methods may be used to develop the posteriors of age-dependent degradations in process components. Simulation methods are necessary if the prior-likelihood combination models are non-conjugate pairs. The posterior estimation based on the M-H algorithm converges to satisfactory results within 10 000 steady state samples. The first half of the simulated samples are ignored as it represents the transient samples in the Markov chain, only steady state samples are used in the analysis. The acceptance rate of above 65 % is the usual statistical requirement. Laplace approximation results were not encouraging, especially when working with three-parameter distributions. The error accumulates in the variance estimation due to the second order terms. Laplace approximation diverges when the parameter is either too small or too large due to the numerical instability resulting from the use of higher order terms in the computations. Thus, for developing the posteriors of degradation processes, Laplace approximation is not recommended. Further, the change in the location parameter was found insignificant when the M-H algorithm was used. Therefore, instead of using complex three parameter models, the two parameter models are sufficient to develop the posteriors, the location parameter may be added subsequently.

8.3.5 Economic Consequence Analysis

The consequence of failure may be assessed in terms of operational costs. This helps the management to compare the costs against the operational and maintenance budgets. This helps in the choice of an optimal maintenance strategy. The estimated costs are reflected in the estimated risk. The operational costs may be modeled using the varying costs of failure recovery, inspection, and maintenance. The capital costs are not estimated in the analysis as it does not change as the component ages. The failure cost varies depending on various parameters, such as geographic location, type of product, time of failure, national and provincial regulations, injury and fatalities, damage to environment and liability. The inspection and maintenance costs may be modeled using the unit cost and duration of task. The unit costs may be obtained from industry.

Failure Consequences

The cost of failure is obtained as the sum of the following five costs: the loss of commodity due to breakdown, the loss due to shutdown, the cost of spill cleanup, the cost of nature damage, and liability. They may be computed using different formulas based on the unit cost of each item, the quantity of produce released due to failure, the total duration of release. The unit costs are estimated from first principles or they may be extracted from relevant literature. Failure occurrence forces the facility to shutdown for a certain period of time until the proper corrective actions have been implemented. The cost of such a shutdown and the resulting lost profit are the biggest contributor to failure cost. The cost of negative reputation among stakeholders caused by failure is difficult to estimate, however, it will have severe implications.

Inspection Consequences

Inspection is an inevitable part of safe operation as that is the only way to understand if there are any imminent threats from material degradations. The cost of inspection may be modeled using the costs of gaining access to the degraded component, surface preparation, NDT inspection costs, logistic and technical assistance. The logistics costs include the cost of rent, storage and transportation of inspection equipment. The NDT inspection cost includes the type of inspection and the duration required for sufficient data collection. Each of these may be modeled using the unit cost of inspection task and total duration of inspection. Often, maintenance may be followed by inspection tasks. How to link the NDT data, accounting for various sources of uncertainty, to the optimal utilization of maintenance resources is developed and demonstrated in the thesis.

Maintenance Consequences

Inspection can identify potential threats; however, it is the maintenance tasks that do reduce the risk of failure. Since, the operational and maintenance budgets are increasing due to failure, it is essential to optimize the resources. An optimal maintenance strategy reduces the operating and maintenance costs as well as minimizes asset failures and breakdown issues. The cost of typical component maintenance may be modeled using the cost of minimal repair for corrosion and cost of replacement for cracking. The minimal repair leaves the system in a condition similar to its condition just before failure, whereas replacements bring the system back to as good as new condition. If the component is minimally repaired, the lifetime distribution will not change. If it is replaced with identical components, the lifetime distribution may change. The cost of maintenance may be estimated using the cost of accessing the degraded component, the cost of surface preparation, gauging defects, cutting, removal and welding of plates and pipes, technical support and the logistics related to rent storage and transportation. These costs are modeled using the unit cost of maintenance tasks and the total duration of maintenance. The usage of unit cost from an offshore maintenance contracting company makes the model applicable to offshore industry in the North Sea.

8.3.6 Optimization of Maintenance Strategy

The inspection and maintenance strategies are designed to remedy the effects of physical degradation, strength loss and obsolescence of process components. Physical degradation leads to reduction in the efficiency of operation, wall thickness and material strength. Obsolescence occurs as a result of continuous developments of new components. Two types of maintenance strategies are adopted in this thesis: inspection and repair, and inspection and replacement. If it is not economical to repair the component, or required repair resources are unavailable or if the failure is imminent, then one has to resort to a replacement action. Replacement is a maintenance strategy in which the component is replaced with an identical one rather than doing repairs.

Inspection and Maintenance

The optimization of inspection and maintenance has been achieved by optimizing the risk. Risk has two components: the probability of failure and the consequences of failure. The probability of component failure has been estimated using the Bayesian prior-posterior analysis. The posterior probability cumulative density function is used to estimate the probability of failure. The consequence of failure is obtained as explained before. It is modeled using engineering economic analysis. The annual rate cost of failure, inspection and maintenance are developed and combined to estimate the annual equivalent cost (AEC) of failure. The estimated AEC is combined with probability to perform component-level risk analysis. The operational life risk over the remaining service life is estimated using the probability and consequences. The point at which risk reaches its minimum value is used to determine the optimal inspection and maintenance interval. This interval satisfies the two criteria of maintenance: minimizing maintenance costs while keeping risk at the ALARP Level. The results of the analysis are tabulated in Table 8.1. The most critical interval is for PC and CFC degradation, with an inspection and maintenance interval of 4 years. This interval may be revised when a new set of NDT data is obtained. This renders the model developed in this work a dynamic model which is continuously updated using new NDT data.

Replacement Analysis

An economic consequence analysis based on component replacement concept is discussed. The replacement strategy is based on the economic service life of the component and the threat from an imminent failure of component. Replacement strategy is also used for non-repairable components. The annual equivalent cost is calculated by combining failure recovery, inspection and maintenance costs. The failure recovery cost is observed to follow a decreasing trend and the inspection and maintenance interval is observed to follow an increasing trend, due to strength degradations and wall loss. Thus, the annual equivalent cost is a convex function of service life. The replacement intervals based on critical degradation processes are presented in Table 8.1. The smallest one is considered. The smallest one is 7 years for SCC and HIC degradations, which is reported as the optimum replacement interval. By performing replacement at this interval, the risk will be reduced to ALARP level and replacement intervals will be maximized.

Table 8.1. Optimal Interval for the Maintenance and Replacement of Components

Process Component	Deterioration Process	Degradation Model	Replacement Interval (years)	Maintenance Interval (years)
Piping (straight pipes, bends, tees)	UC	3P Weibull	9	5
	PC	Type 1 Ex Val.	10	4
	EC	3P Weibull	10	5
	SCC	Weibull	7	6
	CFC	Weibull	8	4
	HIC	Weibull	7	5

The components have been in operation for 23 years. Since components are deteriorating randomly, by comparing the optimum intervals in Table 8.1, the next inspection and maintenance is due in 4 years and replacement is due in 7 years. By performing maintenances in these intervals, the risk of failure can be reduced to ALARP level.

8.4 NOVELTIES

8.4.1 Identification of Critical Degradation Processes

This study revealed the critical degradation processes which threaten the integrity of offshore process components. It has been observed that the age-dependent corrosion and cracking processes are posing major threats to the structural integrity of components. The analysis of field NDT data has also confirmed the same conclusion.

8.4.2 Stochastic Degradation Modeling using Bayesian Analysis

The degradation is a stochastic process; its modeling is a challenging task to engineers. In this study, this challenge is addressed using the Bayesian analysis. Bayes theorem is used in inferential statistics to learn about the system with the arrival of new data. Since it takes into account the uncertainties in experience and life data, its predictions are more reliable and accurate to model the degradation processes of components.

8.4.3 Development of Non-conjugate Posterior Models

One of the major novelties of this thesis is the development of posterior probability models for the component degradation processes of non-conjugate pairs. The use of conjugate pairs simplifies the posterior estimation; however, it may not produce a realistic posterior. It is proposed that the simulation based M-H algorithm may be used to model posteriors of any time-dependent degradation processes, such as Weibull, lognormal or extreme value processes. This modeling is possible only with the fast developments in the computational facilities in recent years.

8.4.4 Incorporating Real Life NDT Data in the Analysis

Often, industry collects NDT data as a part of the asset integrity management, but the data is rarely used in the development of optimal inspection and maintenance strategies. The present work stresses the benefit of using NDT data to obtain the likelihood function for the system.

8.4.5 Development of Economic Consequence Analysis

Most of the papers in the open literature consider the probability of failure only in the optimization of maintenance. The reliability centered and condition based maintenance methods follow this strategy. However, it is also important to consider the consequence of failure when making decisions regarding optimal inspection and maintenance programs. Some events which have low probability of failure may have high consequences due to failure. Thus, maintenance strategy developed here is based on the consideration of both the probability and consequence of failure, i.e. it is based on the consideration of life risk, and not only the probability of failure.

8.4.6 Risk Based Optimal Maintenance Strategy

Risk based strategies have been gaining predominance in the recent years, mainly due to the development in the area of fast computations. Risk based maintenance strategy has been addressed in this thesis, which is the most recent development in maintenance management. Its importance lies in the fact that it takes into account both the likelihood and consequence of failures. An optimized strategy reduces failures, risk to as low as reasonably practicable level, and simultaneously ensures the safety of operation.

8.4.7 Dynamic Updating

The Bayesian inference theory is used to update the inspection, maintenance and replacement intervals in this study. The latest NDT data may be applied in the developed model to revise the maintenance strategy. This is not equivalent to a constant health monitoring, which is costly. This is far better than breakdown maintenance as well. It tries to find a balance in between these two strategies. It rationalizes the maintenance decision as well as minimizes the operating and maintenance cost. The posterior probability and risk, in turn will keep on modifying as the component ages, reflecting the reality of component performance with age. However, there is a need for structural health monitoring of critical components, which is beyond the scope of this study.

8.4.8 Uncertainty Modeling

The uncertainty in degradation processes may arise from many sources such as, inherent randomness in physical processes, statistical uncertainty and modeling uncertainty. The physical uncertainty means that the repeated measurements of the same physical quantity do not yield the same value due to numerous fluctuations in the environment, test procedure, instruments, and the observer. Statistical uncertainty occurs when one does not have precise information about the variability in the physical quantity of interest due to limited data. Modeling uncertainty occurs due to the limited representation of the system behavior. A computational model strives to capture the essential characteristics of system behavior through idealized mathematical models or numerical procedures. The proposed risk based maintenance model captures the inherent randomness through prior and likelihood data collection in Bayesian analysis, statistical uncertainty through multiple NDT data collection and likelihood modeling, and modeling uncertainty through the use of stochastic models in the analysis.

8.4.9 Integrating Statistics and Economics in Decision Making

This study was planned as a multi-disciplinary project encompassing the concepts of engineering failure analysis, statistics and economics in decision making. This is a novel concept to use the statistical McMC analysis to model the stochastic degradation process, engineering economic analysis to the model the failure consequences. Also, the basic degradation processes are understood from chemistry and physics of failure process, and the decision making is in maintenance engineering. This multidisciplinary research integrating concepts from these areas is a novelty of the developed RBIM.

8.4.10 Industrial Applications

The strategy developed in this thesis provides a solution to a real life asset integrity problem that can benefit industry. Real life NDT, specific to a particular facility can be used to develop degradation models suitable to that facility. The models can be used to determine optimal maintenance intervals and tasks.

8.4.11 Ease of Computational Effort and Time

The model inputs are NDT data and unit cost information. The computational tasks are easy; minimum knowledge is required to run the Matlab code. The computational time depends mainly on the level of accuracy required. Typically, two to three hours and 10000 iterations are sufficient for results to converge to satisfactory maintenance and replacement intervals.

8.5 FUTURE WORK

In the present study, an attempt has been made to develop a risk based integrity modeling for the optimal maintenance decision making of offshore process components. This study can be extended as suggested below:

8.5.1 Non-age Dependent Degradation Processes Modeling

This study has been limited to the age-dependent degradation processes of process components. Other non-age dependent failure mechanisms such as third party damage; ship or boat collision; material and fabrication defects; operational errors; vibration and cyclic stresses may be investigated further.

8.5.2 The Online Risk Monitoring Systems

This study is limited to dynamic updating of the system performance in terms of revised inspection and maintenance strategy. However, if the risk can be monitored online, the system performance can be tracked and the maintenance decisions may be taken on the spot. Such a system will be versatile considering the imminence of failures. There is a broad scope for such studies especially for the far, deeper offshore facilities.

8.5.3 System Effects in the Risk Analysis

This study has been focused on the component level risk analysis. However, the risk analysis shall be conducted on a system level. The approach developed in this thesis can be extended and applied to a group of components which constitute a system. The system safety analysis may be achieved through the fault tree and event tree analysis.

8.5.4 Risk Analysis for Combined Degradation Mechanisms

In reality the degradation process occurs simultaneously, for e.g., UC and SCC, PC and CFC, etc. In this study, they are assumed to be independent and isolated. The modeling of coupled degradation process is a challenging task, which needs to be explored further.

8.5.5 Inclusion of Objective Bayesian Analysis

The Bayesian analysis is inherently subjective, since prior information is usually based on subjective expertise. This subjectivity has been reduced by using generic data from literature. However, the use of objective priors, such as non-informative priors may be explored further to model the priors of degradation processes. Such a study may produce more realistic results.