PhD Thesis

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RELIABILITY ESTIMATION AND RISK-COST OPTIMISATION OF UNDERGROUND PIPELINES

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A thesis submitted in partial fulfilment of the requirements of the University of Greenwich for the Degree of Doctor of Philosophy

May 2014

DECLARATION

"I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree other than that of Doctor of Philosophy being studied at the University of Greenwich. I also declare that this work is the result of my own investigations except where otherwise identified by references and that I have not plagiarised the work of others".

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Lutfor Rahman Khan	Dr Kong Fah Tee

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude and sincere appreciation to my supervisors for their keen support and guidance. I would like to give special thanks to my supervisor Dr Kong Fah Tee who provided me the opportunity to do this research in the difficult time of my life and provided guidance and advice during whole research period. I would also like a special thanks to my supervisor Professor Amir Alani whose support and guidance were great help to complete this research.

I would like to extend my gratitude to Dr Hua-Peng Chen, Dr Ouahid Harrieche, Dr Alexander Coutroubis and Dr Mojtaba Mahmodian – University of Greenwich (UK), Dr Tahani Coolen-Maturi – University of Durham (UK) and Dr Hong-Shuang Li – College of Nanjing University of Aeronautics and Astronautics (China), for their invaluable suggestions and advice to continue the research to this level.

Many thanks also go to my parents and my wife Dr Mahmuda Perven Chowdhury for all support during the research time.

ABSTRACT

The safety of infrastructure facilities is the primary objective of any civil engineering design. A large section of underground pipelines in the UK are classified as structurally deficient and functionally obsolete. Due to low visibility, condition assessment and rehabilitation of underground pipelines are frequently neglected until a catastrophic failure occurs. Providing an acceptable level of service and overcoming the practical difficulties, the concerned industry has to plan how to operate, maintain and renew (repair or replace) the pipeline systems under the budget constraints. This research is focused on estimating pipe reliability and deciding when and how interventions are needed to prevent unexpected failures of flexible underground metal pipelines subject to externally applied loadings and pipe material corrosion during the whole service life at the optimal cost. The time-dependent reliability due to corrosion induced excessive deflection, buckling, wall thrust and bending has been estimated. First, Hassofer-Lind and Rackwitz-Fiessler (HL-RF) algorithm and Monte Carlo Simulation (MCS) have been used to estimate the reliability. Then Subset Simulation (SS) method is developed to enhance the applicability, especially for small failure probability prediction. Accuracy prediction method, Receiver Operating Characteristic (*ROC*) curve has been introduced in this research to assess the accuracy of pipeline reliability analysis. Then the study has been extended to determine the intervention year for maintenance and identify the most appropriate renewal solution by optimising the risk of failure and life cycle cost, including carbon dioxide emissions mitigation cost, using Genetic Algorithm (GA). Optimisation technique, SS has also been developed for risk-cost optimisation of underground pipelines. Examples are presented to validate the proposed methods with a view to prevent unexpected failure of pipes by prioritising maintenance based on failure severity and system reliability. The proposed reliability estimation and risk-cost optimisation approach can be utilised to form a maintenance strategy and to avoid unexpected failure of pipeline networks during service life.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

ASCE = American society of civil Engineers;

AUC = Area under *ROC* curve;

AWWA = American water works association;

A_s = Cross-sectional area of pipe wall per unit length;

BS = British Standards;

B' = Empirical coefficient of elastic support;

C = Hazen-Williams friction coefficient;

C_L = Live load distribution coefficient;

CDF = Cumulative Density Function;

CI = Condition index;

COV = Covariance;

Cov = Coefficient of variation;

CPSA = Concrete Pipeline Systems Association;

D = Mean diameter of pipe;

D_i = Outside diameter of pipe

D_L = Deflection lag factor;

D_0 = Outside diameter of pipe;

D_T = Corrosion pit depth;

E = Modulus of elasticity of pipe material;

EC = Embodied energy coefficient;

EE = Embodied energy;

E_s = Soil modulus;

E' = Soil modulus of reaction;

e_0 = Initial pipe wall roughness

FPF = False positive fraction;

f_d = Burial depth factor;

f_f = Underground pipeline function factor;

f_l = Location factor;

f_s = Embedment soil factor;

f_q = Seismic factor;

F_y = Minimum tensile strength of pipe;

f_z = Size factor;

GA = Genetic Algorithm;

H = Height of the soil above pipe invert;

HDPE = High Density Polyethylene;

HL-RF = Hasofer-Lind and Rackwitz-Fiessler algorithm

H_w = Height of water above top of pipe;

H_t = Head in meters;

I_w = Weighted impact factor;

LCC = Life cycle cost;

L_w = Live load distribution width;

L_1 = Load width parallel to direction of travel;

L_2 = Load width perpendicular to direction of travel;

K_b = Bedding constant;

MCS = Monte Carlo simulation;

M_s = Secant constrained soil modulus;

N = Number of samples;

NPI = Nonparametric Predictive Inference;

p = Actual buckling;

P_{f} = Probability of failure;

p_0 = Conditional probability;

p_{cr} = Critical buckling;

PDF = Probability density function;

PVC = Polyvinyl chloride;

P_{sp} = Geostatic load;

PVC = Polyvinyl Chloride;

Q = Flow rate in gallons per minute;

R = Effective radius of pipe;

ROC curve = Receiver Operating Characteristic curve;

SS = Subset Simulation;

S.G =Specific gravity;

T = Time in years;

TPF = True positive fraction;

T_a = Actual wall thrust;

T_{cr} = Critical wall thrust;

t = Thickness of pipe wall;

V_{AF} = Vertical arching factor;

W = Weight of pipe material;

W_a = Soil arch load;

W_c = Soil vertical load;

X = Relative roughness of the pipe;

Δ_y = Actual deflection;

Δy_{cr} = Critical deflection;

γ_s = Unit weight of soil;

γ_w = Unit weight of water;

ϕ_p = Capacity modification factor for pipe;

φ_s = Capacity modification factor for soil;

η = Pump efficiency;

β = Reliability index;

υ = Poisson's ratio;

σ = Standard deviation;

σ_b = Actual bending stress;

ε_b = Actual bending strain;

μ = Mean value;

ρ = Correlation coefficient;

CHAPTER ONE
INTRODUCTION

1.1 BACKGROUND

Underground pipelines are one of the complex infrastructure systems that have significant impact on economic, environmental and social aspects of all modern life. Municipalities are under increasing pressure to adopt proactive and optimised renewal strategies to reduce the risks, cost and to maintain an acceptable level of performance and service (Halfawy et al, 2008). Huge amount of buried pipelines in the UK and other parts of the world are categorised as structurally deficient and functionally out-dated. To sustainable management of these pipes pose a wide range of difficulties due to deterioration and/or aging of pipes, requirements to comply with environment and limited renewal budgets. According to WRc (2001), maintenance and renewal of these pipes are required hundreds of billions of pounds that cannot be accommodated by water and wastewater agencies. The magnitude of the problem poses great technological and economic challenges, specifically which pipe should be given high priority for maintenance and what is the optimal maintenance strategy, i.e., identify the most effective management strategy. According to Nafi and Kleiner (2010), buried pipeline networks constitute a class of safety-critical infrastructure systems that should be analysed vigorously as their failure can have catastrophic consequences, including multiple fatalities and injuries, complete loss of services and considerable socio-economic impacts. Neglecting regular maintenance of these pipelines adds to life cycle costs and liabilities, and in extreme cases, causes stoppage or reduction of vital services (Abraham et al, 1998).

Underground pipelines are widely used for transportation of fluid (water, sewer, oil and gas etc.) from one place to another. To convey the fluid from one place to another, in many instances, these are placed under runways, railways or roadways. Consequently, pipelines are encountered different internal and external loadings (e.g., overburden soil, traffic loads, fluid pressures etc.), different soil conditions (soil density, soil moisture, etc.) and various temperatures during the operation. Therefore, underground pipelines are required to resist the influence of the overlying surface load as well as the effect of internal fluid pressure. Apart from loadings, another major problem for the metal pipes is corrosion. When the pipe is not capable to resist it-self from the internal or external loadings and/or impairment of corrosion then the pipe breaks or becomes out of service. It is note that the pipes deterioration is varied with respect to loadings and buried environments. In practice, the effects of external soil and traffic loadings in vertical direction of the pipe length are generally considered in the pipeline design. The internal fluid pressures along the length of the pipe are neglected in many cases. Like internal fluid pressure, the external loadings along the longitudinal direction of pipes are also considered insignificant, especially if the pipes are not placed very close to the ground surface (Ahammed and Melchers, 1997). On the basis of these assumptions, it is often assumed that buried pipeline cross-sections remain in a state of plane strain.

Buried pipes can be broadly classified as flexible or rigid, depending on how it performs during installation and operation. All types of underground pipes, whether flexible (steel, ductile iron, PVC, HDPE etc.) or rigid (reinforced concrete, vitrified clay, cast iron, asbestos cement etc.), rely on the backfill properties to transfer the loads into the bedding. As a result, all pipes should be installed as designed to perform as expected. However, only flexible buried metal pipes (e.g., steel, ductile iron pipes etc.) are considered in the current research. Pipe structures are collapsed when the applied stress exceeds the limiting or ultimate strength of the pipe wall material. Therefore, solid knowledge related to failure modes and consequence of failure is a key issue in the pipeline structure design. Different failures modes can be found for buried pipelines due to loadings and aggressive environments as shown in Figure 1.1 (Salem and Najafi, 2008). A vital failure criterion of flexible buried metal pipeline systems is localised or overall reduction in pipe wall thickness due to corrosion. The size of the resulting thickness undermines the pipe resistance capacity which in turn reduces the factor of safety of the pipe. The reduction of pipe strength which influences the pipe failure most are pipe leaking, blockage, excessive deflection, buckling, wall thrust or stress, bending stress and bending strain, etc. (Tee et al, 2013a).

Corrosion is a continuous and time-variant process and may be uniform or nearly uniform in nature or localised, e.g., pitting or crevice corrosion. Furthermore, corrosion may act either internally or externally or both on the surface of pipe wall which influences the other modes of failure, such as deflection, buckling, bending, etc. The major type of corrosion on the iron-based pipes is corrosion pit. When corrosion pit depth is increased with time, the magnitude of deflection, buckling, wall thrust and bending (stress and strain) are also increased. Evidently, the effect of the failure due to corrosion induced excessive deflection, buckling, wall thrust and bending are practically significant in the structural analysis of a flexible buried metal pipeline design. However, sometimes extra pipe wall thickness or external coatings or linings are provided to protect from the destructive effects of corrosion. But this practice is not always found totally effective, particularly where pipe sections are joined together (Ahammed and Melchers, 1997). Sometimes, coatings are damaged during installation. Moreover, different researcher (ASCE, 2001; Rajani and Makar, 2000; Berardi et al, 2008) show that how much extra wall thickness is needed for effective corrosion protection for a given design lifetime, is still a big concern to buried pipeline designers. These coatings significantly increase the total pipe installation cost as well as the life cycle cost.

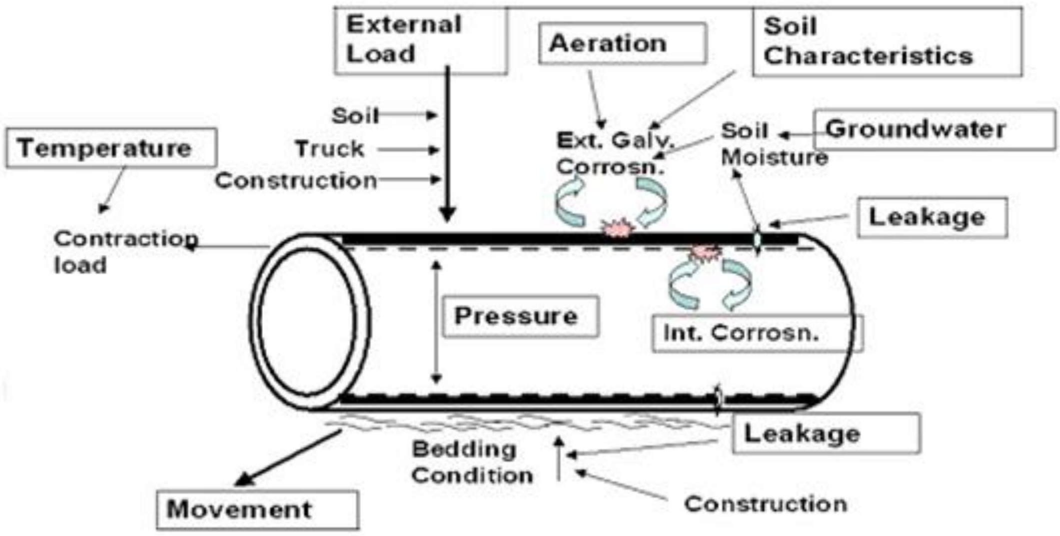


Figure 1.1: Modes of failure of a flexible buried metal pipe (Salem and Najafi, 2008)

Due to increasing fear of failure risk and requirements to comply with environments and accounting regulations within limited budgets, the reliability based sustainable management strategy is very useful to overcome these complications. A complicated approach to scheduling pipe maintenance is to determine individual pipes that are approaching unsafe condition and repair or replace these before fail. This type of approach requires a robust methodology to determine the remaining safe service life of each pipe segment within the distribution network system. The long-term planning of the renewal of underground pipe distribution networks requires the ability to predict system reliability as well as assess the economic impact. To estimate the reliability and associated cost management, attention should be given on the types of pipes, ages, environments and loading conditions on the applicable pipes. Pipe materials are varied from country to country or even city to city. The mechanical properties (i.e., elasticity of modulus, Poisson's ratio etc.) of different pipe materials are different and their modes of failure also different, even for same failure criteria within same environments and loading conditions. For example, the magnitude of steel pipes failure due to buckling is significantly different from ductile iron pipes (ASCE, 2001). It is also worth noting that corrosion rate of different materials are not same, such as steel pipes are different from those of the ductile iron and cast iron pipes (as corrosion empirical parameters k and n or a, b and c are different) (Watkins and Anderson, 2000). Similarly, different age and loading conditions also affects pipe service life. For these reasons, with respect to pipe materials, location and loading conditions, development of a systematic and an effective approach is required for ensuring adequate reliability and optimising the maintenance strategy.

Figure 1.2: A typical pipe failure due to external loadings

In the past, various researchers and organisations recognised the importance and the applicability of the reliability estimation of flexible buried pipeline systems. The development of reliability analysis in pipeline systems is receiving considerable attention nowadays and the guidelines on the targeted reliability indices have been suggested recently (Babu and Srivastava, 2010). Complex models in reliability and risk analysis often involve uncertain input parameters which can be determined using the reliability based optimum management methods with varying degrees of accuracy. These uncertain parameters are best explained by random variables with known or assumed probability distributions in the optimum management process. The output of such a reliability analysis is therefore also a random variable with measurable uncertainties.

Due to corrosion induced failure modes are time variant process, the safety or serviceability margin and the corresponding reliability of pipeline is decreased (or failure probability is increased) with respect to time. Since the life of an underground metal pipeline is related to corrosion deterioration and the developed stresses, the available design equations for pipeline as well as wall thickness loss due to corrosion can be modified for the purpose of establishing a probabilistic functional relationship between loads, corrosion, related soil and pipe materials. In the probabilistic approach, some input parameters are treated as continuous random variables and the performance of the structure resulting from different failure criteria is expressed in a probabilistic pipeline framework, i.e. either probability of failure or in terms of reliability index. The key component of this approach is to estimate the probability of failure to predict the expected safe service life with optimum cost.

This research is focused on estimating pipe reliability and deciding when and how interventions are needed to prevent unexpected failures of flexible underground metal pipelines subject to externally applied loadings and pipe material corrosion during the whole service life at the minimal cost. The reliability with respect to time due to corrosion induced excessive deflection, buckling, wall thrust and bending has been estimated. Methods of probabilistic reliability analysis, such as, First Order Reliability Method (FORM), Second-Order Reliability Method (SORM), Point Estimate Method (PEM), Monte Carlo simulation (MCS), Path Enumeration (PE), Hasofer-Lind and Rackwitz-Fiessler algorithm (HLRF) and State Enumeration (SE) etc., are available in literature (Baecher and Christian, 2003). Due to randomness of the failure modes, probabilistic reliability methods, HL-RF algorithm and MCS are applied to predict the reliability of pipelines due to above mentioned time-dependent multiple failure cases in this research. Newly developed, Subset Simulation (SS) has been applied in pipeline reliability analysis to enhance the applicability. Then Receiver Operating Characteristic (*ROC*) curve has been introduced in reliability analysis for underground pipeline network due to these failure modes. The *ROC* curve provides a performance assessment for pipe failure state functions of reliability prediction.

The main challenges of pipe reliability based management strategy are to ensure that life cycle costs are reduced while achieving required performance and reliability. Currently, various methodologies are using in this field, such as Genetic Algorithm (GA), Fuzzy Set Method (FSM), Ant Colony Optimisation Approach (ACOA), Shuffled Frog Leaping Algorithm (SFLA), Linear Programming (LP) and Dynamic Programming (DP), etc. (Afshar and Marino, 2005). It is commonly believed that there is no available solution techniques which can provide 100% guarantee to minimise the total risk, cost and project duration with respect to available resources. However, Genetic algorithm (GA) has been applied in the current management process, as GA has gained popularity as a powerful evolutionary and robust optimisation technique and increasingly used in solving difficult engineering distribution network design problems. GA has proven to be successful in finding the near optimal solutions and it can handle discrete pipe elements (Afshar and Marino, 2005; Tolson et al, 2004). Then SS optimisation process has been developed in the current research to make the optimisation process more robust and to verify the outcomes of the GA.

The proposed practice of pipe management strategy is based on flexible underground pipelines risk and cost where life cycle cost (LCC) of the network has been used as an objective function. The LCC represents the present value of all costs incurred throughout the life cycle of a pipe structure, including the costs of design, construction, maintenance, repair, replacement, demolition and costs of failure (Newton and Vanier, 2006). In addition, CO_2 emissions mitigation cost also been included in LCC management process. This management system mainly depends on a reliability performance prediction model and an effective optimisation algorithm or technique. An optimum life cycle cost is assessed based on pipe reliability. Then a pipe renewal time and renewal strategy is suggested. The prioritisation of this renewal strategy is predicted based on the conventional pipe condition ratings systems (condition index) of pipe elements. Then priority index is predicted based on the pipes condition and ages. This approach is a quite fundamental for the long-term and short-term analysis of hundreds or thousands of pipes in a network.

The proposed management aims to improve the overall performance of the pipeline network through the conflicting objectives, such as minimisation of risk of failure, minimisation of life cycle cost and maximisation of service life. This strategy is also called multi-objective optimisation technique. Multi-objective optimisation techniques provide a practical tool for optimal prioritisation for management of the asset.

1.2 RESEARCH AIMS AND OBJECTIVES

Numerous obstacles have faced by water and wastewater industry during placing or maintenance the flexible underground metal pipelines over time. The most common obstacles are found as pipe material deterioration due to corrosion as well as deflection, buckling, wall thrust and bending behaviour due to external loadings. Providing an acceptable level of service and overcoming these critical difficulties, the concerned industry has to plan how to operate and manage the system under the budget constraints.

To overcome the aforementioned complications, the aims of this research are as follows:

- To develop a probabilistic approach to measure the time-dependent reliability for flexible underground pipelines.
- To develop a rational method for risk and cost optimisation process for the flexible buried metal pipeline distribution network based on reliability.

The objectives of this research can be presented as follows:

(a) To analyse and develop rational methods for reliability prediction of flexible underground metal pipelines due to corrosion induced deflection, buckling, wall thrust and bending.

(b) To investigate the correlation among failure modes and influencing parameters and to examine the behaviour of pipeline due to effects of various uncertain parameters, such as pipe thickness, diameter, soil height, etc.

(c) To assess the accuracy of the pipeline reliability analysis for pipe failure conditions due to corrosion induced deflection, buckling, wall thrust and bending.

(d) To develop the reliability based risk-cost optimisation process for pipeline network using life cycle cost, including carbon dioxide emissions mitigation cost.

(e) To predict the optimum risk as well as cost with renewal time and renewal methodologies in the decision making process.

1.3 RESEARCH METHODOLOGIES

This research firstly investigated how flexible buried metal pipeline deteriorate and how to incorporate with the effect of corrosion as a time dependent process. Existing and new reliability prediction methods are employed for multiple failures, namely, corrosion induced deflection, buckling, wall thrust and bending. The correlations among failure modes and between some random variables are estimated. The parametric and sensitivity analyses for different influencing parameters have been conducted over service life of the pipeline. New reliability accuracy prediction method has been introduced in pipeline reliability due to these multiple failure criteria. Then life cycle costs are estimated, including carbon dioxide emissions mitigation cost for pipeline network. Finally, existing and new reliability based optimisation processes are applied in the risk-cost management of flexible underground metal pipelines.

The following methodologies are used to achieve the objectives of this research:

<u>Objective (a)</u>

To achieve objective (a), a comprehensive literature survey has been carried out on the subject to acquire in-depth knowledge of the design procedure of flexible buried metal pipes and behaviour under corrosion and various loading conditions. Structural reliability analysis and failure assessment of buried pipes cannot be achieved without extensive knowledge about loading, design principles and failure modes. Available current research on the design principles, corrosion process, failure mechanism, service life prediction methods for buried pipes has been reviewed. Recently published design manuals and codes of practice are referenced for this purposes, for example, ASCE (2001), BS EN (1997), BS 9295 (2010), Moser and Folkman (2008), Watkins and Anderson (2000), Ahammed and Melchers (1997), Gabriel (2011), Moser and Folman (2008), etc. The multi-failure criteria, namely, deflection, buckling, wall thrust and bending (stress and strain) are modified to time dependent failure phenomenon to interact with corrosion for flexible metal pipes, such as steel and ductile iron pipes. Then limit state functions and probability of failure are predicted based on the modified formulas for these failure modes.

Probabilistic theory has been employed to develop analytical models for deterioration and reliability analysis of pipeline systems. For this purpose, HL-RF and MCS techniques are used. Then SS has been developed to analysis the reliability of buried pipeline systems which is very efficient method compared to HL-RF and MCS. All these methods have been conducted in MATLAB software. An in-depth probability theory and numerical studies are carried out and different published papers are used as references, such as Melcher (1999), Sadiq et al (2004), Au and Beck (2001), Ahammed and Melchers (1994), Au and Beck (2003), Au et al (2007), ASCE(2001), AWWA (1999), Haldar and Mahadevan (2000), Cameron (2005), etc.

<u>Objective (b)</u>

To accomplish objective (b), a comprehensive literature review and mathematical analysis are carried out to understand the mechanism of above failure criteria interaction or correlation using MCS method and the approximate moments for general functions in the MATLAB environment. First, the correlation among failure modes are estimated, then correlation between random variables, such as soil density and soil modulus as well as loading and pipe stiffness with known correlation coefficients (0 – 0.9) in different failure modes have been assessed with varying time of 0, 25, 50, 75 and 100 years. Parametric and sensitivity analysis are conducted for different parameters to assess the effect of different random variables, such as soil density, soil height, pipe diameter, pipe wall thickness, corrosion empirical parameters, etc. Published works, such as Rajani and Kleiner (2001), Zhao et al (2011), Melchers (1999), Ahammed and Melchers (1997), Rao (2003), Babu and Rao (2005), Babu and Srivastava (2010), Riha and Manteufel (2001), etc., are used as a reference in the analysis.

Objective (c)

To predict the accuracy of pipeline reliability analysis, Receiver Operating Characteristic (*ROC*) curve has been employed, where classical (or empirical) and Nonparametric Predictive Inference (*NPI*) technique are used for describing the performance of the analysis. Due to lack of real case data, the Monte Carlo simulation has been used to generate 100 pipe sample data for every failure case assuming 10%, 20% and 30% failure and non-failure condition data are incorrect in this study. MCS is applied in MATLAB software. All calculations of ROC curve prediction are performed in R software. A wide-ranging of literature reviews have been conducted and recent published works are analysed, such as Coolen-Maturi et al (2012), Coolen-Maturi et al (2011), Devon et al (2010), Arian et al (1998), Zhou et al (2002), Coolen (1996) and Indrayan (2012), Hill (1968), etc.

Objective (d)

To achieve objective (d), a comprehensive literature review, such as Ambrose et al (2008), AWWA (1999), Ahammed and Melchers (1994), Hinow et al (2008), Halfawy et al (2008), Barbosa et al (1989), Newton and Vanier (2006), etc., have been conducted and the most adoptable and time dependent methods are applied for life cycle cost (LCC) prediction. The life cycle cost, including carbon emissions mitigation cost has been analysed and estimated for pipe service life. Existing GA is developed for this purpose, where LCC is used as an objective function which includes cost and risk (failure probability). Then new SS optimisation algorithm is developed to optimise the risk and consequence of cost due to failure over life cycle of pipes. Finally, both results obtained from GA and SS are compared. These optimisation methods are conducted in MATLAB software.

Objective (e)

To accomplish objective (e), the LCC has been used as an objective function in management process. The capital cost, maintenance cost, failure cost, carbon emissions mitigation cost and failure probability are used in LCC to optimise risk and cost of the flexible buried metal pipeline system. The study has been extended to determine intervention year for maintenance and identify the most appropriate renewal solution by minimising the risk of failure and whole life cycle cost. Renewal methodologies are estimated using condition index (CI) and priority index (PI). A good number of published papers are referenced in the process, such as Newton and Vanier (2006), Moneim (2011), Wirahadikusumah and Abraham (2003), Woodhouse (1999), McDonald and Zhao (2001), Halfawy et al (2008), Mohr **(**2003), Nafi et al (2008), Hinow et al (2008), Halfawy et al (2008), Sarma and Hojjat (2002), etc.

1.4 RESEARCH CONTRIBUTIONS

This research is concerned with estimating the reliability and risk-cost optimisation for deciding when and how interventions are needed to prevent unexpected failures of flexible buried metal pipelines, subject to corrosion and externally applied loadings conditions during the service life at optimal cost.

The contributions of this research can be briefly described as follows:

1. The available failure modes of deflection, buckling, wall thrust and bending are modified to time dependent failure phenomenon to interact with corrosion for flexible metal pipes, such as steel and ductile iron pipes. The structural reliability analysis for buried pipeline has been analysed according to the modified formulas for every failure mode using HL-RF algorithm and then it has been verified by MCS. The results show that there is a good agreement with both methods.

2. The correlations among the time-dependent failure modes, namely, corrosion induced deflection, buckling, wall thrust and bending have been predicted which are not available in literature. The effects of influencing random variables, such as soil density and soil modulus or loading and pipe stiffness with known correlation coefficients have also been analysed with varying time.

3. New reliability prediction method, Subset Simulation (SS) has been developed for buried pipeline reliability analysis to overcome the difficulties of the existing HL-RF and MCS methods. HL-RF is inefficient when many random variables are involved and/or failure probabilities are low. Likewise, MCS needs a high number of samples to simulate which is a time consuming procedure. In the current application of MCS, the order of 10^6 samples is needed to obtain accurate estimates of small probabilities

of failure where the study showed that the SS is quicker method compared to MCS and 500 samples are enough to produce a good result.

4. Receiver Operating Characteristic (*ROC*) curve has been introduced in application for reliability analysis for underground pipeline network due to corrosion induced deflection, buckling, wall thrust and bending. The *ROC* curve plays an important role in many areas such as signal detection, radiology, machine learning, data mining and credit scoring, etc. However, no such works have been found on buried pipeline reliability analysis due to above failure modes in literature. The *ROC* curve provides a model performance assessment for pipe failure state in reliability prediction.

5. Optimisation method, GA has been developed in pipe reliability based risk-cost optimisation process to determine the intervention year for maintenance and identify the most appropriate renewal solution by minimising the risk of failure and whole life cycle cost. Then SS optimisation approach has been developed in risk-cost optimisation process to make the proposed approach more robust. GA is a computationally expensive traditional algorithm. In addition, there is no absolute assurance that a GA will find a global optimum. In contrast, SS is capable to perform optimisation efficiently with a shorter time. SS is a relatively new method and has not yet been applied in pipe maintenance optimisation.

These developed methodologies can be used as a rational tool for decision makers with regard to strengthening and rehabilitation of existing and new pipelines. Precise prediction of reliability (probability of failure) and reliability based management of pipeline system can help structural engineers and asset managers to obtain a cost-effective strategy in the controlling of the pipeline system. The output of this research will permit infrastructure managers and construction professionals to:

a) Predict reliability of buried pipeline systems by a rational and reliable time dependent analysis.

b) Examine the influence of design parameters and random variables by sensitivity and parametric analysis techniques.

c) Assess the risk of failure and cost in the developed management strategies that will reduce or keep the failure risk and cost at an acceptable level.

1.5 THESIS STRUCTURE

The structure of the whole thesis can be presented as follows:

CHAPTER ONE – *Introduction*: This Chapter describes the background of the research, introduces the aims and objectives, methodologies, research contributions and structure of the thesis.

CHAPTER TWO – *Literature Review*: This Chapter can be broadly classified into two parts: (1) Literature reviews for reliability of buried pipes, and (2) Literature reviews for risk-cost optimisation process for underground pipeline network. A comprehensive literature reviews have been undertaken to acquire knowledge of the underground pipeline design process, corrosion mechanism involved, pipe service life prediction, methods of reliability analysis, pipeline risk and failure cost, carbon emission cost, challenges, risk-cost optimisation processes and renewal techniques for buried pipeline system.

CHAPTER THREE – *Structural reliability analysis using HL-RF and MCS methods*: The basic structural reliability on pipeline systems have been studied, where the flexible metal pipe failure due to corrosion induced deflection, buckling, wall thrust and bending are presented using HL-RF and MCS methods. Correlations among different failure modes as well as random variables have also been discussed. A numerical example has been presented to validate the concept of pipe failure probability and correlation for the failure modes. At the end, parametric studies and sensitivity analysis have been conducted to scrutinise the behaviour of pipeline due to effects of various uncertain parameters.

CHAPTER FOUR – *Structural reliability analysis using Subset Simulation*: The Subset Simulation (SS) has been developed for estimate the reliability of underground flexible metal pipeline due to corrosion induced deflection, buckling, wall thrust and bending. The application of SS method is verified by direct MCS method to scrutinise the robustness and effectiveness of SS method. A real case study has also been conducted to verify the methodology and checked with MCS and HL-RF.

CHAPTER FIVE – *Application of Receiver Operating Characteristic (ROC) curve for pipeline reliability analysis:* In this Chapter, *ROC* curve has been introduced for reliability analysis for underground pipeline network due to multi-failure modes, namely, corrosion induced deflection, buckling, wall thrust and bending stress. A numerical example has been presented to validate the concept of *ROC* curve in pipe reliability analysis for different failure modes with different percentages of inaccurate data.

CHAPTER SIX – *Risk-Cost optimisation using Genetic Algorithm*: The life cycle cost has been discussed which included installation, maintenance and failure risk cost. Risk-Cost optimisation technique, genetic algorithm (GA) has been studied for flexible underground metal pipeline network. Then the study has been extended to estimate the optimum life cycle cost with renewal time and newel methodologies based on pipe reliability.

CHAPTER SEVEN – *Risk-Cost optimisation using Subset Simulation*: Risk and cost have been optimised for underground pipeline network using Subset Simulation process in this Chapter. A numerical example has been used to estimate the optimum life cycle cost with renewal time and renewal methods. Then the results of the SS process are compared with GA to validate the process.

CHAPTER EIGHT – *Conclusions and Recommendations*: Concluding remarks on the research are made. Recommendations are outlined to address the future research work relating to reliability analysis for buried flexible metal pipes and the reliability based risk-cost optimisation process.

CHAPTER TWO

LITERATURE REVIEW

2.1 RELIABILITY OF BURIED PIPELINES

2.1.1 Consequence of pipe failures

A major portion of the underground water and wastewater infrastructure in Europe is rapidly approaching the end of its useful service life and therefore, large scale construction works will need to be undertaken for rehabilitating or renewing these vital infrastructure assets (Pritla et al, 2012). The failure modes of buried pipes may include the loss of serviceability, loss of functionality and possibly the partial or total collapse. Magnitude of failure modes is different among pipelines and varies with life cycle (Fares and Zayed, 2008). Though the loss of serviceability and the loss of functionality are normally not life-threatening, but involve significant cumulative costs. Davies et al (2001) pointed out that OFWAT, the water services regulation authority in England and Wales, spent a huge amount of money every year on buried pipeline replacement in the UK. According to CPSA (Concrete pipeline systems association) (2008), OFWAT estimated that replacing or renovating the UK's 309,000 km sewerage and drainage network required about £200 billion. A survey estimated that the United States will be required US $77 billion for upgrading water distribution and transmission systems by 2017. In Canada, CWWA (Canadian Water and Wastewater Association) estimated that CAN $11.5 billion will be required for water main upgrading by 2013 (Kleiner et al, 2001). The consequences of failure are multiple and may include loss of life, injury, excessive maintenance costs, user costs, environmental impacts etc. and it is clear that some of these consequences are incommensurable and cannot be evaluated in monetary terms (Lounis, 2006). The pipe deterioration of both water treatment facilities and the distribution system can pose a significant health threat to end-users. More than 25% of waterborne diseases outbreak in the United States each year from failure of the water distribution system (Lin et al, 2001).

2.1.2 Causes of pipe failures

According to Chughtai and Zayed (2008) lack of detailed knowledge on the condition of underground pipelines escalates vulnerability to catastrophic failures. Different pipelines are made from different materials for different pipeline projects and employed different failure mechanisms. Pipe material, diameter and age, with or without additional factors such as soil types and/or land use above the pipes have shown important influence on pipe failure (Berardi et al, 2008; Fenner et al, 2000). The underground pipes in European Union (EU) mainly fail due to pipes age, material, length, diameter, type of soil and ground water conditions (Chughtai and Zayed, 2008). For buried pipelines subject to both internal and external loading, a vital failure criterion is the loss of structural strength which is influenced by localised or overall reduction in pipe wall thickness (Ahammed and Melchers, 1997). Factors affecting structural deterioration of buried pipelines are well defined by Rostum (2000) as shown in Table 2.1.

Table 2.1: Factors affecting structural deterioration of buried pipelines (Rostum, 2000)

Structural variables	External/Environmental variables	Internal variables	Maintenance variables
Location of pipe	Soil type	Passing material velocity	Date of failure
Diameter	Loading	Passing material quality	Date of repair
Length	Ground condition	Internal corrosion	Location of failure
Year of construction	Direct stray current		Type of failure
Pipe material	Leakage rate		Previous failure history
Joint method	Other networks		
Internal protection	Salt for de-icing of roads		
External protection	Temperature		
Pressure class	External corrosion		
Wall thickness			
Laying depth			
Bedding condition			

Ahammed and Melchers (1994) stated that loss of pipe wall thickness for metal pipes arises from pitting and/or crevice corrosion and the size of the resulting thickness undermines the pipe resistance capacity which in turn reduces the factor of safety of the whole distribution system. Besides, there are a number of age-related factors that can be linked directly to material properties. At the microscopic level, change in strength and stiffness are two aspects that can be associated with pipes long-term behaviour (Farshad, 2006). The performance of a buried pipeline depends upon its operational condition over time. In reality, a buried pipe's mechanical strength begins to decrease as soon as it is installed, because of the environmental conditions surrounding the pipe (Gabriel, 2011). The reduction of the strength of pipe which influences the pipe failure most are pipe leaking, blockage, deflection, buckling, wall thrust, bending stress and bending strain (ASCE (2001), AWWA (1999), BS EN 1295: 1-1997 (2010), BS9295 (2010), Gabriel (2011) and Hancor (2009)).

2.1.3 Buried pipes service life

The service life analysis of buried pipes is not as straightforward and simple as many would expect (CPSA, 2008). The pipe service life of a network is typically determined by the performance parameter, i.e. the annual number of failures in a given section of pipe networks (Rostum, 2000). According to Rajani and Makar (2000), the pipe service life analysis depends largely on what has happened in the past and what is expected to happen in the future. However, the pipe failure models require detailed analysis of the failure data for all pipe assets and some require specific failure curves for each class (Rajani and Kleiner, 2004). If the concerned authority has a database of recorded failures, it can be used in the development of statistical failure models. However, sometimes databases on pipe failure statistics are often incomplete and/or limited and in many cases it is difficult to ascertain whether a failure resulted from a repair or replacement (if the pipe was replaced at the end of its economic life) (Rajani and Kleiner, 2004).

The deterioration of a buried pipeline network with age has been well studied in the past. Knowing the age of a pipeline segment, the condition and how the pipe deteriorates over time, makes it possible to estimate the remaining service life of a specific pipe (Ahammed and Melchers, 1997). Shamir and Howard (1979) reviewed various methods used for predicting the deterioration in the structural capacity of pipes with age to estimate the service life. The service life of a buried pipe can be affected by any or all of the following factors: type of embedment soil, pipe size or diameter, pipe depth, class (water, sewer, gas etc.), pipe material, level of maintenance, overburden and soil type (Ana et al, 2008; Wirahadikusumah et al, 2001). Depending upon the material and pipe diameter, the estimated service life can be range from 50 to 125 years (Newton and Vanier, 2006). Mailhot et al (2000) used data from a Quebec municipality (Canada), to simulate the deterioration of a buried pipeline network from a good to poor state; Wirahadikusumah et al (2003) modelled the deterioration of combined sewer pipe using data from the city of Indianapolis (USA); Ariaratnam et al (2001) used data from the city of Edmonton (Canada) to model buried pipeline deterioration, while

Micevski et al (2002) modelled the deterioration of storm buried pipe for the Newcastle city council (Australia) based on pipe materials and diameter. All four of the models have predicted the service life of the buried pipes is approximately 100 – 125 years.

2.1.4 Pipe reliability estimation

Pipe structural reliability analyses have been received greater attention in world, though predictions of small failure probabilities techniques are very few till now. In recent years, attention has been focused on reliability problems with complex system characteristics in high dimensions, i.e., with a large number of uncertain or random variables (Schueller and Pradlwarter, 2007). Prediction of small failure probabilities is one of the most important and challenging computational problems in reliability engineering (Zuev et al, 2012). In the past, different researchers and organisations recognised the importance and the applicability of probabilistic approach for reliability calculation in the buried pipeline systems. The development of reliability based design procedures is receiving considerable attention and the guidelines on the targeted reliability indices have been suggested in the present time (Babu and Srivastava, 2010). Methods of reliability analysis such as First Order Reliability Method (FORM), Second-Order Reliability Method (SORM), Point Estimate Method (PEM), Monte Carlo simulation (MCS), Path Enumeration (PE) and State Enumeration (SE) are available in literature (Baecher and Christian, 2003). However, many of the methods are inefficient when there is much number of random variables and failure probabilities are small. Moreover, some need a large number of samples which is a time consuming procedure. Advanced Monte Carlo methods, often called ‘variance reduction techniques’ have been developed over the years. In this respect, a promising and vigorous approach is Subset Simulation (SS) which is originally developed to solve the multidimensional problems of structural reliability analysis (Au and Beck, 2001; Au et al, 2007; Zio and Pedroni, 2008).

A detailed review of various performance measures used in pipeline distribution networks can be found in works done by Goulter et al (2000), Engelhardt et al (2000) and Jayaram and Srinivasan (2008). Complex models in reliability analysis often involve uncertain input parameters which can be determined with varying degrees of accuracy. According to Rajani and Kleiner (2004), these parameters are best explained by known or assumed random variables within the probability distributions. The output of such an analysis is, therefore also a random variable with measurable uncertainties. The reliability factors represent the combined influence of total variability and derivations of analytical formulations are often difficult to quantify (Babu and Srivastava, 2010). According to Ahammed and Melchers (1997), since the life of the underground metal pipeline is related to the developed stresses (for external loadings) and to corrosion deterioration, the available expressions for pipeline stresses as well as pipeline thickness loss due to corrosion can be used for the purpose of establishing a probabilistic functional relationship between loads, corrosion and related soil and material random variables. The prediction of the reliability of the pipe structure throughout its life cycle is depends on probabilistic modelling of the load and strength of the system as well as the use of appropriate analytical or numerical structural reliability analysis methods (Estes and Frangopol, 2001). According to Au and Beck (2003), the probabilistic assessment of the engineering system performance may involve a significant number of uncertainties in system behaviour.

The performance assessment of a buried pipeline distribution system can be defined in terms of the probability of failure or in terms of indices or substitute measures that are determined to reflect the operational requirements of the system serviceability (Jayaram and Srinivasan, 2008). To implement probabilistic assessment for an engineering system, main difficulties arise from: (1) the relationship between the random variables, (2) too many random variables involved, (3) information about rare scenarios and (4) many interactive response variables in the description of performance criteria (Fetz and Tonon 2008). In a probabilistic approach, the input parameters are treated as continuous random variables and the performance of the structure resulting from different failure criteria is expressed in a probabilistic framework, i.e., either probability of failure, P_f or in terms of reliability index, *ß* (Babu and Rao, 2005). Babu and Rao (2005) further stated that the key component of the reliability methodology is to estimate the reliability index and the probability of failure to predict the expected safe service life of pipe with respect to the mechanical strength over time. To take care of different sources of uncertainties involved in the estimation of input strength and stiffness parameters of pipe as well as performance assessment of the buried pipes, a selection of appropriate value of factor of safety comes from past experiences and good engineering judgments (Babu et al, 2006).

2.1.5 Accuracy of reliability prediction

Measuring the accuracy of a reliability analysis is an effective approach to enhance the applicability and management process. Good methods for determining the threshold value for a pipe failure state provide a useful guidance on selection of the reliability prediction methods and compare different analysis techniques. For example, Receiver Operating Characteristic (*ROC*) curve (Coolen-Maturi et al, 2012; Coolen-Maturi et al, 2011, Pepe, 2003, Hill, 1968, Coolen, 1996.) is such method which plays a vital role in many research areas, such as signal detection, radiology, machine learning, data mining and credit scoring. ROC curve has been commonly used for describing the performance of medical tests for parametric and non-parametric analysis. It is a statistical method yields ordinal or continuous data, tends to use concepts like sensitivity and specificity to express the accuracy of a reliability assessment.

2.2 OPTIMISATION APPROACHES FOR UNDERGROUND PIPELINE MANAGEMENT

2.2.1 Optimisation challenges

Most of the engineering, maintenance and operating decisions are involved with some aspect of cost and risk trade-off. Lack of suitable information and complexity of the interaction of the involving parameters is a barrier of proper management (Woodhouse, 1999). Structural design methodologies for pipeline risk-cost optimisation systems are still in their infancy condition when compared to those components in bridges, buildings and other civil structures, though optimum design approaches for pipe structural systems are continuously evolving and improving (McDonald and Zhao, 2001). The challenges to the decision maker are to determine the most cost-effective plan in terms of what pipes in the network to rehabilitate, by which rehabilitation alternative and at what time in the planning horizon, subject to the constraints of service requirements (system reliability, service pressure, etc.,) (Kleiner et al, 2001). The optimisation processes are involved in cautious expenditure in order to achieve some hopes for reliability, performance or other benefits. Involving costs of the pipe structure may be known but it is often difficult to quantify the potential impact of risks, the efficiency or safety and longevity of pipe service life (Guice and Li, 1994).

Finding the optimal strategy is difficult and the wrong maintenance strategy may result in excessive costs, risks or losses. The decision to repair or replace the underground pipes are typically based on performance indicators such as structural integrity, hydraulic efficiency, system reliability and type of fluid passing into them (Rajani and Makar, 2000). Rajani and Kleiner (2004) stated that the implementation of a quantitative risk-based maintenance management is a very complex task due to the difficulties of assessing quantitatively the probability and the consequences of failure, especially for a large network of pipeline system. Many challenges have faced by water and wastewater industry for maintenance the underground pipeline networks, such as behaviour of pipe under hydrostatic pressure, poor design detailing and installation practices during placing the pipes, insufficient corrosion protection procedures, pipe material deterioration, scouring underneath the ground level, frost heave action and insufficient understanding of the product limitations (Tee et al, 2011). The long-term planning of the renewal of pipeline distribution network requires the ability to predict system reliability as well as assess the economic impact (Kleiner et al, 2001).

2.2.2 Optimisation techniques

Different approaches in optimisation have been implemented in the different buried pipe management systems ranging from simplified economic models to advanced Markovian decision processes (Lounis, 2006). Given the importance and high consequences of failure of pipe network structures, a risk-based maintenance management methodology can be more effective and independent as it enables the optimisation of different types of structures and systems within a network by considering not only the probability of failure but also the consequences of failure (Rajani and Kleiner, 2004). During the current decade, considerable attention has been given to reliability of pipe distribution networks in conjunction with the optimisation to achieve maximum benefits with the minimum cost (Moneim, 2011). Kleiner et al (2004) dealt with the network renewal planning problem in which, both the structural and the hydraulic capacity deterioration of the network are considered for obtaining the optimal rehabilitation schedule. In fact, an optimum management strategy must ensure hydraulic performance after rehabilitation and to provide reliable service with minimum interruptions (Halfawy et al, 2008).

According to Afshar and Marino (2005), many optimisation techniques have been developed and used for the optimal design of buried pipeline networks, such as Genetic Algorithms (GA), Ant Colony Optimisation algorithms (ACO) and Particle Swarm Optimisation Algorithms (PSO), etc. Some researchers, such as Berardi et al (2009), Rasekh et al (2010), Pan and Kao (2009), Abraham et al (1998), Stansbury et al (1999) and Li and Matthew

(1990) adopted heuristic approaches for the simplicity and used for buried pipeline network design problems with good solutions.

Multi-objective optimisation approach is suitable for most of the civil engineering structures. Multi-objective optimisation approaches can be utilised effectively to formulate whole life costing models that can provide optimal trade-offs between economic, hydraulic, reliability and quality performance criteria (Engelhardt et al, 2000). Different costs are involved in buried pipeline distribution systems as shown by Woodroffe and Ariaratnam (2008) in Figure 2.1. Walters et al (1999) stated that conventional optimisation techniques are poorly suited to handle the problem of choosing optimal network improvements and hence used a Structured Messy Genetic Algorithm (SMGA) to arrive at the trade-off between capital cost and benefit for the pipeline rehabilitation problem. Walters et al (1999) solved the network rehabilitation problem measuring the improvement in network performance on rehabilitation using a benefit function which was computed as a weighted average of hydraulic benefit, physical integrity benefit, flexibility benefit and quality benefit. According to Jayaram and Srinivasan (2008), an initial estimate of the optimal age at which a pipe needs to be replaced can be obtained solely on the basis of the structural costs and this age is termed as the minimum cost replacement time. Following this, the evaluation and selection of the rehabilitation alternatives can be predicted on the basis of both structural and hydraulic conditions in a staged manner.

Engelhardt et al (2002) developed a whole life costing framework for determining the long-term maintenance expenditure requirements for pipeline networks, considering the factors such as demand projections, leakage and changes in hydraulic capacity, customer interruptions and water quality through interconnected modules. Moreover, Engelhardt et al (2002) established a rigorous framework to estimate the costs arising from the operation, maintenance and management of a pipe distribution network, including operational costs, capital expenditure (cost of replacement), public costs (social and environmental costs) and costs associated with leakage and pipe bursts.

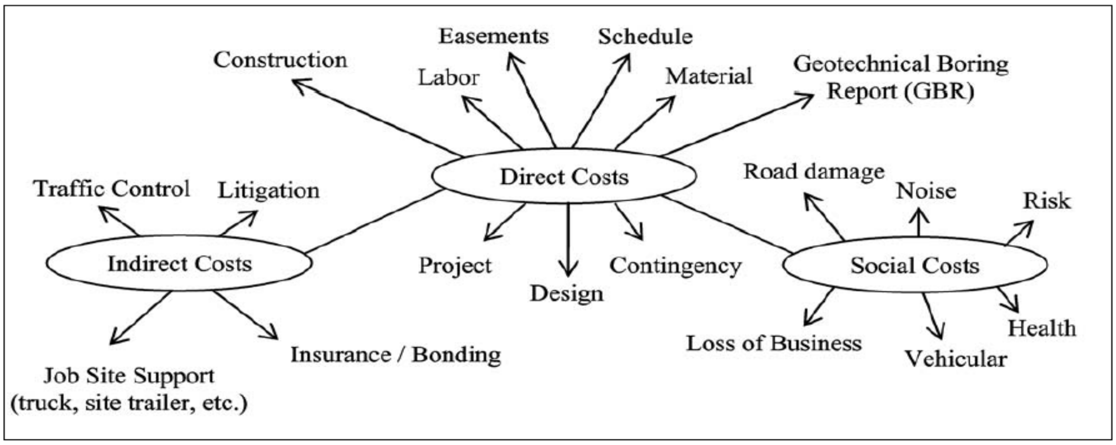


Figure 2.1: Cost identification for buried pipeline project (Woodroffe and Ariaratnam, 2008)

Dandy and Engelhardt (2006) obtained the trade-off between cost and reliability measure using multi-objective GA for buried pipeline. This method involves the identification of the optimal pipe replacement schedule for an existing pipe network that minimises the cost and the expected number of customer interruptions due to pipe failure over the service life of the network. In this method, it is assumed that the pipes can be replaced at any pre-specified time step over a defined planning horizon, though the diameter of the pipes is considered to remain the same after replacement. Pan and Kao (2009) developed Genetic Algorithm and Quadratic programming (GA-QP) versions of hydraulic and topographical constrained problem for optimal design of Kaohsiung City, Taiwan underground pipeline network. The results showed considerable improvements in the convergence and quality of the solutions. Shamir and Howard (1979) indicated that the replacement age of the pipe is that at which pipe replacement would minimise the present value of the total cost (sum of the present values of replacement costs and repair costs) which was obtained by analytical process. Shamir and Howard (1979) predicted the pipe break growth rate where the expected pipe break repair cost was as an exponential function. In this process, break data are examined and used to forecast how the number of breaks in the existing pipe is going to change over time and estimated the number of breaks. By combining these forecasting with economic data for replacing the pipe and fixing a break, the optimal management strategy can be determined.

Recently, Subset Simulation (SS) (Au and Beck, 2001; Au and Beck, 2003; Au et al, 2007; Song et al, 2009), which is originally a reliability analysis method, is used to solve constrained and unconstrained global optimisation problems by introducing artificial probabilistic assumptions on design variables. Finding the global optimum, involves simulating the extreme events and also be considered as rare occasions in the design variable space. Furthermore, if stochastic algorithms are adopted, the objective function is evaluated at the random points in the design variable space. Based on the idea that an extreme event i.e., optimisation problem is a special case of a rare event in reliability problem (Li, 2011).

The life-cycle assessment (LCA) tool has been applied in evaluating environmental effects to assess the environmental performances (carbon footprint) in risk-cost optimisation process. The life-cycle activities include extraction of raw materials, manufacturing the pipe used in the project, transporting pipe to the construction site, laying the pipe in the trench, operating and maintaining, dismantling and disposal or recycling the pipe. There are several LCA studies in the wastewater and drinking water infrastructure systems which have been found in literature. Emmerson et al (1995) used the LCA tool to evaluate the environmental effects of small scale sewage treatment works. Zhang and Wilson (2000) performed an LCA analysis for a large sewage treatment plant in Southeast Asia and reinforced the results by Emmerson et al (1995). Skipworth et al (2002) investigated the entire life-cycle costs for water distribution systems in the UK. Vidal et al (2002) also used LCA for understanding the environmental consequences for wastewater treatment plant. Filion (2004) developed a LCA model to quantify the energy consumption of a water distribution system in New York tunnels and to compare life-cycle energy for different pipe replacement schedules.

2.2.3 Risk assessment of buried pipes

Assessing the risk of failure is essential for prioritising pipelines for renewal as well as for inspection scheduling and performance monitoring (Rahman and Vanier, 2004). Existing approaches, such as WRc (2001) typically categorised the renewal process based on pipes criticality. However, there is no standard risk assessment or rating scheme for quantitatively assesse the risk (Chughtai and Zayed, 2011). The risk assessment typically is performed in a subjective and heuristic manner. Halfawy et al (2008) stated a risk index that ranges between 5, most critical and 1, least critical where risk index of 1 would be equivalent to a risk category C manuals, while an index of 5 would be equivalent to a risk category A, as in WRc (2001). The risk index is calculated by multiplying two components representing the consequence and likelihood of failure. Chughtai and Zayed (2008) used a ‘risk factor’, which is also measured on a 1–5 scale, linguistically ‘acceptable’ to ‘critical’ to reflect the relative criticality or consequence of failure of a buried pipeline, instead of using a monetary value. Risk factor can be used as a risk assessment criterion of pipeline system as also suggested by Halfawy et al (2008). According to Halfawy et al (2008), the risk factor is calculated as a weighted average of the criticality level perceived for user defined criticality criteria. The criteria may include all or a subset of factors such as passing liquid type, function, diameter, depth, soil, site seismicity, land use, road classification, traffic volume, proximity to critical assets and overall socio-economic impact.

2.2.4 Renewal of buried pipes

Buried pipes have certain priority levels to select the further renewal planning process. The decision to repair or replace current pipe is typically based on performance indicators such as structural integrity, hydraulic efficiency and system reliability (Rajani & Makar, 2000). The buried pipeline renewal planning process remains fundamentally heuristic and subjective in nature and is still largely considered as much an art as it is science (Halfawy et al, 2008). As the network ages, since, the hydraulic capacity of the network decreases, renewal (replacement and/or cleaning and lining of pipes) would be necessary to restore the hydraulic capacity of the underground pipeline network (Sharp and Walski, 1988). Like risk index, WRc (Water Research Centre, UK), use the 'priority index' to determine the emergency of pipe management. A 'priority index' is defined for each pipe to indicate the level of urgency for intervention. The priority index range A – F is used to indicating the urgency of renewal, where index A, immediate intervention is needed and index F, no action is required (WRc, 2001). Similar to WRc (2001), McDonald and Zhao (2001) proposed the rating system 1 – 5 which can be customised to assess the priority index for a group or a particular pipe in the network, given its condition and risk indexes. Shamir and Howard (1979) developed an analytical approach to solve the pipe replacement problem based on pipe breaks per year. Abraham et al (1998) used the condition improvement approach in terms of extension of the service life for pipeline renewal, for example, shotcrete extends the service life by 20 years, and while cured in place pipe extends the pipe service life by 50 years.

A number of options are used for underground pipeline renewal actions, namely replacement, duplication, relining, cleaning, cleaning and lining and other techniques such as detection techniques and pressure reduction schemes (Jayaram and Srinivasan, 2008). Dandy and

Engelhardt (2006) stated that most commonly chosen options are replacement and cleaning and lining. However, if the hydraulic capacity deterioration is not considered of the network management then the pipe rehabilitation option remains cleaning and lining of the pipes only. Halfawy et al (2008) grouped the renewal methods into four main categories: replacement (conventional open-cut or trenchless methods with same or larger diameter), structural, semi structural and non-structural lining methods. Each renewal category includes a number of renewal options. For example, structural liners are designed to carry the hydrostatic, soil and live loads and expected to be independent i.e., bonding with original pipelines is not required. Semi structural liners are designed to withstand hydrostatic pressure or perform as a composite with the existing pipelines and could be designed as interactive or independent (Halfawy et al, 2008). Semi structural liners are typically for pressured pipes, not used for gravity pipelines. On the other hand, non-structural liners are mainly used for gravity pipelines, mainly to improve flow, resist corrosion, or to seal minor cracks in pipelines (Heavens, 1997).

2.3 LIMITATIONS OF THE CURRENT STATE OF WORKS

In the Sections 2.1 to 2.2, the previous works on reliability analysis and risk-cost optimisation for underground pipelines are reviewed. The comprehensive literature review revealed the areas lacking in knowledge in the flexible underground flexible metal pipes. In this section the gaps that have been found in reliability analysis and risk-cost optimisation are as follows:

2.3.1 Limitations in buried pipelines' reliability

Most of the works found in literature on flexible buried metal pipes are based on pipe installation time. For example, Babu and Rao (2005), conducted reliability analyse on flexible buried pipe (steel pipe) in terms of two failure modes, namely, deflection and buckling; Babu et al (2006) analysed underground steel pipe reliability due to deflection, buckling and wall thrust; ASCE (2001) and Gabriel (2011) predicted the underground flexible pipe (steel and corrugated polyethylene pipe, respectively) failure due to four failure criteria, namely, deflection, buckling, wall thrust and pipe bending. These analyses were based on pipe installation time only, i.e., non-time dependent. However, no such work has been found for flexible buried metal pipelines in the literature which is time-dependent. In reality, underground pipeline failure is a continuous process. In general, the strength of buried metal pipe decreases due to corrosion, fatigue and overloading which then lead to pipe failure by excessive deflection, buckling, wall thrust and bending. As a result, the safety or serviceability margin and the corresponding reliability index is decreased (or failure probability is increased) with respect to time. Therefore, an intensive reliability analysis for corrosion induced time-dependent multi-failure events, namely, deflection, buckling, wall thrust and bending for flexible buried metal pipelines is required.

Another limitation in the current state of the art of reliability analysis of flexible buried metal pipes which was found in literature review is the lack of the research on the correlation among time-dependent multi failure modes and other influencing random variables. Since the life of an underground metal pipeline is related to corrosion deterioration and the developed stresses, the design equations as well as pipe wall thickness loss due to corrosion can be used for the purpose of establishing a probabilistic functional relationship between loads, corrosion, related soil and material random variables. The literature survey showed that effectiveness and contributions of these variables on service life of pipelines have not been intensively studied by the researchers. This lack of knowledge necessitates an extensive correlation, sensitivity and parametric analysis on reliability of flexible buried pipelines.

Methods of reliability analysis for pipeline, such as FORM, SORM, PEM, MCS, PE and SE etc., are available in literature. Many of the methods are inefficient when there is much number of random variables and failure probabilities are small. Moreover, some need a large number of samples which are time consuming procedure. In this respect, a promising and robust reliability approach is needed to solve the multidimensional problems of structural reliability analysis, especially for small failure probabilities prediction.

Classical reliability theory and methodologies rarely consider the actual state of a pipe system and therefore, these are not capable to reflect the dynamics of runtime systems and failure processes. Conventional methods are typically useful in design and prediction of long term pipe behaviour. However these are not good enough in pipe reliability evaluation with good accuracy. Measuring the accuracy of a reliability analysis technique is an effective approach to enhancing its applicability and provides guidance on selection of reliability prediction methods. But in pipeline reliability field the accuracy prediction method is rare, although in many other research areas, such as signal detection, radiology, machine learning, and data mining sectors already used the accuracy prediction techniques. Therefore, an accuracy prediction method is needed to enhance the reliability analysis for buried pipeline network. Normally, ROC curve is useful in evaluating the discriminatory ability of an analysis, finding optimal cut-off point and comparing efficacy of two or more assessment or tests results.

2.3.2 Limitations in Risk-Cost optimisation

Reliability based risk-cost optimisation process for underground pipeline network provides the selection of rehabilitation methods have been studied extensively by many researchers (Berardi et al (2009), Rasekh et al (2010), Recio et al (2005), Pan and Kao (2009), Abraham et al (1998), Stansbury et al (1999) and Li and Matthew (1990)). These studies primarily focused on cost, duration and failure problems but not extensive studied on maintenance or future renewal time. Therefore an extensive analysis is required for estimation future renewal time prediction during pipe's whole service life.

In most cases, available optimisation methods, such as GA, ACO, PSO, etc., have been used as a strong numerical method for buried pipes risk-cost optimisation process. Many of these are very time consuming and not absolute guaranteed global optimum procedure. Therefore, a robust and less time consuming method should be implemented in the risk-cost optimisation processes for buried pipeline network within a shorter period.

Most of the available previous studies dealt with the scheduling of pipeline rehabilitation and cost optimisation process which are based on current time only, not future scheduling. Therefore, intensive research needs to done to solve the previous limitations by considering future scheduling rehabilitation methods in the buried pipeline management system which will provide when and how interventions are required to prevent unexpected collapse the pipes within budget constraints. The management aims to improve the overall performance of the pipeline network through the conflicting objectives, such as minimisation of risk of failure, minimisation of life cycle cost and maximisation of service life. Thus a municipality or an owner can be obtained a cost-effective strategy with respect to the available rehabilitation scheduling time and available budget for managing the buried pipeline system.

2.4 SUMMARY

At the first step of reliability analysis and risk-cost optimisation process, it is necessary to gain knowledge about the design principles and cost affecting factors for buried pipes service life. The previous studies for reliability analysis, failure risk and cost optimisation process of buried pipes are studied. The loads and stresses acting on buried pipes are reviewed in this Chapter. Then pipeline service life prediction and reliability methods are studied. The accuracy of the reliability analysis method, *ROC* curve has also been studied. The available literature on reliability based risk-cost optimisation methodologies and their applications are reviewed. Finally, literature review on buried pipes renewal techniques is conducted. All the literature reviews are accompanied to achieve the current research aim and objectives (refer to Chapter One). Therefore, all available literature reviews are based on specific field which are directly or indirectly are related to the underground flexible metal pipeline reliability and risk-cost optimisation process.

CHAPTER THREE

STRUCTURAL RELIABILITY ANSLYSIS USING HL-RF AND MCS METHODS

3.1 INTRODUCTION

Structural reliability management of buried pipeline systems is one of the fundamental issues for the water and wastewater collection industry managers. When the residual ultimate strength of a buried pipeline is exceeded the limit, breakage becomes imminent and the overall reliability of the pipe distribution network is reduced. The behaviour of buried pipes is considerably influenced by uncertainties due to external loading, pipe materials and surrounding soil properties, etc. Many challenges have faced by water and wastewater industry during placing or maintenance the underground pipeline networks. The most common challenges are found as buckling, deflection, wall thrust and bending behaviour of pipe under hydrostatic pressure, poor design detailing and installation practices during placing the pipes, insufficient corrosion protection procedures, pipe material deterioration, scouring underneath the ground level, frost heave action and insufficient understanding of the product limitations (Tee et al, 2013a). The decision to repair or replace the current pipe is typically based on performance indicators such as structural integrity, hydraulic efficiency and system reliability (Rajani and Makar, 2000). Ahammed and Melchers (1994) stated that the pipe replacement or rehabilitation is typically determined by the performance parameter, i.e., the annual number of failure in a given section of pipe network. This approach depends largely on what has happened in the past and what is expected to happen in the future.

A complicated approach to scheduling of pipelines maintenance is to determine individual pipe that is approaching unsafe condition and repair or replace before it fails. This approach requires a robust methodology to determine the remaining safe service life of each pipe segment within the distribution network system. In reality, a buried pipes mechanical strength begins to decrease as soon as it is installed because of the environmental conditions surrounding the pipe. Due to their low visibility and lack of proper information regarding underground pipes condition, assessment and maintenance are frequently neglected until a disastrous failure occurs. The long-term planning of the renewal of underground pipe distribution networks requires the ability to predict system reliability as well as assess the economic impact (Tee and Li, 2011).

For buried metal pipelines subject to both corrosion and external loadings, a vital failure criterion is the loss of structural strength which is influenced by localised or overall reduction in pipe wall thickness (Ahammed and Melchers, 1997). The pipe wall thickness reduction weakens the pipe resistance capacity which in turn reduces the reliability of the whole distribution system. For a given component of a system and a given failure mode, the load effect and strength are time-dependent and present considerable uncertainty in mean values as well as in the levels of scatter which increase with time (Rajani and Kleiner, 2004). In general, the strength decreases due to corrosion, fatigue and overloading and these affects the pipe reliability. As a result, the safety or serviceability margin and the corresponding reliability index decrease with time to time.

Due to uncertainty associated with the rate of failure and location, a probabilistic approach is required for the analysis of pipeline reliability. A probabilistic approach provides a quantitative measure of safety as well as provides both qualitative and quantitative information about the effects of various uncertain parameters on the safety measure estimation (Babu and Srivastava, 2010). In this approach, the input parameters are treated as continuous random variables and the different failure criteria are expressed in a probabilistic manner, i.e. either probability of failure or in terms of reliability index. The workable or safe service life of a buried pipe structure then can be defined as the time at which the reliability index or failure probability reaches a minimum acceptable level. This minimum probability of failure or reliability index value depends on the loadings on pipe, pipe element properties, backfill and system of failure. Complex models in risk and reliability analysis often involve uncertain input parameters which can be determined using these methods with varying degrees of accuracy. These parameters are best explained by random variables with known or assumed probability distributions. The output of such a reliability analysis is therefore also a random variable with measurable uncertainties (Babu and Rao, 2005).

Gabriel (2011), Babu et al (2006), Babu and Rao (2005) and ASCE (2001) conducted reliability analyse on flexible buried pipes in terms of deflection, buckling, wall thrust and pipe bending. These analyses were based on pipe installation time only, i.e., non-time dependent. But in reality, underground pipeline failure is a continuous and time-variant process. Hence the practical motivation of this analysis is to investigate how the effect of corrosion corporate with these different failure modes with respect to time. Since the life of a flexible underground metal pipeline is related to corrosion deterioration and the developed stresses, the available design equations for pipeline can be modified for the purpose of establishing a probabilistic functional relationship between loads, corrosion, related soil and material random variables. Based on these conventions, this Chapter focuses on the reliability analysis of the flexible buried metal pipes, conducted in the light of the aforementioned points and has the following objectives:

a) To predict the probability of failure of flexible buried metal pipe system for different failure criteria, namely, corrosion induced excessive deflection, buckling, wall thrust and pipe bending, based on modified design equations.

b) To estimate the correlation among above failure modes as well analyse the influencing random variables, such as soil density and soil modulus or loading and pipe stiffness with known correlation coefficients in different failure modes with varying time.

c) To perform a parametric and sensitivity analysis for different factors, such as corrosion empirical constants, pipe diameter, thickness, soil height, etc., to determine the impact of different influencing variables on the reliability of pipeline structure system with respect to pipe service life.

The contents of this Chapter are structured as follows. Formulation for pipe failures is discussed in Section 3.2, where corrosion on flexible buried metal pipes, loading conditions and dominating failure modes, namely, deflection, buckling, wall thrust and bending are discussed. In Section 3.3, the probabilistic reliability analysis and two reliability prediction methods, HL-RF and MCS are presented. The system failure and correlation prediction procedures are discussed in Section 3.4. A numerical example is presented for reliability analysis in Section 3.5. In Section 3.6, results and discussion are presented, where failure probability, correlations among failure modes and asses the influencing random variables with respect to known correlation over service life, some parametric studies and sensitivity analysis are conducted. Finally, some concluding remarks are made on basis of outcomes in this study in Section 3.7.

3.2 FORMULATION FOR PIPE FAILURES

3.2.1 Corrosion of flexible buried metal pipes

Buried pipes are normally made of plastic, concrete or metal, e.g. steel, galvanised steel, ductile iron, cast iron or copper. Plastic and non-reinforced concrete pipes tend to be resistant to corrosion. On the other hand, reinforced concrete and metal pipes are susceptible to corrosion. Under certain environmental conditions, flexible buried metal pipes, such as steel, ductile iron, etc., can become corroded based on the properties of the pipe, the soil surrounding the pipe wall, water or waste properties and stray electric currents (Rajani and Makar, 2000). The predominant deterioration mechanism on the iron-based pipes is corrosion pit. Corrosion pit is a continuous and variable process. It reduces the thickness and mechanical strength of the pipe wall with time. This process eventually leads to breakage of the pipeline system. Corrosion pits have a variety of shapes with characteristic depths, diameters (or widths) and lengths.

The corrosion rate of in-service buried metal pipes is believed to be higher in the beginning and then slow down over time as corrosion appears to be a self-inhibiting process (Sadiq et al, 2004). Furthermore, due to the variation of service environment, it is rare that the corrosion occurs uniformly along the pipe but more likely in the form of a random pit. A number of models for corrosion of metal pipes have been proposed to estimate the depth of corrosion pit (Sheikh et al, 1990; Kucera and Mattsson, 1987; Ahammed and Melchers, 1997; Rajani et al, 2000; Sadiq et al, 2004). For example, Sheikh et al (1990) suggested a linear model in corrosion growth for predicting the strength of metal pipes. Later, Rajani et al (2000) proposed a two-phase corrosion model, where the first phase is a rapid exponential growth and the second phase is a slow linear pit growth.

Kucera and Mattsson (1987) first proposed a widely accepted model, a power law Eq. to measure the corrosion pit depth (D_T) for atmospheric corrosion which can be expressed as follows:

$$D_T = kT^n \tag{3.1}$$

where k is multiplying constant, n is exponential constant, determined from experiments and/or field data and can be used as an approximate value only. T is exposure time. This model should be seen as an engineering model rather than corrosion science. In many circumstances, it may be possible to use past experience to derive estimates for the constants in Eq. (3.1), but somewhat more effort would be necessary to estimate a constant corrosion rate as conventionally used (Ahammed and Melchers, 1997).

Rajani et al (2000) proposed a two-phase modified corrosion model to accommodate the self-inhibiting process as follows:

$$D_T = aT + b(1 - e^{-cT}) \tag{3.2}$$

where *a*, *b* and *c* are constant parameters. In the first phase, the initial rate of pipe thickness loss is high due to the porous surface and having poor protective properties. As corrosion proceeds, the protective properties of its products (generally iron oxides) improve, thus reducing the corrosion rate over time. Subsequently, prediction of pit depth in the first 15 – 20 years of pipe life should be considered highly uncertain when Eq. (3.2) is used.

External corrosion is most common form of metal pipe deterioration due to impact of surrounding environmental conditions and metal properties. On the other hand, internal corrosion is not as common as external. The available evidence suggests that internal corrosion is less likely to occur under fluid flow conditions. On the other hand, localised corrosion (external) at the outer surface of the pipeline is more likely occurred (Ahammed and Melchers, 1994).

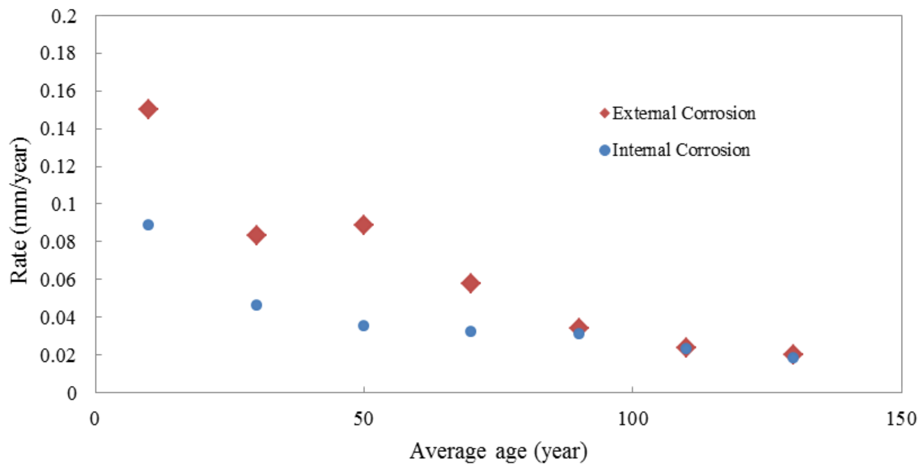


Figure 3.1: Internal and external corrosion rate for iron pipes (Marshall, 2001)

An example of field data regarding the rate of internal and external corrosion for a buried iron pipe is illustrated in Figure 3.1 (Marshall, 2001), which shows that external corrosion rate is higher than internal corrosion rate. Figure 3.1 also shows that corrosion rate is higher at early age of pipe and then gradually slows down over time. Figure 3.2 also shows the severity of external corrosion compare to internal corrosion.

(a) (b)

Figure 3.2: Typical buried pipe corrosion, (a) External corrosion and (b) Internal corrosion (EPA, 2005)

Thin walled plain pipes are considered with $D/t > 10$, where t is the thickness of the pipe wall and D is mean diameter in this Chapter. According to Watkins and Anderson (2000) the moment of inertia of pipe wall per unit length and cross-sectional area of pipe wall per unit length of a thin walled plain pipe can be expressed as below Eqs. (3.3) and (3.4) respectively:

$$I = t^3/12 \quad (3.3)$$

$$A_s = t \quad (3.4)$$

For simplification, the corrosion pit depth is considered as uniform around the entire circumference of the pipe. For a plain pipe, due to reduction of wall thickness given by Eq. (3.1) or (3.2), the moment of inertia of pipe wall per unit length, I and the cross-sectional area of pipe wall per unit length, A_s can be modified as below Eqs. (3.5) and (3.6) (Khan et al, 2013; Tee et al, 2013a):

Moment of inertia,

$$I = (t - D_T)^3/12 \quad (3.5)$$

Cross-sectional area,

$$A_s = t - D_T \quad (3.6)$$

Eqs. (3.1) – (3.6) show that $D_{T,}$ I and A_s are time dependent variables. The corrosion parameters *a, b, c,* or *k* and *n* are highly uncertain and are typically determined from regression analysis on observed and experimental data obtained for specific soil and environmental conditions (Sadiq et al, 2004). When there is little or no information on which is the base a choice for corrosion constant parameters, then known values from other situations might be used, with judicious selection of means and variances (Ahammed and Melchers, 1994). Corrosion constant parameters are measured according to the experiments or field data to predict the pit depth. For different environmental conditions the corrosion pit depths are different even for the same material. For example, buried ductile iron pipes exhibit different corrosion pit depth with respect to clay soil, submerged silty sand and highly granular soil. For estimation of corrosion constant parameters, all the given pit depth values for different environmental conditions in the given time interval are plotted. A regression analysis is performed to get an upper and lower range of pit depth values with mean and standard deviation. Then applying Eq. (3.1) or (3.2), the empirical constants (*a*, *b* and *c* or *k* and *n*) are measured. A typical regression analysis curve is shown in Figure 3.3.

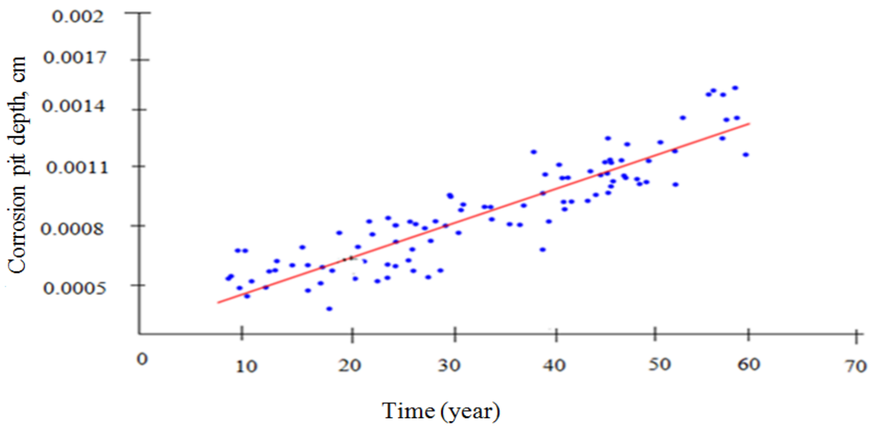


Figure 3.3: A typical regression curve for estimation of corrosion constant parameters

To determine the corrosion constant parameters the following procedures are follows:

1. Predict the corrosion pit depth at different particular years (say 10, 20, 30,… years) for different locations.
2. Draw a regression line (best fitting line) for different years of pit depths.
3. Select any two points (for Eq.3.1) or three points (for Eq. 3.2) on the best fitting line (Figure 3.3).

4. Solve the Eq. 3.1 or 3.2 based on the points and calculate *k* and *n* or *a, b* & *c* values.

It is noted that this approach is applicable to unprotected pipelines, i.e. pipelines without painting, bituminous coating/lining or cathodic protection. However, this analysis also has applicability for protected pipelines once the protection has been damaged or breached significantly by some mechanical means or through ageing (Ahammed and Melchers, 1994).

3.2.2 Loadings and failure modes of flexible pipes

All pipelines are designed to withstand against the various external and internal loadings which are expected to be experienced during construction and operation. The external loadings include loads due to the backfill, surface surcharge or traffic and self-weight of the pipe. According to Najafi and Gokhale (2005), anything that puts a pressure on the outside of a pipe is considered an external load. The internal loadings include water weight and fluid pressure (if different from atmospheric).

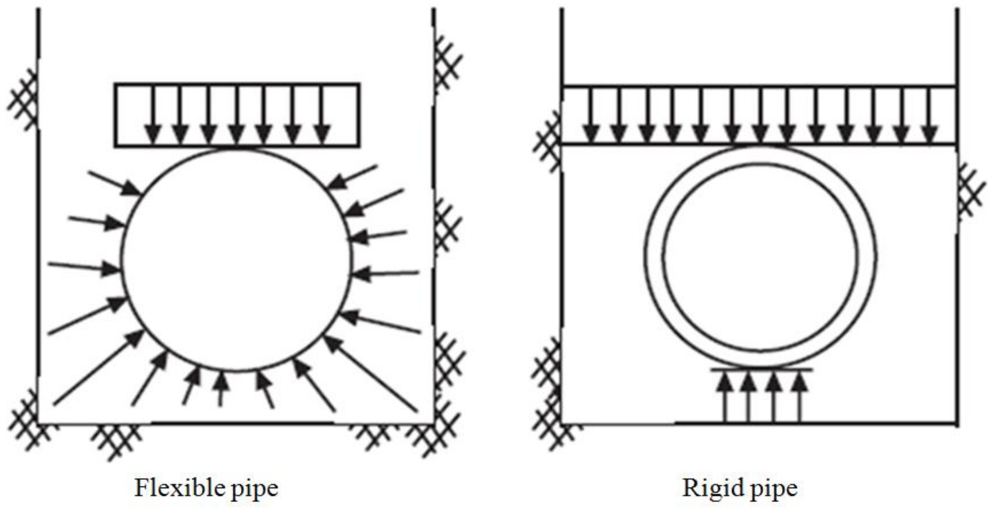


Figure 3.4: Pipe and backfill interaction of flexible and rigid pipes (Gabriel, 2011)

Buried pipes can be broadly classified as flexible or rigid based on the behaviour and performance during installation and operation. When loads are applied on flexible pipe, the loads are transferred and carried by the backfill. On the other hand, when loads are applied to rigid pipe, the loads are transferred through the pipe wall into the bedding. Figure 3.4 shows a typical pipe and backfill interaction and the corresponding load transfer for flexible and rigid pipes (Gabriel, 2011). All types of pipes whether flexible or rigid, rely on the backfill properties to transfer the loads into the bedding. For this reason, proper backfill is very important in allowing this load to transfer properly. In many situations, a properly installed flexible pipe can be buried much deeper than a similarly installed rigid pipe because of the flexible pipe and backfill interactions. A rigid pipe is often stronger than the backfill material and thus it support the whole earth loads itself. On the other hand, a flexible pipe is not as strong as the surrounding backfill and this mobilises the backfill envelope to carry the earth load (Figure 3.4). The flexible pipe and backfill interaction is so effective at maximising the structural characteristics of the pipe that it allows the pipe to be installed in very deep installations, many times exceeding allowable design pipe cover (Gabriel, 2011).

Flexible and rigid pipe respond to loadings in a different ways and therefore, the failure principles and service life cycle also different. Figure 3.5 illustrates the differences between flexible and rigid pipe responses to loadings based on 21 years of observation (Rahman, 2010), which shows that loadings on rigid pipe (concrete pipe) are higher than on flexible pipe (steel pipe) with varying time.

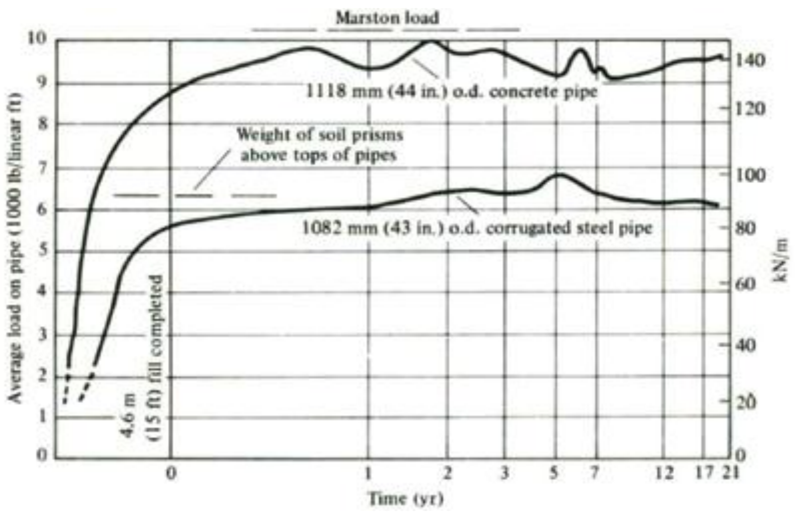


Figure 3.5: Pipe response to loadings for flexible and rigid pipes in 21 years study (Rahman, 2010)

How much load a pipe can sustain depends on the relative height of cover, the nature of the backfill material and soil, the geometry of the trench installation and the relative stiffness of the pipe to the backfill (Cameron, 2005). Marston load theory, as cited by Moser and Folman

(2008), recognises that the amount of load taken by a pipe is affected by the relative movement or settlement among the pipe material, backfill and the natural soil.

Due to external and internal loadings, pipe structural failure is occurred when the applied stress exceeds the limiting or ultimate strength of the pipe wall material. The failure modes can be significantly different for flexible and rigid pipes due to pipe behaviour and respond to loadings as shown in Figures 3.4 and 3.5. The knowledge related to failure modes and integrity management for flexible pipes have developed continuously over the decades. For a flexible buried metal pipe structure, the numbers of potential failure modes are very high for all systems failure definitions. This is true in spite of the simplifications imposed by assumptions such as having a finite number of failure elements at given points of the structure and only considering the proportional loadings. It is therefore, important to have a method by which the most critical failure modes can be identified. The critical failure modes are those contributing significantly to the reliability of the system at the chosen level. However, this study is concerned with knowledge for flexible buried metal pipes failure criteria only. In this Chapter, the dominating failure modes of flexible pipes are characterised by limit states as follows:

a) Excessive deflection (Serviceability);
b) Actual buckling pressure greater than the critical or allowable buckling pressure (Ultimate);
c) Actual wall thrust greater than critical or allowable wall thrust (Ultimate);
d) Actual bending stress and strain greater than the allowable stress and strain (Ultimate).

The above dominating failure modes are discussed as follows:

3.2.2.1 Excessive deflection

A buried pipe tends to deflect under the effects of earth and live loads. The performance of a flexible pipe in respect to ability to support the load is typically assessed by measuring the deflection from its initial shape. Deflection is quantified in terms of the ratio of the horizontal increase in diameter (or vertical decrease in diameter) to the original pipe diameter (Figure 3.6). Rigid pipe is sometimes classified as pipe that cannot deflect more than 2% of internal diameter without significant structural distress, such as cracking (Hancor, 2009). Flexible pipe takes advantages of its ability to move, or deflect under loads without structural damage. The critical or allowable deflection, Δy_{cr} for flexible pipe can be estimated up to 5% – 7% of inside diameter of pipe (Gabriel, 2011).

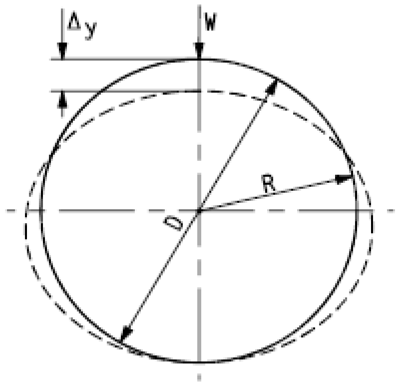


Figure 3.6: A typical flexible pipe deflection

According to BS EN 1295:1-1997 (2010) and BS 9295 (2010), the actual deflection, Δ_y can be calculated as below Eq. (3.7) after substituting by Eq. (3.5) (Tee et al, 2013a):

$$\Delta_y = \frac{K_b(D_L W_c + P_s)D}{\left(\dfrac{8EI}{D^3} + 0.061E'\right)}$$

$$= \frac{K_b(D_L W_c + P_s)D}{\left(\dfrac{8E(t-D_T)^3/12}{D^3} + 0.061E'\right)} \qquad (3.7)$$

where K_b is deflection coefficient, D_L is deflection lag factor, D is mean diameter = D_i + 2c, D_i is inside diameter and c is distance from inside diameter to neutral axis, E is modulus of elasticity of pipe material, I is moment of inertia per unit length and $E^{'}$ is modulus of soil reaction $= \dfrac{k'E_s(1-\nu_s)}{(1+\nu_s)(1-2\nu_s)}$, where E_s is modulus of soil, k' is a numerical value depends on poison's ration, ν_s. The deflection coefficient reflects the degree of support provided by the soil which is based on the type of installation. The loads acting on the pipe are governed by the term $D_L W_c + P_s$, where W_c is soil load and P_s is live load. The soil load and live load can be calculated as follows:

Soil load, $W_c = \gamma_s H$ (3.8)

Live load, $P_s = \dfrac{W_s I_f}{L_1 L_2}$ (3.9)

where γ_s is unit weight of the soil, H is height of soil on the top of pipe, W_s is traffic load, I_f is impact factor = 1.1 for 0.6 m < H < 0.9 m, or 1 for $H \geq$ 0.9 m, L_1 is load width parallel to direction of travel = 0.253 + 1.75H and L_2 is load width perpendicular to direction of travel = 0.51 + 1.75H for 0.6 m < H < 0.76 m, or (13.31 + 1.75H)/8 for $H \geq$ 0.76 m (Sarplast, 2008).

3.2.2.2 Buckling

External loadings from soil pressure or external hydrostatic pressure can cause inward deformation known as wall buckling. If the soil and surface loads are excessive, the pipe cross-section could buckle (Figure 3.7). Buckling is a premature failure in which the pipe is not able to maintain its initial circular shape when the tangential compressive stress reaches a limit value and the pipe distorts unstably in buckling. Wall buckling can occur due to insufficient pipe stiffness. The more flexible the pipe, the more unstable the wall structure will be in resisting wall buckling. Pipe encased in soil may buckle due to excessive loads and deformations.

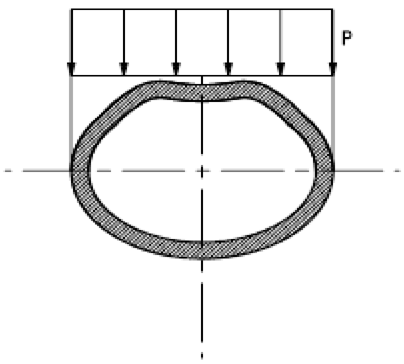


Figure 3.7: A typical flexible pipe buckling

The two buckling forms are usually found, called general (global) buckling and local buckling (Berti et al, 1998). Global buckling is a load response mode due to compressive effective axial force but not a failure mode. Pipe is safe from buckle globally whereas local buckling is an important limit state. The total load or the actual buckling pressure must be less than the critical buckling pressure for the safety of the structure. The actual buckling (local) pressure for flexible pipe, *p* can be calculated as follows (AWWA, 1999):

$$p = R_w \gamma_s + \gamma_w H_w + P_S \tag{3.10}$$

where R_w is water buoyancy factor = 1 – 0.33 (H_w/*H*), γ_w is unit weight of water, H_w is height of groundwater above the pipe and P_s is live load as calculated in Eq. (3.9).

The critical buckling (local) pressure p_{cr} can be calculated as follows (AWWA, 1999):

$$p_{cr} = \frac{1}{S_{fb}} \sqrt{\left(32 R_w B' E' \frac{EI}{D^3} \right)}$$
$$= \frac{1}{S_{fb}} \sqrt{\left(32 R_w B' E' \frac{E(t - D_T)^3 / 12}{D^3} \right)} \tag{3.11}$$

where S_{fb} is design safety factor for buckling
= 2.5 for H/D ≥ 2 or 3.0 for H/D < 2 (ASCE, 2001; Moser and Folman, 2008)

B' is empirical coefficient of elastic support,
$= 1/(1 + 4e^{-0.213H})$ (ASCE, 2001)

3.2.2.3 Wall thrust

Wall thrust or wall crushing is characterised by localised yielding when the in-wall stress reaches the yield stress of the pipe material. If the buried depth is not enough then the pipe wall can crush due to earth and surface loading. Buried depth should be sufficient to avoid the crushing of the side wall (Figure 3.8). Thrust or stress on the pipe wall is the total load on the pipe wall including soil loads, traffic loads and hydrostatic loads.

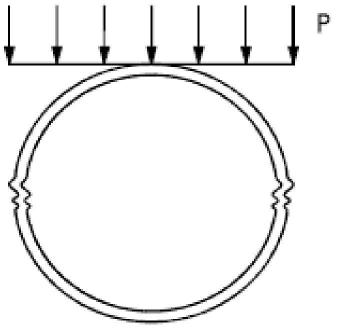


Figure 3.8: A typical flexible pipe wall thrust or stress

If only dead load is involved during the installation, the long-term material properties are considered throughout the calculation of wall thrust analysis. However, if both dead loads and live loads are present (typically any vehicular load with 2.4 m of cover or less), two wall thrust analyses are required (Gabriel, 2011) as follows:

(a) Accounts both dead load and live load and employs the short term material properties throughout the procedure;

(b) Accounts only dead load and employs the long-term material properties throughout the process.

Then, the more conservative limit state function value is used for wall thrust analysis. Note that some flexible pipes have both short-term and long-term material properties (elasticity of modulus), where short-term value is higher than long-term value, such as, polyethylene pipe and therefore, two wall thrust analyses are applicable but some have no such classification, for example, ductile iron pipes, steel pipes etc. and for these cases, only above option a) is considered for analysis, where short-term and long-term properties are the same.

The critical and actual wall thrust can be estimated by applying Eq. (3.12) and Eq. (3.13), respectively (Gabriel, 2011). The allowable or critical thrust must be equal to or greater than the actual thrust in order to remain structurally stable.

The critical wall thrust can be calculated as Eq. (3.12) after modifying by Eq. (3.6) (Tee et al, 2013a):

$$T_{cr} = F_y A_s \phi_p = F_y (t - D_T) \phi_p \tag{3.12}$$

where F_y is the minimum tensile strength of pipe, D_T is the corrosion pit depth, A_s is cross-sectional area of pipe wall per unit length and ϕ_p is capacity modification factor for pipe.

The actual wall thrust (T_a) can be estimated as Eq. (3.13) (Gabriel, 2011):

$$T_a = 1.3(1.5W_A + 1.67P_sC_L + P_w)(D_0/2) \tag{3.13}$$

where D_0 is the outside diameter and C_L is live load distribution coefficient = the lesser of (L_w/D_0) or 1.0 and L_w is live load distribution width. The loads acting on the pipe considered in wall thrust analysis are soil arch load, W_A, live load, P_s and hydrostatic pressure P_w. The soil arch load and hydrostatic pressure can be calculated as follows:

$$W_A = P_{sp}V_{AF} \tag{3.14}$$

$$P_w = \gamma_w H_w \tag{3.15}$$

where P_{sp} is geostatic load $= \gamma_s(H + 0.11\times10^{-7}(D_0))$, V_{AF} is vertical arching factor = 0.76-0.71((S_h - 1.17)/(S_h + 2.92)), S_h is hoop stiffness factor = $\varphi_s M_s R/EA_s$, φ_s is soil capacity modification factor, M_s is secant constrained soil modulus, R is effective radius of pipe = $D_i/2+c$.

3.2.2.4 Pipe bending

Under the effect of earth and surface loads, the through-wall bending is found in the buried flexible pipes (Figure 3.9). The moment curvature relationship provides information necessary for pipe design against failure due to bending. If a pipe is part of a carrying structure, the elastic limit may be an obvious choice as the design limit. A pipe subjected to increasing pure bending will fail as a result of increased ovalisation of the cross section and reduced slope in the stress-strain curve (Tee et al, 2013). Up to a certain level of ovalisation, the decrease in moment of inertia will be counterbalanced by increased pipe wall stresses due to strain hardening (ignoring soil reaction). When the loss in moment of inertia can no longer be compensated for by the strain hardening, the moment capacity has been reached and catastrophic cross sectional collapse will occur if additional bending is applied (Hauch and Bai, 1999).

For the safety of the pipe, the bending stress should not exceed the tensile strength of the pipe material and the longitudinal bending strain should not exceed the allowable strain (ε_{cr}) limit of pipe materials. Typically, the longitudinal allowable bending strain limit for flexible pipes is 0.15% to 2% (Kashani and Young, 2005; Mohr, 2003).

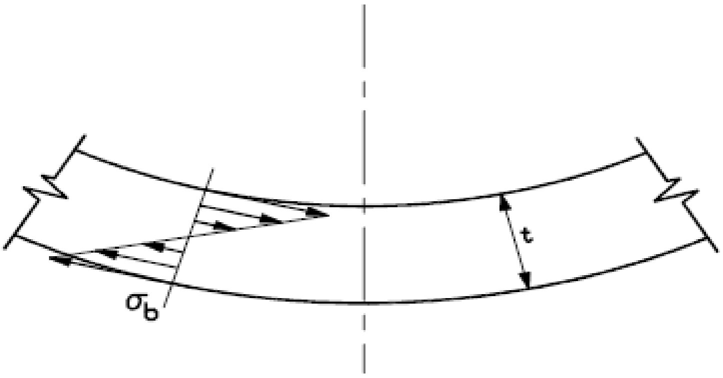


Figure 3.9: A typical flexible pipe bending

The allowable bending stress, σ_{cr} is the long term tensile strength of the pipe material. Therefore, checking the bending stress and strain is important to ensure that these are within material capability. Actual bending stress, σ_b and bending strain, ε_b can be calculated as following Eqs. (3.16) and (3.17) respectively (Gabriel, 2011)

Actual bending stress,

$$\sigma_b = 2D_f E\Delta_y y_0 S_f / D^2$$

$$= \frac{2D_f K_b (D_L W_c + P_s) DEy_0 S_f}{((8E(t - D_T)^3 / 12)/D^3 + 0.061E')D^2} \tag{3.16}$$

Actual bending strain,

$$\varepsilon_b = 2D_f \Delta_y y_0 S_f / D^2$$

$$= \frac{2D_f K_b (D_L W_c + P_s) Dy_0 S_f}{((8E(t - D_T)^3 / 12)/D^3 + 0.061E')D^2} \tag{3.17}$$

where D_f is shape factor, y_0 is distance from centroid of pipe wall to the furthest surface of the pipe. S_f is the safety factor for bending. Δ_y is pipe deflection which can be calculated as shown in Eq. (3.7).

Note that in the pipe failure modes analysis, k and n or a, b and c, t, K_b, γ_s , E, E_s, P_s and H are considered as random variables.

3.3 PROBABILISTIC RELIABILITY ANALYSIS

Methods for estimating structural reliability using probability ideas are well established. Methods of reliability analysis such as First Order Reliability Method (FORM), Second-Order Reliability Method (SORM), Point Estimate Method (PEM), Monte Carlo simulation (MCS), Path Enumeration (PE), Hasofer-Lind and Rackwitz-Fiessler algorithm (HL-RF) and State Enumeration (SE) and so on are available in literature (Tee and Khan, 2013). However, Hasofer-Lind and Rackwitz-Fiessler algorithm and Monte Carlo simulation are used in this study for estimating structural reliability of underground flexible metal pipes. Pipe failure can be defined in relation to different possible mechanisms as mentioned in Section 3.2.

In the assessment of reliability, normally some measures are used in terms of capacity or resistance and the demand of the system, such as central factor of safety (*CFS*), safety margin (*SM*) and reliability index (β) etc. These measures are related to the probability of failure (P_f) of the system (Babu and Rao, 2005). *SM* is the difference between expected capacity and expected demand. In the reliability prediction, *SM* < 0 corresponds to a failure condition, whereas *SM* > 0 represents a safe condition and *SM* = 0 is the limit state boundary. The *SM* for the failure modes are defined as follows to examine the performance of pipe reliability in this study:

$SM = \Delta y_{cr} - \Delta_y$ (for deflection)

$SM = p_{cr} - p_a$ (for buckling)

$SM = T_{cr} - T_a$ (for wall thrust)

$SM = \sigma_{cr} - \sigma_b$ (for bending stress)

$SM = \varepsilon_{cr} - \varepsilon_b$ (for bending strain)

Failure can be defined in relation to different possible failure modes, commonly referred as limit states. Reliability is considered to be the probability that these limits will not exceeded and is equal to the probability of survival. Each of the limit state function variables is attributed to a probability density function that presents its statistical properties. The limit state functions for the failure modes are defined as follows:

$Z(X) = \Delta y_{cr} - \Delta_y$ (for deflection)

$Z(X) = p_{cr} - p_a$ (for buckling)

$Z(X) = T_{cr} - T_a$ (for wall thrust)

$Z(X) = \sigma_{cr} - \sigma_b$ (for bending stress)

$Z(X) = \varepsilon_{cr} - \varepsilon_b$ (for bending strain)

where Δy_{cr}, p_{cr}, T_{cr}, σ_{cr} and ε_{cr} are critical pipe deflection, buckling, wall thrust, bending stress and bending strain respectively, whereas Δ_y, p_a, T_a, σ_b and ε_b are actual pipe deflection, buckling, wall thrust, bending stress and bending strain, respectively.

Like *SM*, limit state function, *Z*(*X*) < 0 represents the failure state, *Z*(*X*) > 0 indicates a safe state, and the limit state boundary which separates the safety and failure domains, exits at *Z*(*X*) = 0. A general illustration of a reliability problem is shown in Figure 3.10 (Phoon, 2008).

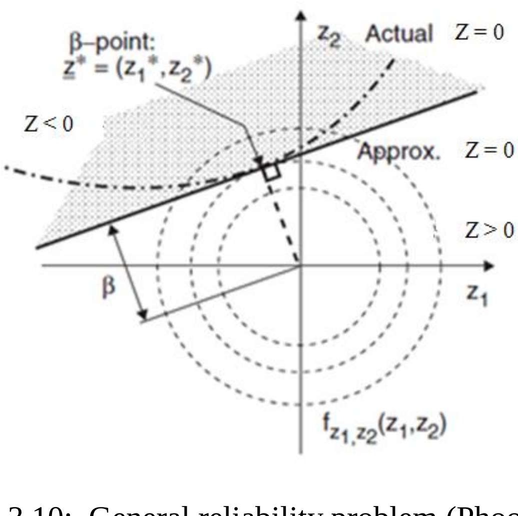


Figure 3.10: General reliability problem (Phoon, 2008)

The probability of failure, (p_f) for each limit state function can be evaluated by Eq. (3.18) as below:

$$P_f = P[Z(X) \leq 0] = \Phi(-\beta) \tag{3.18a}$$

Or $p_f = 1/\{1+\exp(\frac{\pi\beta}{\sqrt{3}})\}$ (Barbosa, 1989) (3.18b)

where Φ = the cumulative standard normal distribution function, β is known as the safety index or reliability index, a rational assessment of safety on the basis of the coefficients of variation of parameters and the correlation among variables. Eq. (3.18) is used for each limit state function to calculate the probability of failure of due to each failure mode. Eq. (3.18) implies that when β increases, the probability of failure decreases and vice versa. A general guideline for reliability index and the corresponding probability of failure is suggested by United States Army Corps of Engineers (USACE 1997) (Phoon, 2008) as shown in Figure 3.11.

Note that, *SM* and *Z(X)* are formulated using standard design equations for buried pipes including safety factors for different failure modes except deflection. These factors are used in design to ensure some reliability level and should not be included in a probabilistic analysis. Therefore, in reliability prediction these factors of safety are not considered.

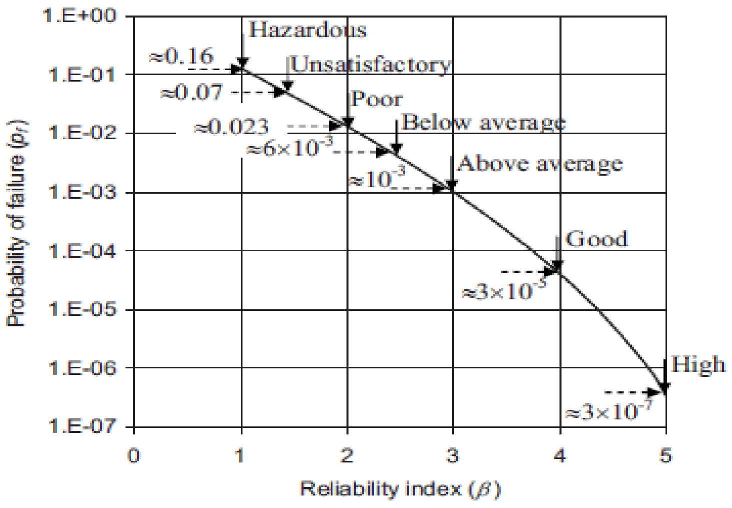


Figure 3.11: USACE (1997) guidelines for reliability index and probability of failure

3.3.1 Hasofer-Lind and Rackwitz-Fiessler (HL-RF) algorithm

The primary benefit of HL-RF is believed to lie in accuracy comparable with other rigorous techniques, such as MCS and FORM. HL-RF requires significantly less computational effort than MCS. Another benefit to HL-RF is that it evaluates a limit state function at a point known as design point or most probable point $x_i^*, i = 1,2,....,n$ instead of mean value as used in FORM. The design point is a point on the failure surface, Z = 0. Since this design point is generally not known a priori, an iteration technique must be used to solve for reliability index (Section 3.3.1.1). Pipe reliability can be estimated using HL-RF algorithm where all the variables should be normally distributed. For non-normally distributed variable, Rackwitz-Fiessler (RF) algorithm is applied to transform it to a normally distributed variable. Mathematically RF techniques can be expressed as below (Haldar and Mahadevan, 2000)

$$F_x(x^*) = \Phi\left(\frac{x^* - \mu_x^e}{\sigma_x^e}\right) \tag{3.19}$$

$$f_x(x^*) = \frac{1}{\sigma_x^e}\phi\left(\frac{x^* - \mu_x^e}{\sigma_x^e}\right) \tag{3.20}$$

where $F_x(x)$ = Cumulative Distributed Function (CDF), $f_x(x)$ = Probability Density Function (PDF), Φ is the CDF for the standard normal distribution and ϕ is the PDF for the standard normal distribution, μ_x^e is the equivalent normal mean and σ_x^e is the equivalent standard deviation. Eq. (3.19) simply requires the cumulative probabilities to be equal at x^* and Eq. (3.20) is obtained by differentiating both sides of first Eq. (3.19) with respect to x^*. By manipulating Eqs. (3.19) and (3.20), the expressions μ_x^e and σ_x^e can be obtained as follows (Haldar and Mahadevan, 2000; Li and Kim, 2006)

$$\mu_x^e = x^* - \sigma_x^e\left[\Phi^{-1}(F_x(x^*)\right] \tag{3.21}$$

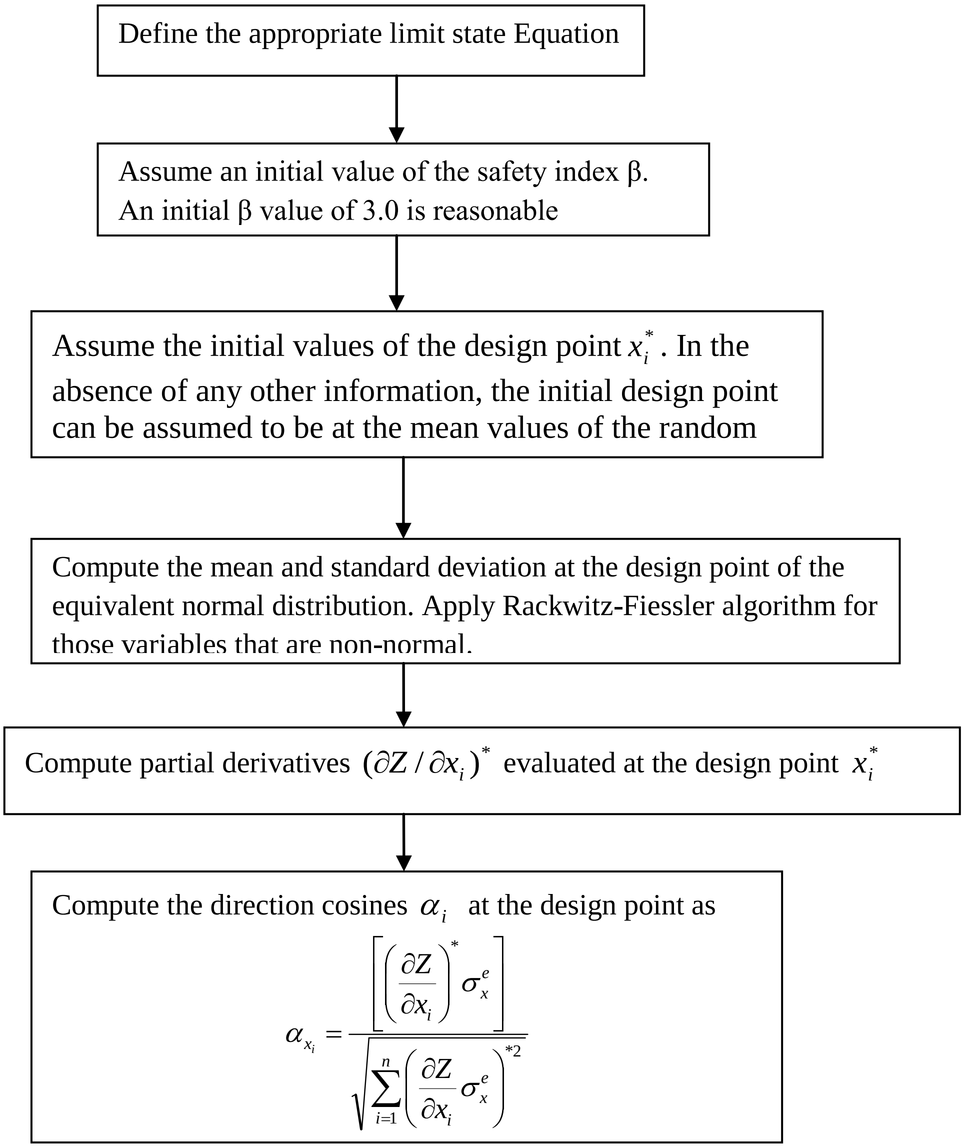
$$\sigma_x^e = \frac{1}{f_x(x^*)}\phi\left(\frac{x^* - \mu_x^e}{\sigma_x^e}\right) = \frac{1}{f_x(x^*)}\phi\left[\Phi^{-1}\left(F_x(x^*)\right)\right] \tag{3.22}$$

To evaluate the relative contribution of each random variable in the limit state function $Z(X)$, sensitivity coefficient $\alpha_{x_i}^2$ can be calculated as follows:

$$\alpha_{x_i}^2 = \frac{\left[\left(\frac{\partial Z}{\partial x_i}\right)^* \sigma_x^e\right]^2}{\sum_{i=1}^{n}\left(\frac{\partial Z}{\partial x_i}\sigma_x^e\right)^{*2}} \tag{3.23}$$

3.3.1.1 Procedure

The procedure of HL-RF algorithm can be described briefly as follows:



The procedure of HL-RF algorithm (Cont.)

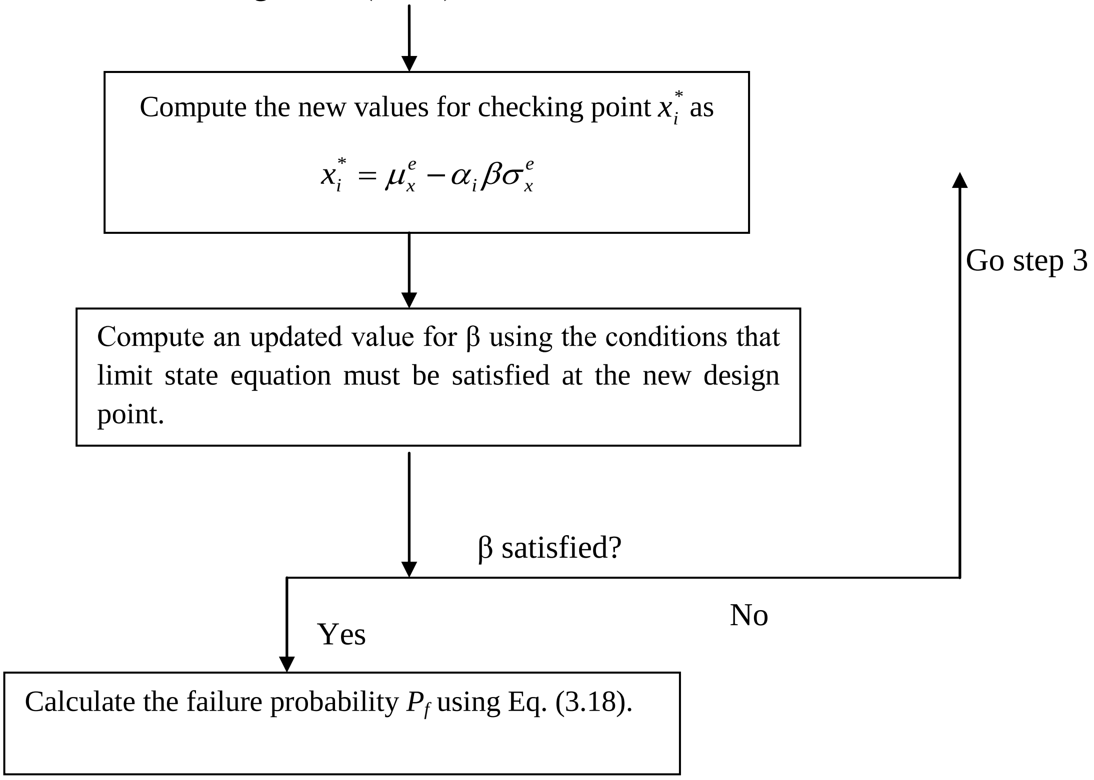


Figure 3.12: Flow chart for HL- RF algorithm

3.3.2 Monte Carlo simulation

A reliability problem is normally formulated using a failure function, $Z(X_1, X_2, \cdots, X_n)$, where $X_1, X_2, \cdots, X_n$ are random variables. Violation of the limit state is defined by the condition, $Z(X_1, X_2, \cdots, X_n) \le 0$ and the probability of failure, P_f, is expressed by the following expression:

$$P_f = P[Z(X_1, X_2, ..., X_n) \le 0] \tag{3.24}$$

The Monte Carlo simulation method allows the determination of an estimate of the probability of failure, given by

$$P_f = \frac{1}{N} \sum_{i=1}^{N} I(X_1, X_2, ...X_n) \tag{3.25}$$

where $I(X_1, X_2, ...X_n)$ is a function defined by

$$I(X_1, X_2, \cdots, X_n) = \begin{cases} 1 & if \quad Z(X_1, X_2, \cdots, X_n) \le 0 \\ 0 & if \quad Z(X_1, X_2, \cdots, X_n) > 0 \end{cases} \tag{3.26}$$

According to Eq. (3.25), *N* independent sets of values $X_1, X_2, \cdots, X_n$ are generated based on the probability distribution of each random variable and the failure function is computed for each sample. Using MCS, an estimate of the probability of structural failure is estimated as follows

$$p_f = \frac{N_H}{N}$$

where N_H is the total number of cases where failure has occurred.

3.4 SYSTEM FAILURE AND CORRELATION

Practically, a structure is composed by many elements and every element is consisted of many limit sates for its different behaviour, such as bending action, shear, buckling, axial stress, deflection, etc. Such a composition is referred to a ‘structural system’. Individual structural components and subsystems have different service life ranges that do not necessarily coincide with one another. Reliability evaluation of structural systems describes how the individual limit states interact on each other and how the overall reliability can be estimated. All individual failure modes are combined in a series or parallel system. In a series system, also called a weakest link system, any one element exceeds limit state constitutes failure of the system. All components of a parallel system, also called a redundant system, must be failed for a system failure. Combining parallel and series subsystems can make composite systems which is called complex system. The basic of series, parallel and complex systems are shown in Figure 3.13.

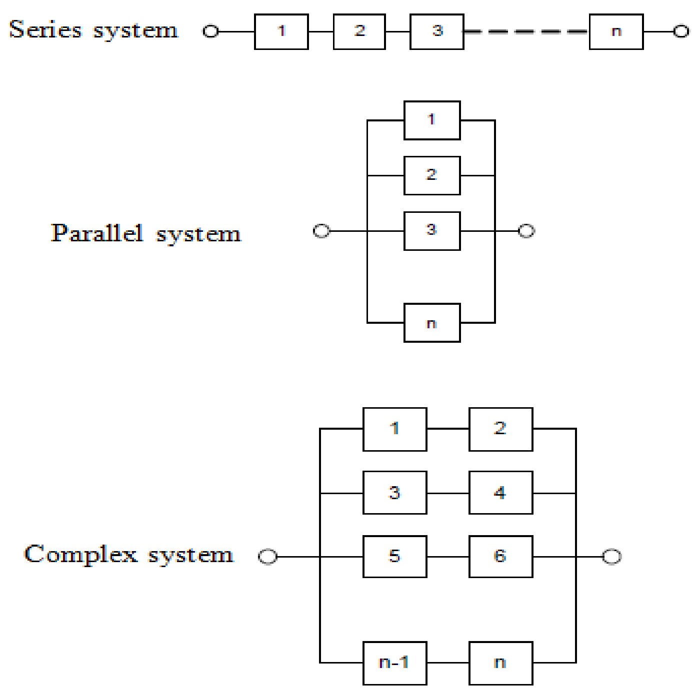


Figure 3.13: System definitions

Underground pipeline structures may contain multiple failure events or modes in which any of the modes can lead to a system failure. The failure modes may be correlated due to common random variables between the failure events. In many cases, the events are assumed independent and the system failure is evaluated neglecting the correlations between the events. However, neglecting correlation between different failure events may lead to gross error over predicting the underground pipeline reliability (Cherubini, 2000). As the occurrence of either failure mode can constitute its failure. Therefore, a series system is more appropriate for the assessment of pipe failure prediction.

Two types of correlation are found in structural system, (a) positive correlation, and (b) negative correlation. When value of one variable increases or decreases then other one also increases or decreases is called positive correlation. For example, the higher the soil density, the higher is the soil modulus. Similarly, loadings on pipe and failure modes are also positively correlated. On the other hand, when value of one variable is increased, then other one is decreased and vice versa is called negative correlation. For example, pipe stiffness and loadings are negatively correlated. If load is increased, the pipe stiffness is decreased.

Correlation coefficients or simply correlations are used to measure how strong a relationship is between two variables. Harr (1987) indicated that correlation (ρ) ranging from -1 to +1 between various random parameters influences reliability assessment. The higher the correlation coefficient, the higher is the reliability. The correlation between random variables can be measured based on covariance (*COV*). *COV* provides a measure of strength of the correlation between two or more sets of random variants. For example, the *COV* for two random variants *X* and *Y*, each with sample size *N*, can be defined explicitly by Eq. (3.27) as follows (Melchers, 1999):

$$COV(X,Y) = \{(X-\mu_X)(Y-\mu_Y)\} \tag{3.27}$$

Eq. (3.27) can be written out explicitly as below:

$$COV(X,Y) = \sum_{i=1}^{N} \frac{(X_i-\mu_X)(Y_i-\mu_Y)}{N}$$

or

$$COV(X,Y) \equiv E[(X-\mu_X)(Y-\mu_Y)]$$
$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\mu_X)(y-\mu_Y)f_{XY}(x,y)dxdy \tag{3.28}$$

where $f_{XY}(x,y)$ is the joint probability density function of *X* and *Y*.

For uncorrelated variables, the covariance is zero. However, if the variables are correlated in some way, then their covariance will be non-zero. After estimation of *COV*, the correlation of coefficient ρ, can be calculated as below Eq. (3.29a) (Melchers, 1999):

$$\rho_{XY} = \frac{COV(X,Y)}{[\mathrm{var}(X)\,\mathrm{var}(Y)]^{1/2}} = \frac{COV(X,Y)}{\sigma_X\sigma_Y} \tag{3.29a}$$

Alternatively, the correlation coefficient between two variables can be determined using Eq. (3.29b) without calculating *COV* as follows:

$$\rho_{XY} = \frac{N(\sum XY)-(\sum X)(\sum Y)}{\sqrt{\{N\sum X^2-(\sum X)^2\}\{N\sum Y^2-(\sum Y)^2\}}} \tag{3.29b}$$

where μ_X and μ_Y are respective means for *X* and *Y* and σ_X and σ_Y are standard deviations of variables *X* and *Y*, respectively. ρ_{XY} = correlation coefficient between variables *X* and *Y*.

However, sometimes, the mean and variance of general functions are found difficult to perform the integrations as required in Eq. (3.28). To overcome this problem, a useful approach is to calculate the approximate moments by expanding the function $Y = Y(X_1, X_2, ..., X_n)$ in a Taylor series about the point defined by the vector of the means $(\mu_{x_1}, \mu_{x_2}, ..., \mu_{x_n})$. By truncating the series at linear terms, the first-order mean and variance can be estimated as below (Melchers, 1999):

$$E(Y) \approx Y(\mu_{x_1}, \mu_{x_2}, ..., \mu_{x_n}) \tag{3.30}$$

$$Var(Y) \approx \sum_i^n \sum_j^n c_i c_j COV(X_i, X_j) \tag{3.31}$$

where $c_i \equiv \frac{\partial Y}{\partial X_i} \mid \mu_{x_1}, \mu_{x_2}, ..., \mu_{x_n}$. If the X_i are independent, then $COV(X_i, X_j) = 0$ for $i \neq j$ and $COV(X_i, X_j) = \mathrm{var}(X_i)$ for $i = j$.

If common random variables are present among the failure modes, then each failure mode is itself a random variable, and the failure modes should correlate with each other. The probability of failure for a series system can be estimated after predicting the correlation, ρ, between the different failures modes as suggested by Riha and Manteufel (2001) in Eqs. (3.32) as follows:

$$\underset{i=1,...,m}{Max} P(F_i) \le P_f \le 1 - \prod_{i=1}^{m} (1 - P(F_i)), \qquad for \quad 0 \le \rho \le 1 \tag{3.32a}$$

$$\sum_{i=1}^{m} P(F_i) - \prod_{i=1}^{m} P(F_i) \le P_f \le \sum_{i=1}^{m} P(F_i), \qquad for \quad -1 \le \rho \le 0 \tag{3.32b}$$

$$\underset{i=1,...,m}{Max} P(F_i) \le P_f \le \sum_{i=1}^{m} P(F_i), \qquad for\ unknown\ \rho \tag{3.32c}$$

where $P(F_i)$ is the probability of failure due to i^{th} failure mode of pipe and m is the number of failure modes considered in the system.

3.5 NUMERICAL EXAMPLE

An underground steel pipe with a mean diameter of 1.21 m and initial wall thickness of 21.0 mm under a roadway subjected to heavy traffic loading conditions is taken as a numerical example. Calculations are presented for the case of a typical pipe section, as shown in Figure 3.14. Numerical values are based on practice and have been obtained from the literature (Ahammed and Melchers, 1997; Sadiq et al, 2004; Babu and Rao, 2005). The pipe is thin walled circular (plain) pipe and buried in a trench of 2 m width and 3.75 m depth over ground water table. The backfill material has a unit weight of 18.0 kN/m^3 and soil modulus of 10^3 kPa. The buried pipe is considered under a heavy traffic condition where the wheel load is 80 kPa. Other parameters are listed in Table 3.1. There are 9 random variables where the mean and coefficient of variation are listed in Table 3.2. The random variables are deflection coefficient (K_b), soil density (backfill) (γ_s), elasticity of pipe material (E), height of soil above pipe (H), pipe wall thickness (t), multiplying constant (k), exponential constant (n), live load (wheel load) (P_s) and soil modulus (E_s).

According to the references by Babu and Rao (2005) and Riha and Manteufel (2001) most of the random variables in Table 3.2 are normally distributed as these variables are found symmetric around their mean. However, the deflection coefficient (K_b) accounts for the bedding support which varies with the bedding angle and this variable's logarithm is found normally distributed.

Table 3.1: Parameter values of worked example

Symbol description	Value
Buoyancy factor, R_w	1.00
Trench width, B_d	2.00 m
Outside pipe diameter, D_o	1.231 m
Inside pipe diameter, D_i	1.189 m
Shape factor, D_f	4.0
Deflection lag factor, D_L	1
Capacity modification factor for soil, φ_s	0.90
Capacity modification factor for pipe, ϕ_p	1.00
Minimum tensile strength of pipe, F_y	400 MPa
Live load distribution coefficient, C_L	1
Poisson's ratio, ν_s	0.3
k' value	1.5
Allowable strain, ε_{cr}	0.2%
Correlation coefficient between γ and E_s	0 to 0.90
Correlation coefficient between P_s and E	-0.9 to 0

Table 3.2: Statistical properties of random variables

Material properties	Mean (μ)	Cov (%)	Distribution
Elastic modulus of pipe, E	210×10^6 kPa	1.0	Normal
Backfill soil modulus, E_s	10^3 kPa	5.0	Normal
Unit weight of soil, γ_s	18.0kN/m^3	2.5	Normal
Wheel load (Live load), P_s	80.0 kPa	10.0	Normal
Deflection coefficient, K_b	0.11	1.0	Lognormal
Multiplying constant, k	2.0	10.0	Normal
Exponential constant, n	0.3	5.0	Normal
Thickness of pipe, t	0.021 m	1.0	Normal
Height of the backfill, H	3.75 m	1.0	Normal

Cov = Coefficient of variation.

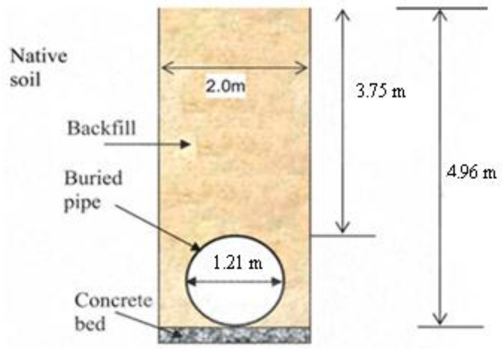


Figure 3.14: Geometrical details of the flexible buried pipe section (not to scale)

Thus Rackwitz-Fiessler algorithm has been applied to transform its distribution from log-normal to normal in this study. The pipe is subjected to corrosion and its corrosion rate is modelled using Eq. (3.1). As a conservative case, assuming the change of pipe surface due to corrosion is uniform over the entire surface area. Ahammed and Melchers (1997) predicted the corrosion constants *k* and *n* values by fitting the power law Eq. (3.1) to the various sets of underground corrosion data given by Schwerdtfeger (1971), applying the regression analysis. The obtained *k* and *n* constant parameters are used in this example as shown in Table 3.2. The geometrical parameters, such as pipe diameter (inside and outside diameter), pipe wall thickness *t*, and corrosion constant parameters (*k* and *n*) contain uncertainties and highly dependent on workmanship and quality control after the ditch construction and pipe installation process.

3.6 RESULTS AND DISCUSSION

The reliability analysis has been performed based on the above example in this Section. The failure probability, correlations among failure modes and between influencing random variables with respect to service life, some parametric studies and sensitivity analysis for every failure mode are conducted. The results and discussion on the analysis are presented as follows:

3.6.1 Probability of failure

In the case of buried pipes, the assessment of probability of failure on year basis is useful which enables to calculate the safe serviceable life. The probabilities of failure, P_f for corrosion induced excessive deflection, buckling, wall thrust and bending with respect to time have been estimated using the material properties and random variables which are presented in Tables 3.1 and 3.2 using MATLAB software. First, the probability of failure due to corrosion induced deflection is calculated using HL-RF algorithm and MCS (with 10^6 samples) as shown in Figure 3.15.

Next, the failure probability for limit states due to corrosion induced buckling, excessive wall thrust and bending is predicted using both above mentioned methods. The results from both methods are in reasonable agreement as shown in Figures 3.15 – 3.18 for every failure case. The results show that excessive bending stress is the most critical failure mode whereas buckling has the lowest probability of failure (Figure 3.15) during the whole service life of the pipe. Considering the failure probability of 0.1 (10%) as a threshold level for the safe service life (Babu and Srivastava, 2010; Phoon, 2008), the study illustrates that the safe service life in the worst case scenario is about 50 years.

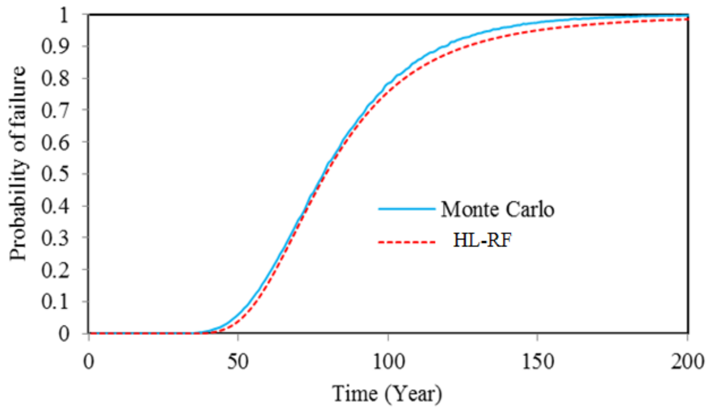


Figure 3.15: Probability of failure for limit state due to corrosion induced deflection using MCS and HL-RF

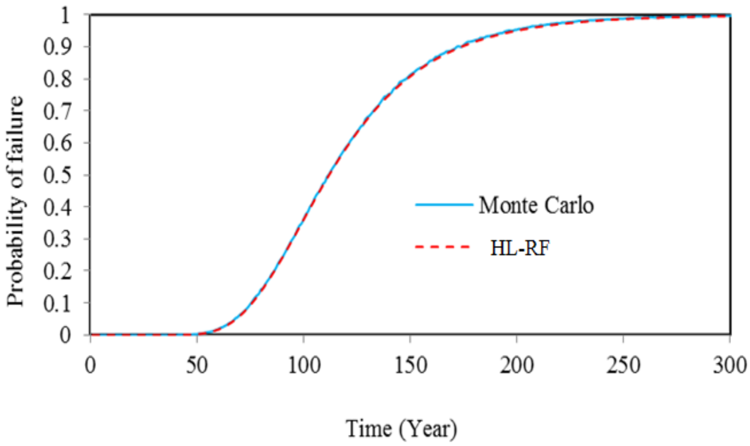


Figure 3.16: Probability of failure for limit state due to corrosion induced buckling using MCS and HL-RF

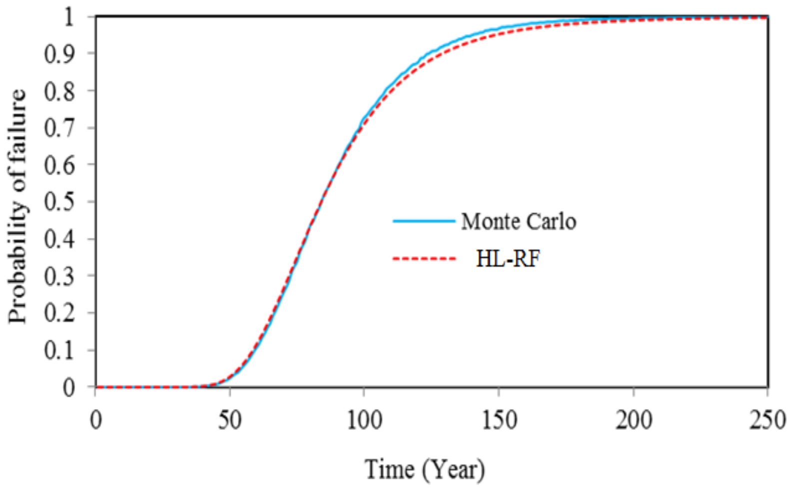


Figure 3.17: Probability of failure for limit state due to corrosion induced wall thrust using MCS and HL-RF

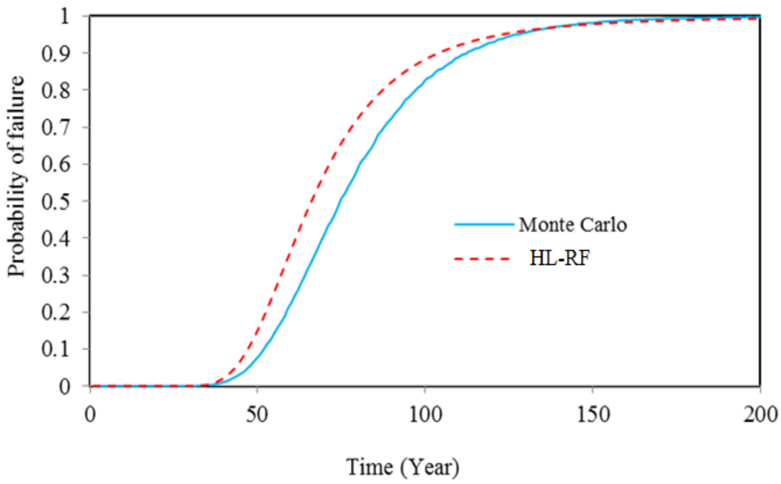


Figure 3.18: Probability of failure for limit state due to corrosion induced bending using MCS and HL-RF

3.6.2 Correlations and failure probability of series system

Every failure mode is a product of some random variables, hence every failure mode itself is a random variable (refer to Section 3.2). Therefore, according to the example data, the correlation among time-dependent failure modes, namely, corrosion induced deflection, buckling, wall thrust and bending have been estimated using Eq. (3.29b) in this study. The failure system is considered as a series system. Then the probability of system failure has been estimated based on the correlation among failure modes. The pipe failure modes correlation and probability of failure in series system are performed by MCS method, using

MATLAB software. In different years, the magnitude of deflection, buckling, wall thrust and bending (stress or strain) are used as a value of X and Y. For example, in determination of correlation between corrosion induced pipe deflection and buckling, the every year's deflection values are considered as X and the corresponding buckling values are considered as Y and then using Eq. (3.29b), the correlation coefficient is predicted. Similar approach is applied for correlation between deflection and wall thrust; deflection and bending; bending and buckling; buckling and wall thrust; and wall thrust and bending. The study shows that the failure modes are positively correlated and ranging within 0 to +1. The correlation coefficients between different failure modes are computed and summarised in Table 3.3. The study shows that all the failure modes are strongly and positively correlated where the failure modes might happen concurrently within a buried pipeline system.

Table 3.3: Correlation among failure modes

	Deflection	Buckling	Wall thrust	Bending
Deflection	1	0.999	0.9995	0.9999
Buckling	0.999	1	0.9999	0.9996
Wall thrust	0.9995	0.9995	1	0.9998
Bending	0.9999	0.9996	0.9998	1

The study shows that the correlations among failure modes are not time-dependent, i.e., the correlation for 10, 50, 100 and 200 years of pipe service life have the same correlation between different failures modes.

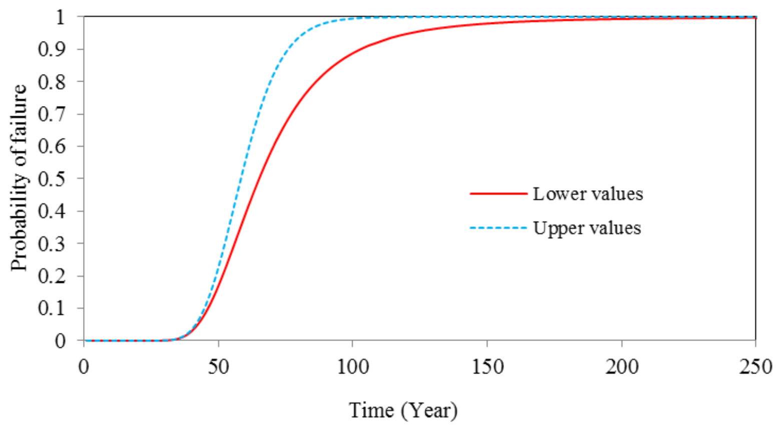


Figure 3.19: Probability of failure bounds in series system

Based on the above correlation analysis between the failure modes, failure probability of the series system, P_f has been estimated using Eq. (3.32a) ($0 < \rho < 1$) as shown in Figure 3.18. The expected value of P_f for series system is determined between upper and lower bounds of failure probability curve. The study shows that the probability of failure at beginning of pipe service life are very small (nearly zero) and remains unchanged until 40 years of service life, and then gradually increases as time increases. After 50 years, the values of P_f increases to about 10% and then it drastically rises, while at 150 years of life time it becomes almost 100% (Figure 3.19).

3.6.3 Correlations between two random variables

The study shows that soil modulus, soil density, loading and pipe stiffness are the significant controlling variables for the above mentioned failure modes (Tee et al, 2013a). Therefore, correlations analyses between only these variables are performed in this study. Soil density and soil modulus are positively correlated, whereas pipe stiffness and loadings are negatively correlated as discussed earlier. The correlation analysis between these random variables during pipe installation and pipe operation are presented as follows:

3.6.3.1 Correlation during pipe installation

At installation time (T = 0), no corrosion is initiated and this is attributed to the fact that corrosion does not cause any problem to new pipes and therefore reliability index is very high at this time. The reliability indices and corresponding Cov have been estimated for all the failure modes with the following cases of correlations between random variables:

(a) Soil modulus and soil density with positive correlations 0, +0.25, +0.50, +0.75 and +0.90.
(b) Loadings and pipe stiffness with correlations of –0.9, –0.75, –0.5, –0.25 and 0.

Figure 3.20 shows that the reliability indexes are reduced with increasing Cov of variable parameters for all the four failure modes due to corrosion induced deflection, buckling, wall thrust and bending stress. The analysis shows that among the failure modes, the lowest reliability index β (highest probability of failure) is occurred when the pipe fails due to corrosion-induced wall thrust whereas pipe failure due to corrosion induced deflection exhibits a higher reliability index (lower failure probability) for uncorrelated variable condition at time T = 0.

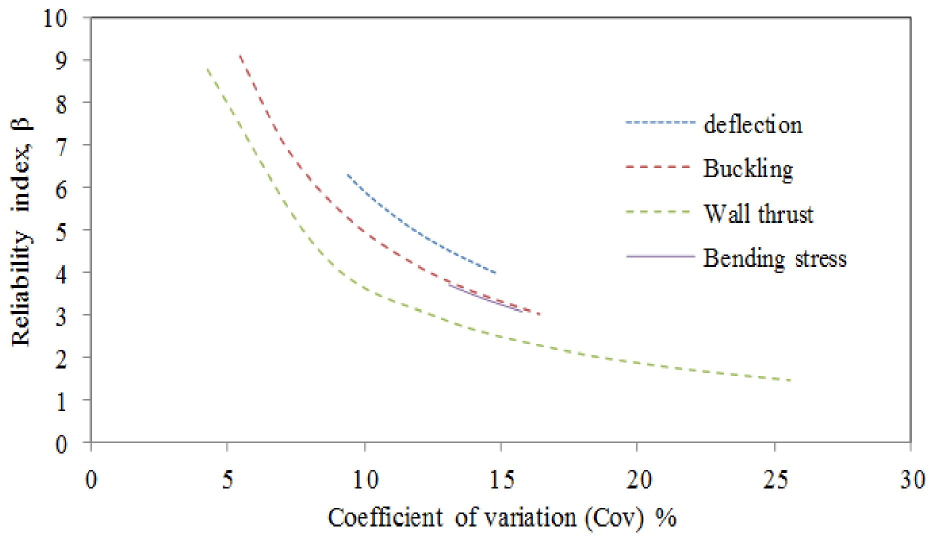


Figure 3.20: Reliability index versus Cov for different pipe failure criteria when variables are uncorrelated at installation time

Table 3.4**:** Reliability indices for different Cov of corrosion induced wall thrust with positive correlation between soil density and soil modulus at installation time

Cov_w	β at ρ = 0	Cov_w	β at ρ = 0.25	Cov_w	β at ρ = 0.50	Cov_w	β at ρ = 0.75	Cov_w	β at ρ = 0.9
4.260661	8.77267	4.260656	8.772681	4.260656	8.772691	4.260646	8.772701	4.260643	8.772707
8.521322	4.386335	8.521312	4.38634	8.521312	4.386345	8.521293	4.386351	8.521287	4.386354
12.78198	2.924223	12.78197	2.924227	12.78197	2.92423	12.78194	2.924234	12.78193	2.924236
17.04264	2.193168	17.04262	2.19317	17.04262	2.193173	17.04259	2.193175	17.04257	2.193177
21.30331	1.754534	21.30328	1.754536	21.30328	1.754538	21.30323	1.75454	21.30322	1.754541
25.56397	1.462112	25.56394	1.462113	25.56394	1.462115	25.56388	1.462117	25.56386	1.462118

Cov_w = Coefficient of variation for wall thrust

Table 3.5: Reliability indices for different Cov of corrosion induced bending stress with negative correlation between loading and pipe stiffness at installation time

Cov_b	β at ρ = 0	Cov_b	β at ρ = - 0.25	Cov_b	β at ρ = - 0.50	Cov_b	β at ρ = - 0.75	Cov_b	β at ρ = - 0.9
13.19015	3.730409	13.14095	3.721876	13.09156	3.707782	13.04199	3.693847	13.01216	3.680069
13.47991	3.697109	13.38345	3.680549	13.2863	3.653438	13.18843	3.626916	13.12936	3.600965
13.94946	3.612035	13.80945	3.588938	13.668	3.551409	13.52508	3.515032	13.43859	3.479752
14.58146	3.485346	14.40267	3.457742	14.22163	3.413158	14.03826	3.370255	13.92707	3.32893
15.35586	3.329997	15.14347	3.299954	14.92806	3.251639	14.7095	3.205386	14.57679	3.161052
16.25231	3.158698	16.01138	3.127961	15.76677	3.078668	15.51831	3.031635	15.3673	2.986694

Cov_b = Coefficient of variation for bending stress

Table 3.4 shows that reliability index is higher at lower Cov for wall thrust and the value gradually decreases with increasing Cov of the variables. In the case of bending stress (Table 3.5), β values almost remain constant or differ slightly with increasing Cov of random variables (E, E_s, P_s and γ_s). It is observed that the reliability indexes and corresponding Cov differ slightly with changing the correlation for both positive correlation (wall thrust) and negative correlation (bending stress) cases at pipe installation time as shown in Table 3.4 and Table 3.5, respectively. Due to very small changes in reliability index, only correlations of +0.9, 0 and –0.9 are shown in Figure 3.21 to examine the relationship between reliability index and corresponding Cov at $T = 0$ for wall thrust failure criteria.

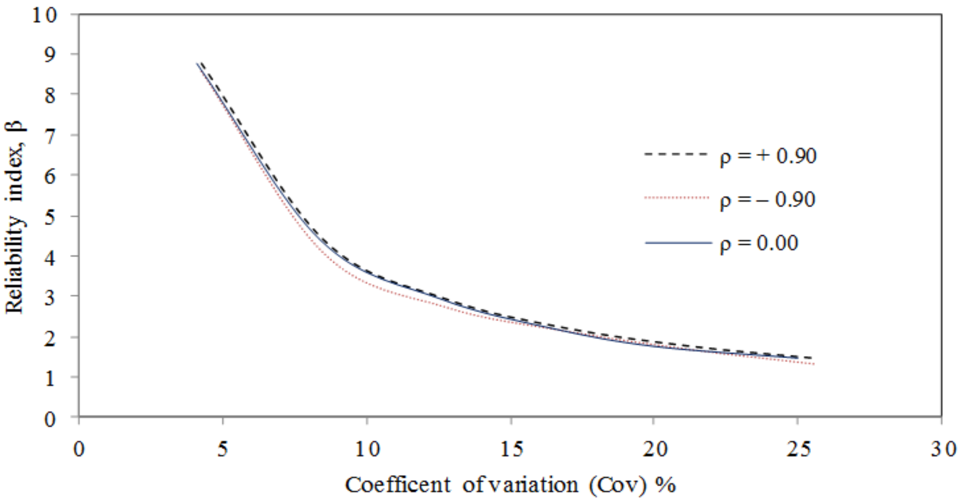


Figure 3.21: Reliability index versus Cov for wall thrust with correlations between soil density and modulus (+0.9), loading and pipe stiffness (–0.9) and uncorrelated condition at installation time

The analysis shows that for positive correlations between soil density and soil modulus, the lowest reliability for corrosion induced wall thrust is found when correlation is zero, i.e., in uncorrelated condition and the highest reliability indices are found when correlation is +0.9 (Table 3.4) which shows a good agreement with Babu and Rao (2005). In contrast, for negative correlations between loading and pipe stiffness, the highest reliability for corrosion induced bending stress is found when correlation is 0, and the lowest pipe reliability when correlation is –0.90 (Table 3.5). It can be postulated that the pipe failure is greatly influenced by soil density, soil modulus, loading acting on pipe and pipe stiffness. Overall, the corresponding Cov for positive correlation are higher than those for negative correlation due to corrosion induced deflection, buckling, wall thrust and bending stress.

3.6.3.2 Correlation during operation

Time dependent reliability index and corresponding Cov for both positive and negative correlation cases have been predicted at different stages in the life cycle of the buried pipe (25, 50, 75 and 100 years of service life). The investigation indicates that pipe service life from installation time to 40 years, the probability of failure is insignificant for both lower and upper bounds as shown in Figure 3.18. Therefore, correlation analysis is performed at 25 years of service life as a representative of insignificant probability of failure. Then 50, 75 and 100 years of pipe service life are considered for different levels of probability of failure. The reliability index and corresponding Cov for pipe service life at 25, 50, 75 and 100 years for pipe failure due to corrosion induced bending stress are shown in Figures 3.22 – 3.24. Based on the previous analysis, three different cases are considered: when variables are uncorrelated, correlation between soil density and soil modulus is +0.9 and correlation between loading and pipe stiffness is – 0.9.

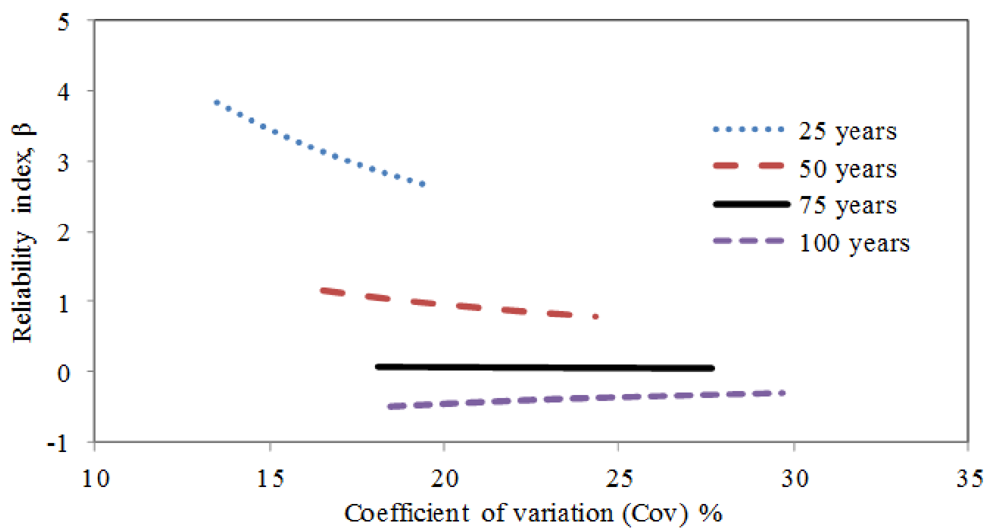


Figure 3.22: Reliability index versus Cov for bending stress when variables are uncorrelated at different stages in the life cycle

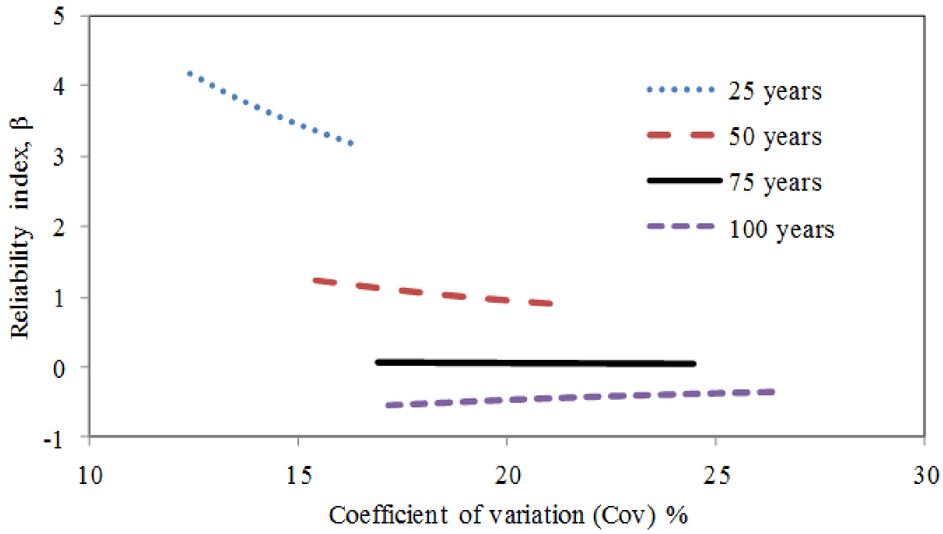


Figure 3.23: Reliability index versus Cov for bending stress with positive correlation between soil density and soil modulus (+0.9) at different stages in the life cycle

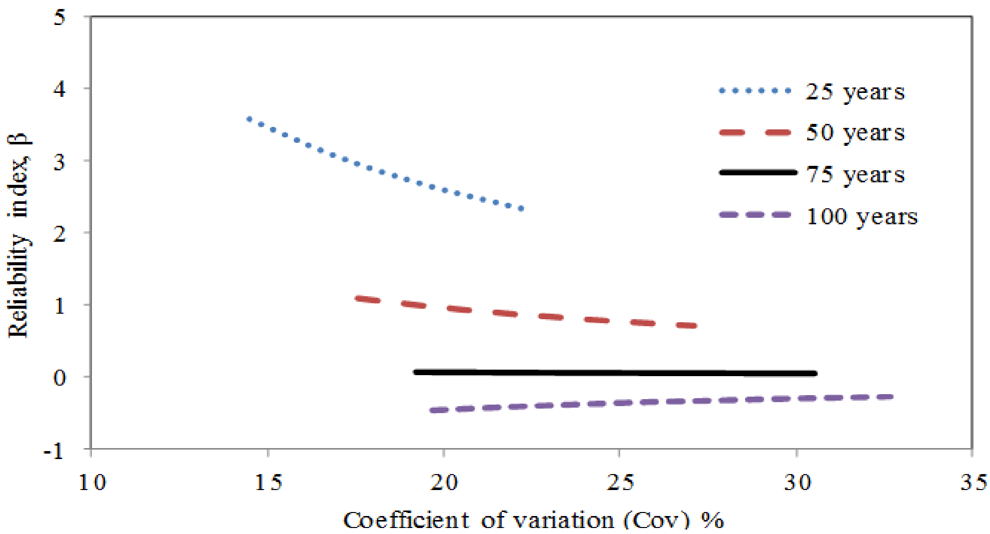


Figure 3.24: Reliability index versus Cov for bending stress with negative correlation between loading and pipe stiffness (–0.9) at different stages in the life cycle

Figures 3.22 – 3.24 show that with increasing pipe service life time, reliability index for pipe failure due to corrosion induced bending stress is decreased (or probability of failure is increased) for all the three cases (uncorrelated, positive correlation and negative correlation). As pipe wall thickness reduces with time due to corrosion, the pipe reliability is moderately changed from 25 to 50 years of pipe service life. It can be seen from Figures 3.22 – 3.24 that the Cov for corrosion induced bending stress are increased, and the corresponding reliability indices are significantly reduced during 25 to 50 years of pipe service time. The change in Cov is found larger when the variables are uncorrelated, and loading and pipe stiffness are negatively correlated (–0.90) compared to when soil density and soil modulus are positively correlated (+0.90). The pipe reliability index continuously reduces and the Cov progressively increases when the pipe goes through different stages of service life. The reliability analysis at 100 years shows that the index has become negative which indicates that the pipe failure probability is more than 0.5. This can be easily proved by using Eq. (3.18).

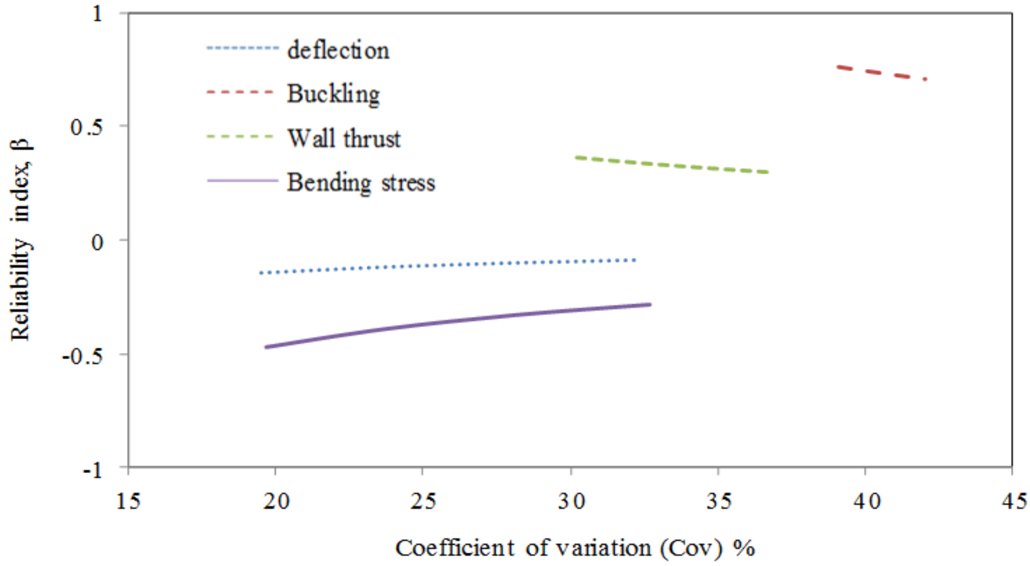


Figure 3.25: Reliability analysis versus Cov for different pipe failure criteria with negative correlation between loading and pipe stiffness (–0.9) at 100 years of service life

As the effect of negative correlation between loading and pipe stiffness is the most significant, the results for reliability analysis at 100 years of service life are shown in Figure 3.25 for different pipe failure criteria for different Cov. As shown in Figure 3.21, the dominating failure mode is wall thrust when no corrosion is occurred at T = 0. However, as pipe ages the dominating failure mode is changed to bending stress because corrosion has more influence on bending stress than those of wall thrust. The reliability index for pipe failure due to corrosion induced bending stress and deflection is negative and the others are still in positive state at 100 years of service life as illustrated in Figure 3.25. The Cov is higher for corrosion induced buckling failure which is about 38% – 40% and wall thrust is about 30% – 37%.

Table 3.6: Reliability indices with corresponding Cov for different pipe failure criteria with zero correlation between loading and pipe stiffness at 100 years of service life

Cov_d	β for deflection	Cov_{bu}	β for buckling	Cov_w	β for wall thrust	Cov_b	β for bending stress
19.51132	-0.14352	39.08781	0.761146	30.21229	0.363306	19.6805	-0.4697
23.49558	-0.11918	39.8687	0.746238	32.01172	0.342884	23.74511	-0.3893
27.7912	-0.10076	40.85078	0.728298	34.18638	0.321073	28.12062	-0.32872
32.27408	-0.08676	42.01994	0.708034	36.66957	0.29933	32.68239	-0.28284

Table 3.7: Reliability indices with corresponding Cov for different pipe failure criteria with negative correlation between loading and pipe stiffness (-0.9) at 100 years of service life

Cov_d	β for deflection	Cov_{bu}	β for buckling	Cov_w	β for wall thrust	Cov_b	β for bending stress
18.27962	-0.15319	38.84623	0.76588	30.21223	0.363307	18.4601	-0.50075
21.66315	-0.12926	39.4467	0.754221	32.01161	0.342885	21.93353	-0.42145
25.3585	-0.11043	40.20556	0.739986	34.18622	0.321074	25.71909	-0.35942
29.2477	-0.09574	41.11404	0.723634	36.66936	0.299332	29.69765	-0.31127

The reliability index and the corresponding Cov are changed with varying time. Both the reliability indices for corrosion induced buckling and wall thrust are still positive at 100 years of service life whereas the reliability indices become negative values for wall thrust and bending stress where the reliability index for wall thrust is close to zero. In addition, the reliability index and the corresponding Cov for pipe failure due to corrosion induced wall thrust remains almost the same when the correlation is changed from 0 to -0.9 at 100 years of service life as shown in Table 3.6 and Table 3.7. On the other hand, the reliability index is decreased for deflection and bending stress whereas the reliability index is increased for buckling towards more negative correlation between loading and pipe stiffness. Therefore, it is evident that changes in soil, loading and pipe properties influence the characterisation of pipe performance for different failure criteria, but in terms of percentages, the assessment is not consistent with respect to time.

From the results of the studied cases, it can be stated that the variability of soil, loading acting on pipe and pipe stiffness are significant parameters affecting the reliability of buried pipe failure system. The results suggest that flexible pipe failure due to deflection is the least vulnerable and wall thrust is the most dominating failure criteria at the beginning of pipe service life. However, during pipe operation at different stages of service life, corrosion induced buckling is the least susceptible and bending stress is the most controlling failure mode. The study also shows that during installation, the overall probability of failure due to corrosion induced wall thrust is lower (i.e. higher reliability) when soil modulus and soil density are positively correlated whereas the failure probability due to corrosion induced bending stress is higher when loading and pipe stiffness are negatively correlated.

3.6.4 Parametric study

To analyse the effect of the design variables on the probability of failure of the underground flexible pipeline system, a parametric study has been carried out. The effect of changing the wall thickness, pipe diameter and backfill height on the probability of failure has been shown in Figure 3.26, Figures 3.27 – 3.30 and Figures 3.31 – 3.34, respectively. The numerical investigation of the example pipeline shows that there is a very significant long-term contribution of the pipe thickness, diameter and soil height to structural reliability and deterioration process which are described as below:

3.6.4.1 Pipe wall thickness

The original thickness of the pipe is 21 mm but the range of the x-axis of the Figure 3.26 (pipe wall thickness) is plotted from 16 mm because pipe failure does not commence (probability of failure is almost equal to zero) in the beginning of the pipe lessening process for all the corrosion induced failure criteria until the residual thickness reaches 15.5 mm. On the other hands, the pipe totally fails (probability of failure is almost equal to one) when the residual thickness reaches 12 mm for all the failure criteria except the failure due to buckling as shown Figure 3.26.

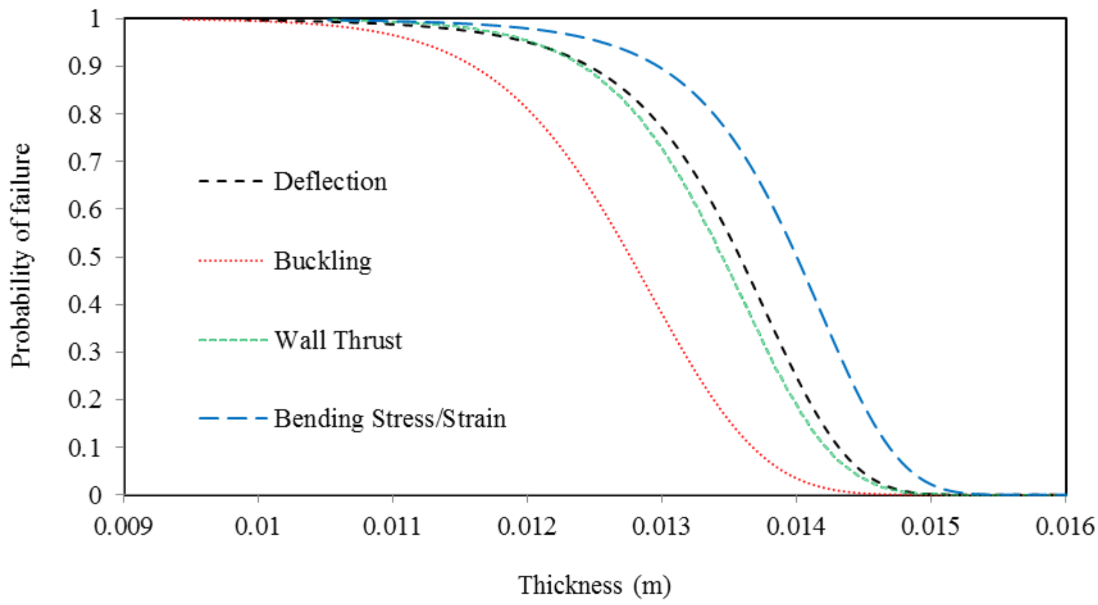


Figure 3.26: Probability of failure for limit states versus wall thickness

The result shows that in the case of failure due to buckling, the pipe needs more thickness reduction to fail than others. In this case, the range is from 14.5 mm to 10.5 mm. Therefore, it can be concluded that buckling is the least susceptible whereas the excessive bending stress is the most susceptible due to reduction of the pipe wall thickness. The research shows that probabilities of failure drastically change due to pipe thickness reduction of 4.5 to 5.0 mm and become zero to one. Based on results, it can be assumed that due to ductility behaviour of steel material, the failure probability increase within a short reduction of pipe wall thickness.

3.6.4.2 Pipe diameter

The probability of failure has been estimated for pipe diameter of 1.16 m, 1.20 m and 1.24 m using all the four different failure criteria. The results are shown in Figures 3.27 – 3.30 for all failure modes. The buckling and wall thrust show the largest effect due to changes in pipe diameter. In fact, the results show that the larger diameter pipes have a higher failure rate than the smaller ones i.e. the service life of pipe decreases as pipe diameter increases. The obtained results are in a good agreement with the results of the previous studies. A number of authors have investigated the relationship between buried pipe size and its structural reliability. Involving large buried pipe samples with length of 180 km, O'Reilly et al (1989) noticed that the incidence of longitudinal cracks increased with diameter and also observed that fractures were much more common in larger size of pipes. O'Reilly et al. (1989) also observed that when all defects were considered, the pipes with middle ranges of diameters

(300 – 700 mm) showed more defects than those with smaller sizes. Larger pipes are more at risk to structural damage due to their bulk and weight making them more difficult to lie accurately (Davis et al, 2001). Similarly, this analysis also shows that the highest failure probability is due to excessive bending stress and the lowest is due to buckling.

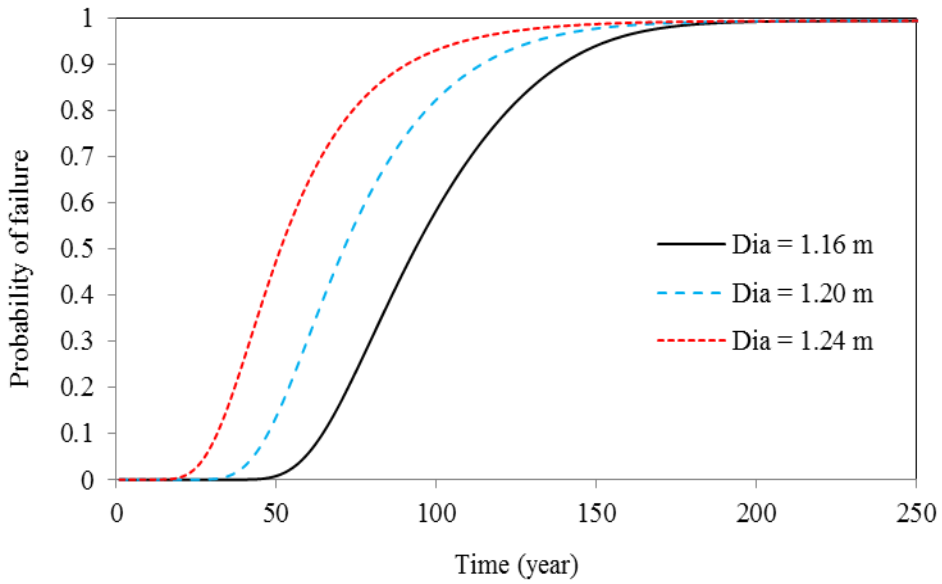


Figure 3.27: Probability of failure for different pipe diameters due to corrosion induced deflection

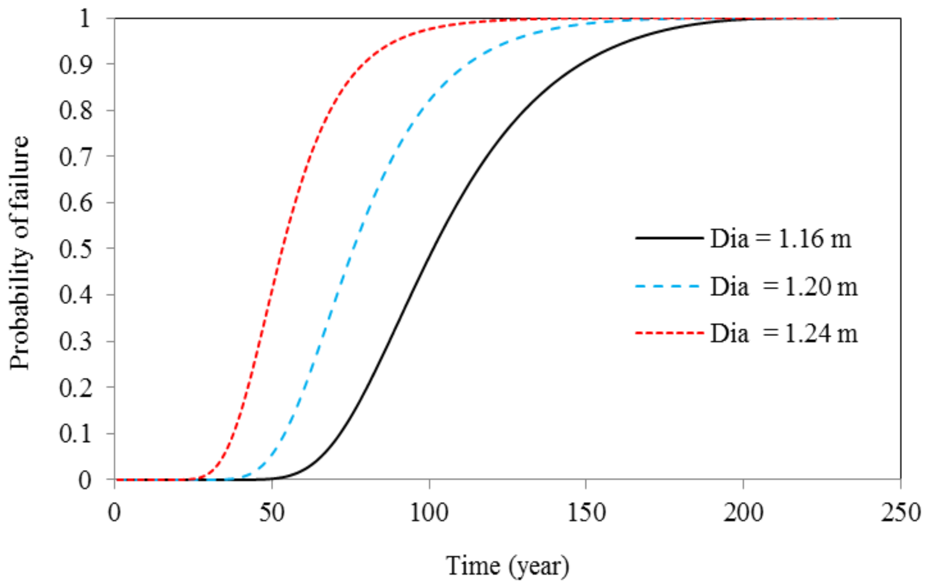


Figure 3.28: Probability of failure for different pipe diameters due to corrosion induced buckling

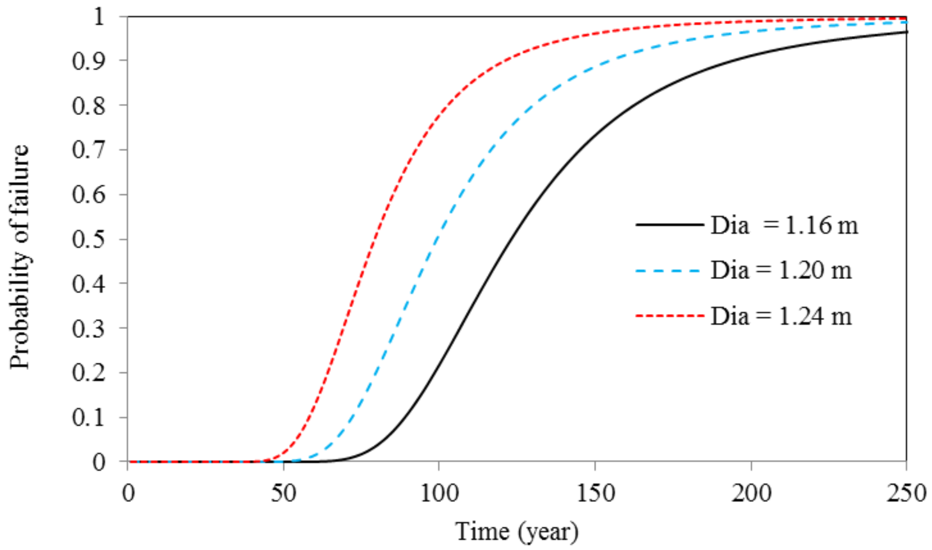


Figure 3.29: Probability of failure for different pipe diameters due to corrosion induced wall thrust

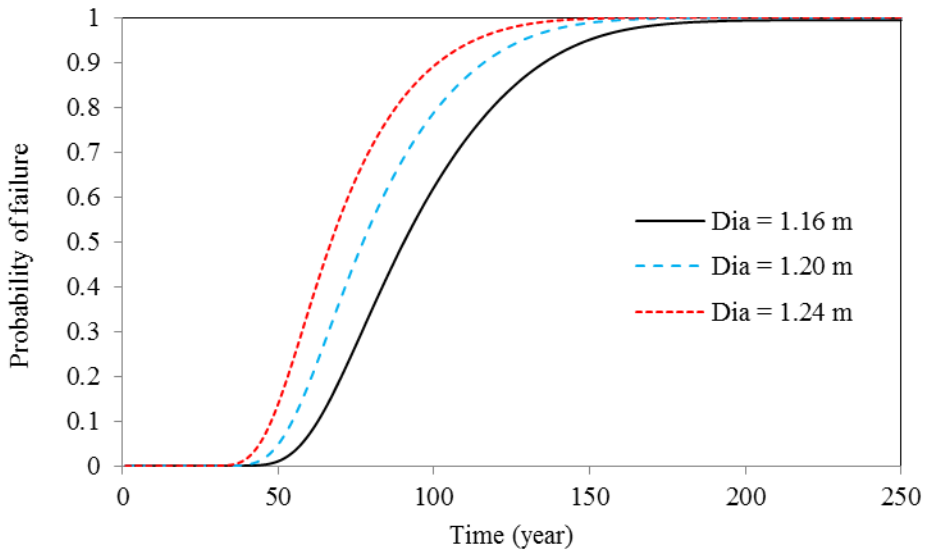


Figure 3.30: Probability of failure for different pipe diameters due to corrosion induced bending

3.6.4.3 Soil height

Like pipe diameter, backfill height also affects the pipe failure rate. The probability of failure for every 250 mm change of soil height has been estimated, i.e., soil height of 3.25 m, 3.50 m and 3.75 m using the above mentioned failure criteria. The results for all failure cases are shown in Figures 3.31 – 3.34. The failure case due to excessive deflection and wall thrust show the largest effect due to changes in soil height. This makes sense because soil height has the most influence on wall thrust compare to others. With increasing the backfill height, this will increase soil pressure or overburden pressure and further reduce the service life of the pipe. Thus, failure rate increases with increasing the soil height above the pipe invert. This leads to the same conclusion given by Davis et al (2001) in investigating the effect of soil depth on sewer structural condition and reliability.

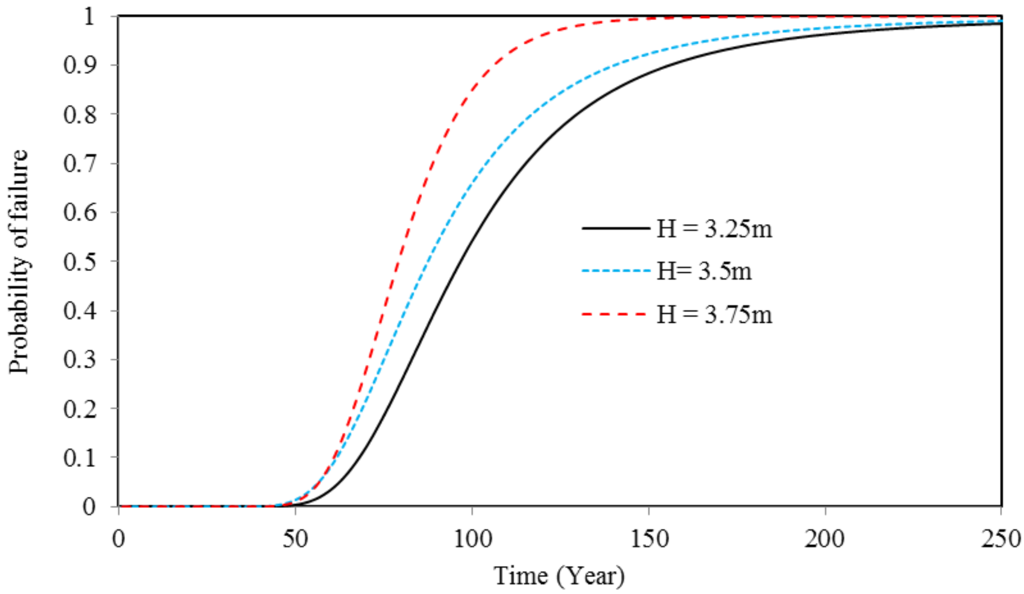


Figure 3.31: Probability of failure for different backfill heights due to corrosion induced deflection

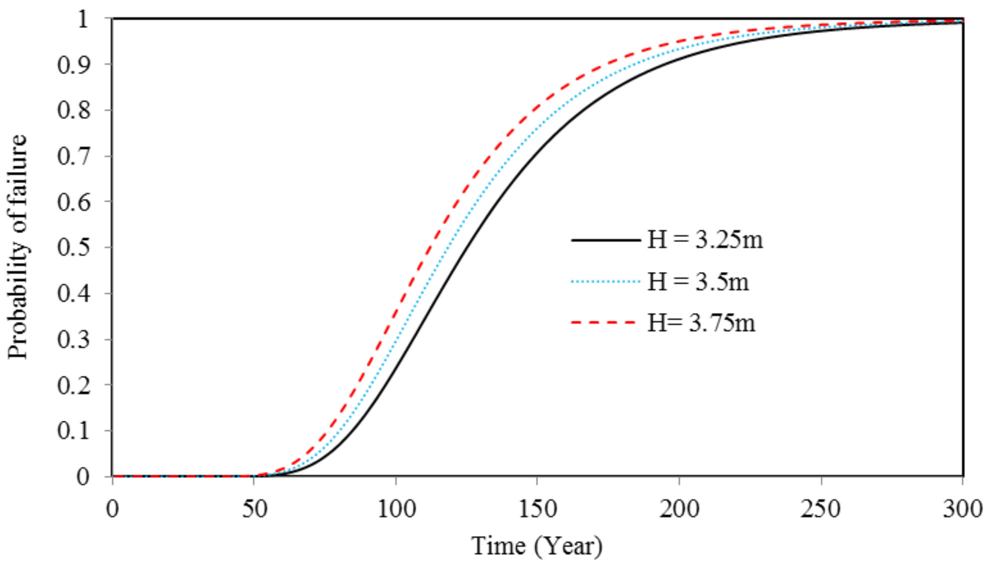


Figure 3.32: Probability of failure for different backfill heights due to corrosion induced buckling

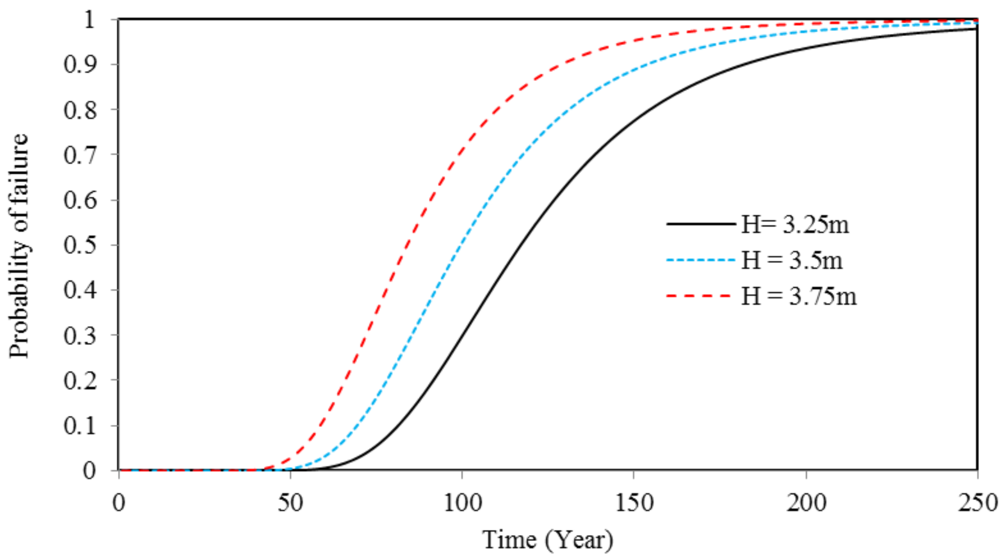


Figure 3.33: Probability of failure for different backfill heights due to corrosion induced wall thrust

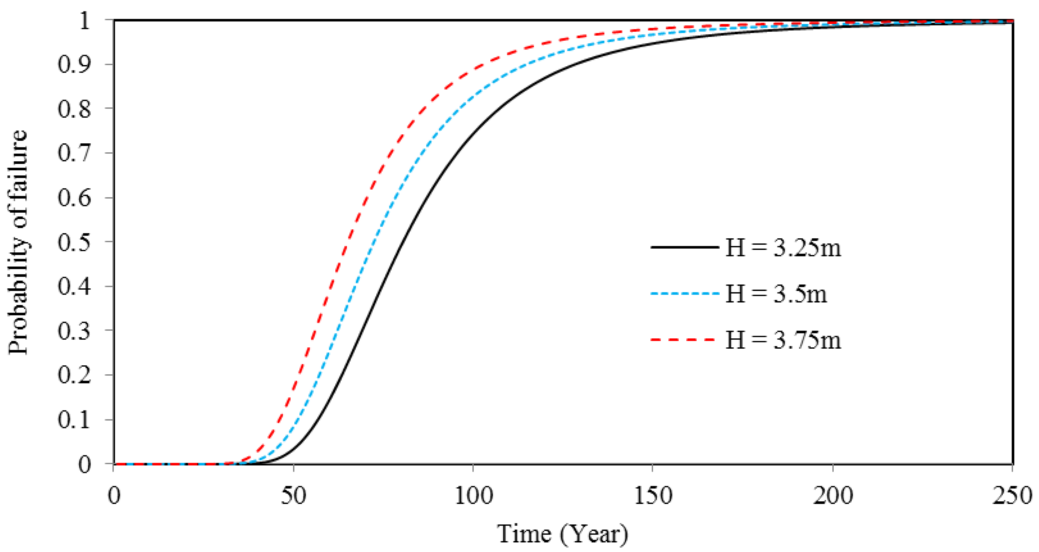


Figure 3.34: Probability of failure for different backfill heights due to corrosion induced bending

3.6.5 Sensitivity analysis

In addition to the parametric studies above, sensitivity analysis has also been carried out to evaluate the relative contribution of each random variable (listed in Table 3.2) in the four limit state functions using Eq. (3.23) in MATLAB software. The analysis shows that soil (backfill) density (γ), soil modulus (E_s), wheel load (P_s), multiplying constant (k), exponential constant (n) and pipe thickness (t) are among larger contributors and on the other hand, elastic modulus of pipe material (E), deflection coefficient (K_b) and soil height above pipe invert (H) have minor contribution to the pipes reliability.

At the early stage of the pipe service life, the impact of multiplying constant has average 10% contribution for pipe failure due to corrosion induced deflection, wall thrust and bending and sharply increase to 35% about 25 years of the pipe life and then this contribution slightly decreases over time. In this case, multiplying constant has 5% impact for corrosion induced buckling failure at the beginning and 25% about 25 years of pipes service life. The sensitivity of the exponential constants in Eq. (3.1) have zero impact and increases significantly with the pipe age for all the four failure criteria as shown in Figure 3.35. This is attributed to the fact that corrosion does not cause any problem to new pipes but mainly the root cause of failure and collapse for aging and external loadings on pipes. The sensitivity analysis also shows that soil modulus has zero impact on the failure due to excessive wall thrust as shown in Figure 3.37, because it does not appear in Eqs. (3.12) and (3.13). In contrast, soil density, live load and backfill have the largest impact on the corrosion induced wall thrust failure as shown in Figures 3.38, 3.39 and 3.42, respectively. The soil modulus, live load and thickness of the pipe have the major contribution and the soil density, pipe elasticity modulus, soil height have the insignificant impact on the corrosion induced buckling failure (Figures 3.37 – 3.42).

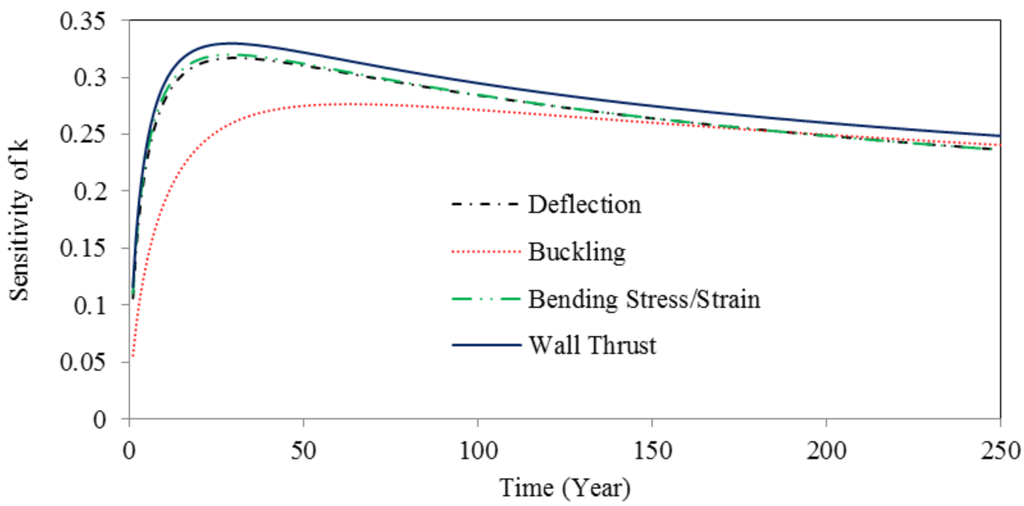


Figure 3.35: Sensitivity of multiplying constant for limit states during pipe service life

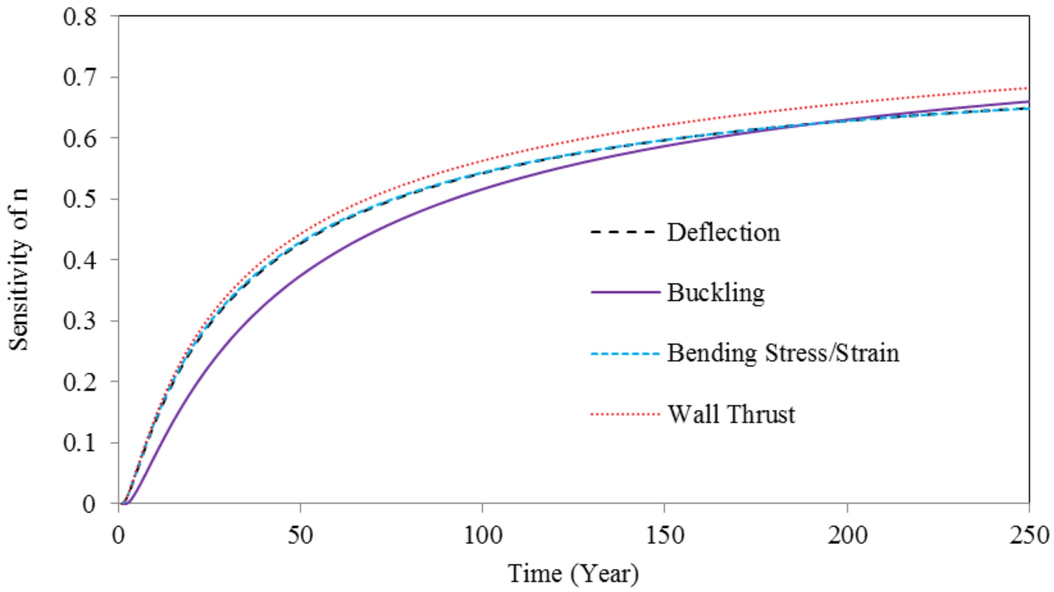


Figure 3.36: Sensitivity of exponential constant for limit states during pipe service life

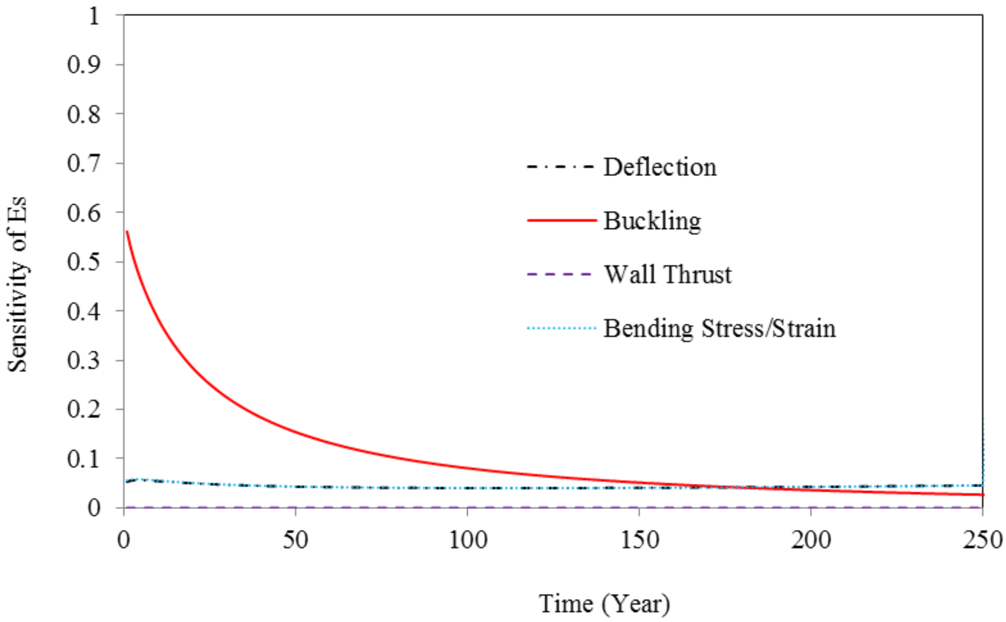


Figure 3.37: Sensitivity of soil modulus for limit states during pipe service life

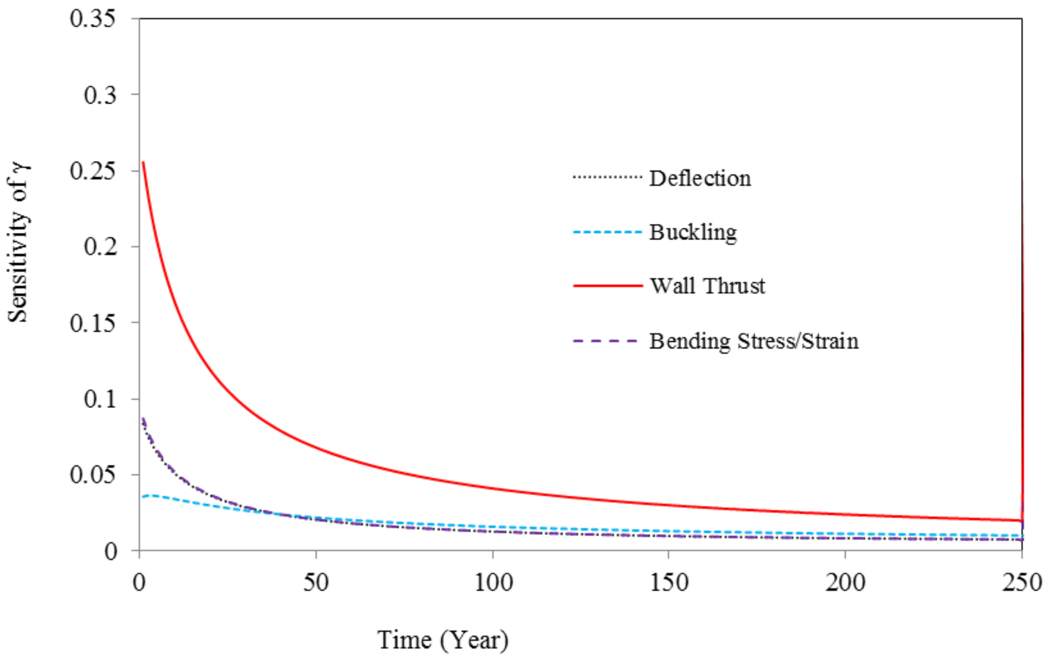


Figure 3.38: Sensitivity of soil density for limit states during pipe service life

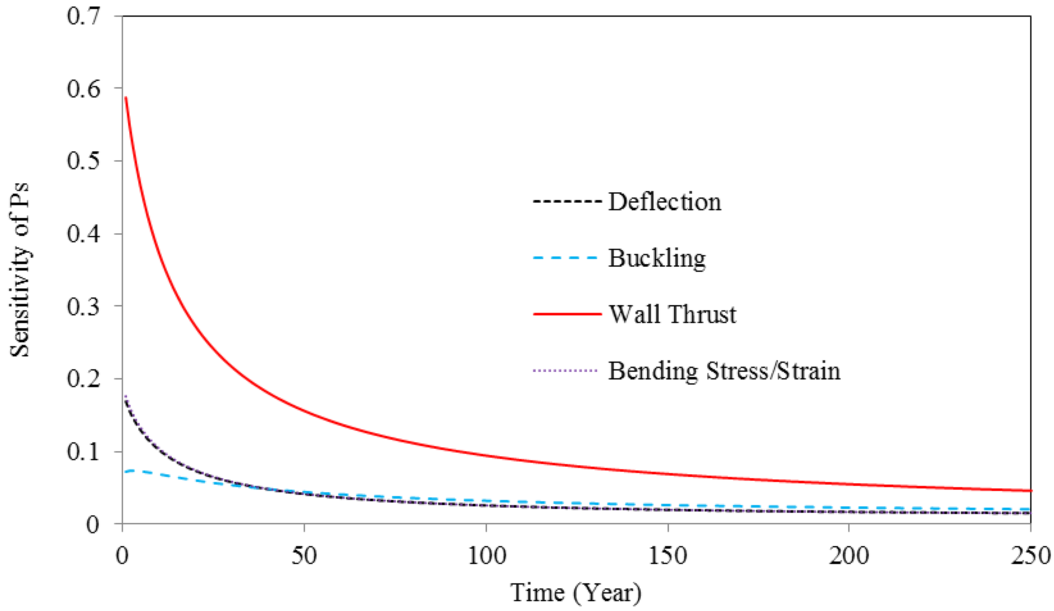


Figure 3.39: Sensitivity of live load for limit states during pipe service life

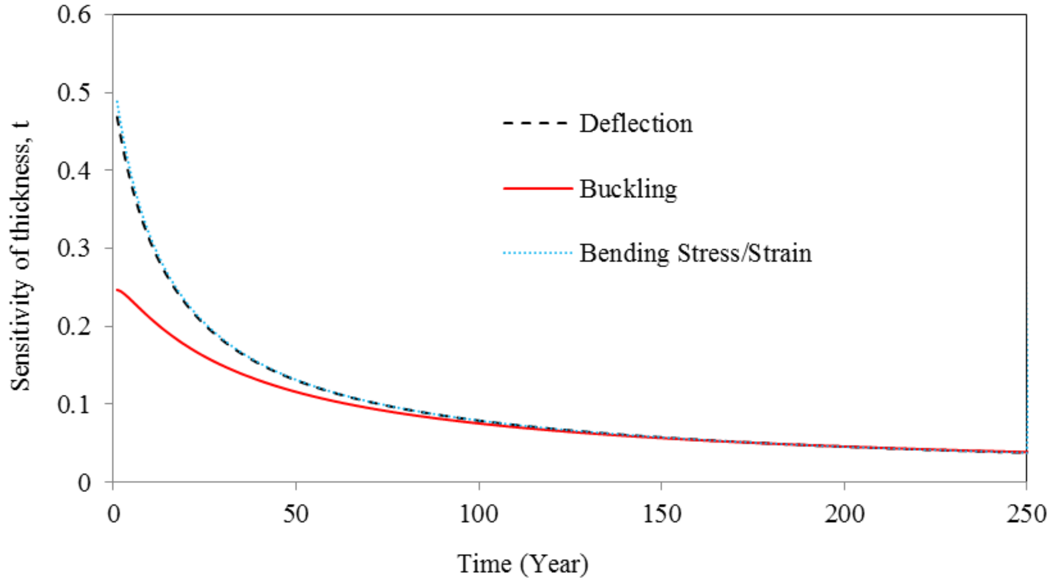


Figure 3.40: Sensitivity of pipe wall thickness for ultimate limit states during pipe service life

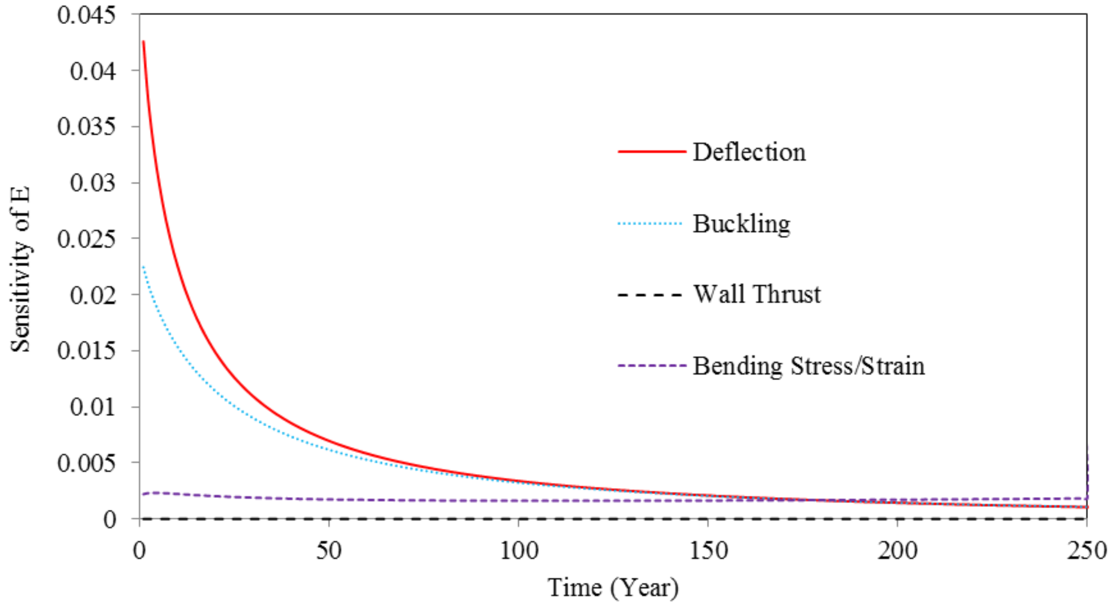


Figure 3.41: Sensitivity of pipe elastic modulus for limit states during pipe service life

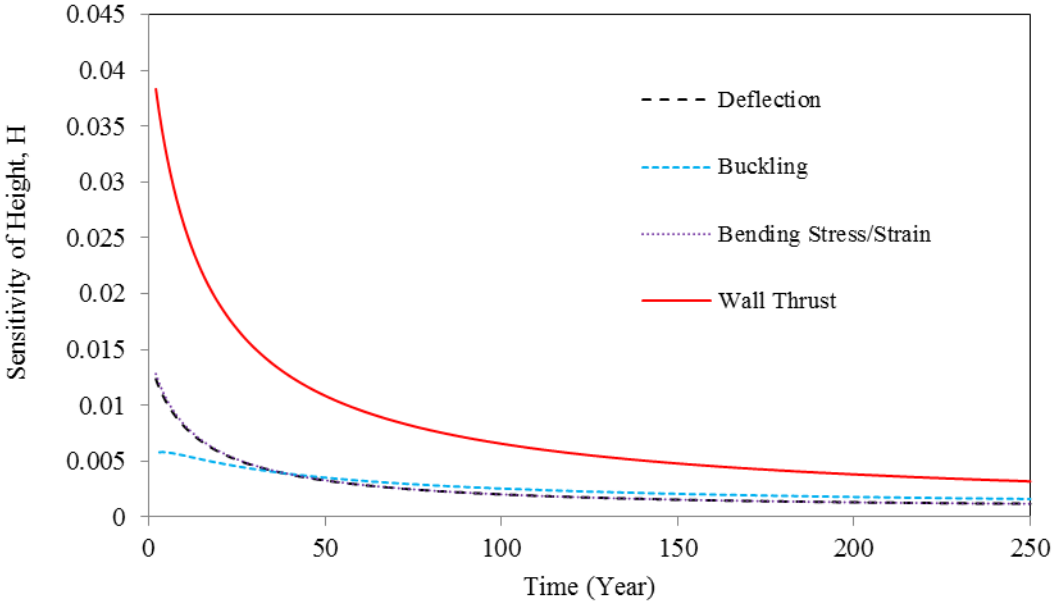


Figure 3.42: Sensitivity of backfill height for limit states during pipe service life

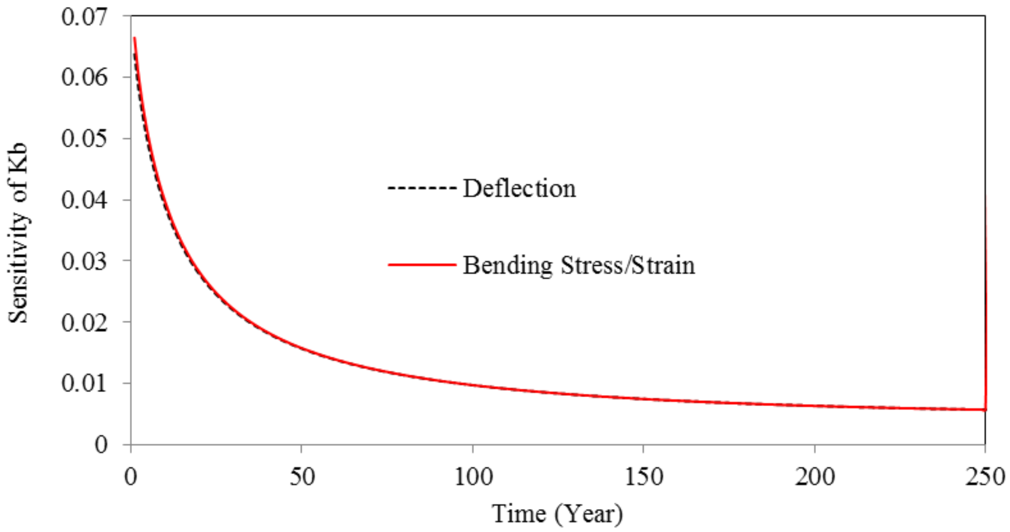


Figure 3.43: Sensitivity of deflection coefficient for limit states during pipe service life

The sensitivity analysis shows that failure due to corrosion induced deflection and bending, soil density, live load and pipe thickness have the more influence than the pipe elasticity modulus and backfill height with respect to time. Deflection coefficient has no impact on buckling and wall thrust failure as it is not applicable (not seen in Eqs. 3.10 – 3.13) for buckling and wall thrust. Only it influences the deflection and bending and the effect is very low (Figure 3.43).

3.7 SUMMARY

A reliability analysis of flexible underground metal pipeline has been presented in this Chapter using HL-RF algorithm and Monte Carlo simulation due to corrosion induced deflection, buckling, wall thrust and bending. The results suggested that excessive bending is the most critical failure mode whereas buckling is the least susceptible during the whole service life of the pipe. Correlation among the failure modes are predicted in this study. The results show that these failure modes are strongly correlated (≈ 1). Correlation between random variables, namely, soil density and soil modulus as well as loading and pipe stiffness with known correlation coefficients in different failure modes have been assessed with varying time. The study shows that the probability of failure due to corrosion induced wall thrust is lower when soil modulus and soil density are positively correlated whereas it is higher when loading and pipe stiffness are negatively correlated due to corrosion induced bending stress. In addition, parametric study and sensitivity analysis have been performed to analyse the effect of the design variables on the reliability of the flexible underground metal pipeline system. The parametric analysis shows that behaviour of buried pipes is considerably influenced by uncertainties due to external loads, corrosion parameters, and surrounding soil properties. The sensitivity analysis reveals that among all random variables in reliability prediction, the relative contribution of the corrosion parameters, such as multiplying constant, k and exponential constant, n are highly remarkable. Note that the results and observations are valid within the considered distributions of random variables. The proposed approach can significantly help decision makers in the assessment of safety and performance of buried pipelines.

CHAPTER FOUR

STRUCTURAL RELIABILITY ANALISIS USING SUBSET SIMULATION

4.1 INTRODUCTION

Structural reliability algorithms have been received greater attention over the world, though prediction techniques of small failure probabilities are very few till now. In recent years, attention has been focused on reliability problems with complex system characteristics in high dimensions, i.e., with a large number of uncertain or random variables (Schueller and Pradlwarter, 2007). Prediction of small failure probabilities is one of the most important and challenging computational problems in reliability engineering (Zuev et al, 2012). The probabilistic assessment of engineering systems may involve a significant number of uncertainties in their behaviour. To implement probabilistic assessment for an engineering system, main difficulties arise from: (1) the relationship between the random variables, (2) too many random variables involved, (3) information about rare scenarios and (4) many interactive response variables in the description of performance criteria (Tee et al, 2013b).

Like other engineering systems, reliability analysis of buried pipeline systems are characterised by a large number of degrees of freedom, time-varying and response dependent nonlinear behaviour. In the presence of uncertainty, the performance of an underground pipeline can be quantified in terms of 'performance margin' with respect to specified design objectives. In reliability engineering, 'performance margin' is denoted as reliability index, probability of failure, safety margin, etc. Failure events in pipe reliability analysis can be formulated as exceedance of a critical response variable over a specified threshold level. By predicting pipeline reliability, the safe service life can be estimated with a view to prevent unexpected failure of underground pipelines by prioritising maintenance based on failure severity and system reliability (Tee and Li, 2011; Khan et al, 2013).

There is no general algorithm available to estimate the reliability of a buried pipeline system. The pipeline reliability is usually given by an integral over a high dimensional uncertain parameter space. Methods of reliability analysis such as FORM, SORM, PEM, MCS, PDEM, etc. are available in literature (Babu and Srivastava, 2010; Tee et al, 2011; Fang et al, 2013a, 2013b). In this context, a robust uncertainty propagation method whose applicability is insensitive to complexity nature of the problem is most desirable. Many methods are inefficient when there are a large number of random variables and/or failure probabilities are small. Moreover, some methods need a large number of samples which is time-consuming.

Advanced Monte Carlo methods, often called ‘variance reduction techniques’ have been developed over the years. In this respect, a promising and robust approach is Subset Simulation (SS) which is originally developed to solve the multidimensional problems of engineering structural reliability analysis (Au and Beck 2001; Au et al, 2007; Tee et al, 2014a). A structural system fails when the applied load or stress level exceeds the capacity or resistance. SS is well suited for quantitative analysis of functional failure systems, where the failures are specified in terms of one or more safety variables, e.g., temperatures, pressures, flow rates, etc. In the SS approach, the functional failure probability is expressed as a product of conditional probabilities of adaptive chosen intermediate events. The problem of evaluating small probabilities of functional failures is thus tackled by performing a sequence of simulations of more frequent events in their conditional probability spaces; then the necessary conditional samples are generated through successive Markov Chain Monte Carlo (MCMC) simulations in a way to gradually populate the intermediate conditional regions until the final functional failure region is reached (Zio and Pedroni, 2008). The SS can provide better resolution for low failure probability level with efficient investigating of rare failure events which are commonly encountered in pipeline engineering applications. In SS method, random samples leading to progressive failure are generated efficiently and they are used for computing probabilistic performance measured by statistical variables. It gains its efficiency for small probability prediction as a product of a sequence of intermediate events with larger conditional probabilities.

Many researchers, such as Au and Beck (2001), Au et al (2007), Ching et al (2005), Song et al (2009) and Zhao et al (2011) have used SS in reliability analysis of engineering structures, such as bridges and buildings. This Chapter focuses on application of SS for computing time-dependent reliability of flexible buried metal pipelines. Failure probabilities for corrosion induced multi-failure events, namely deflection, buckling, wall thrust and bending have been predicted in this study. Firstly, the SS is applied for estimating the failure probabilities for each failure case individually and then due to multi-failure modes, an upper and lower bounds of failure probabilities are predicted as a series system. Besides that, coefficients of variation (Covs) and a sensitivity analysis of pipe failure due to corrosion induced deflection, as an example of failure event, have also been assessed to illustrate the robustness and effectiveness of SS method. The application of SS method is verified with respect to the standard MCS.

The contents of this Chapter are structured as follows. The basic equations, methodology and advantages of SS are discussed in Section 4.2. In Section 4.3, a numerical example is presented to validate the methodology and to scrutinise the effectives of SS. Results and discussion are presented in Section 4.3.1. A real case study has also been presented in this study in Section 4.4 and results are presented in Section 4.5. At the end concluding remarks are made in Section 4.6.

4.2 RELIABILITY PREDICTION

4.2.1 Basic Equations for Subset Simulation

Subset Simulation is an adaptive stochastic simulation procedure for efficiently computing a small failure probability. For simplification, *F* is denoted as the failure event as well as its corresponding failure region in the uncertain parameter space. Given a failure event *F*, let $F_1 \supset F_2 \supset F_3 .... \supset F_m = F$. If the failure of a system is defined as an exceedance of one uncertain demand *Y* over a given capacity y, that is $F = (Y > y)$, then a sequence of decreasing failure events can simply be defined as $F_i = \{Y > y_i\}$ where $0 < y_1 < y_2 < y_3 < \cdots\cdots < y_m = y$ and *i*= 1, 2, 3,...,*m* where *m* is the number of conditional events. In this study, *Y* is the actual value of structural performance such as corrosion-induced deflection, buckling, wall thrust or bending stress whereas *y* represents the allowable or critical limit for the considered failure modes. A conceptual illustration of the SS method is presented in Figure 4.1 for a two-dimensional case (Song et al, 2009).

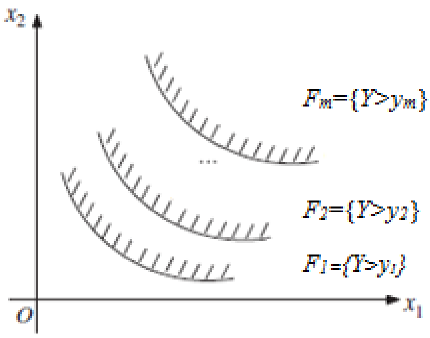


Figure 4.1: Illustration of failure events in SS method

The probability of failure (P_f) can be calculated based on the above sequence of failure domains (or subsets) which enables computation of P_f as a product of conditional probabilities $P(F_1)$ and $P(F_{i+1} | F_i)$ as follows (Schueller and Pradlwarter, 2007; Phoon, 2008).

$$P_f = P(F_m) = P(F_m | F_{m\text{-}1})P(F_{m-1} | F_{m-2})......P(F_2 | F_1)P(F_1)$$

$$= P(F_1)\prod_{\mathrm{i}=1}^{m\text{-}1} P(F_{i+1} | F_{\mathrm{i}}) \tag{4.1}$$

When $P(F_1)$ is denoted by P_1 and $P(F_i | F_{i-1})$ for $i = 2,3,....m$ is denoted by P_i, Eq. (4.1) expresses the failure probability as a product of conditional probabilities P_1 and P_i $(i = 2,3,...,m)$. In the first step, it is natural to compute conditional failure probabilities based on an estimator similar to Eq. (4.2), which requires simulation of samples according to the conditional distribution θ that lies in F_i (Au and Beck, 2001). The probability P_1 can be determined by application of the direct MCS simulation as shown in Eq. (4.2).

$$P_1 = \frac{1}{N_1}\sum_{k=1}^{N_1} I_{F_1}(\theta_k^{(1)}) \tag{4.2}$$

where $\theta_k^{(1)}(k = 1,2,3,......, N_1)$ are independent and identically distributed samples simulated according to probability density function (PDF) *q*. $I_{F_1}(\theta_k^{(1)})$ is an indicator function, when $\theta_k^{(1)} \in F_1$, $I_{F_1}(\theta_k^{(1)})$=1, otherwise 0.

The conditional distribution of θ lies in F_i, that is $q(\theta | F_i) = q(\theta) I_{F_i}(\theta) / P(F_i)$. Computing the conditional probabilities, Markov Chain Monte Carlo (MCMC) simulation provides a powerful method for generating conditional samples on the failure region (Au and Beck, 2001; Au and Beck, 2003). With the application of the MCMC simulation by the modified Metropolis-Hastings algorithm, samples can be generated as follows.

$$P_i = \frac{1}{N_i} \prod_{k=1}^{N_i} I_{F_i}(\theta_k^{(i)}) \qquad (i = 2,3,....,m) \tag{4.3}$$

where $\theta_k^{(i)}(k = 1,2,3,......, N_i; i = 2,3,....,m)$ are independent and identically distributed conditional samples. $I_{F_i}(\theta_k^{(i)})$ is an indicator function which is equal to 1 when $\theta_k^{(i)} \in F_i$, otherwise 0.

Based on Eqs. (4.2) and (4.3), Eq. (4.1) can be rewritten as follows

$$P_f = \frac{1}{N_1} \sum_{k=1}^{N_1} I_{F_1}(\theta_k^{(1)}) \prod_{i=1}^{m-1} \frac{1}{N_i} \prod_{k=1}^{N_i} I_{F_i}(\theta_k^{(i)}) \tag{4.4}$$

On the basis of reliability analysis using SS, the failure probability P_f can be transformed into a set of conditional failure probabilities P_i (i =1, 2, 3,…,m). Based on Eq. (4.4), the partial derivative of the failure probability with respect to distributional parameter α (the mean μ or the standard deviation σ) of normal random variables can be obtained, which is so-called reliability sensitivity as shown in Eq. (4.5) (Song et al, 2009).

$$\frac{\partial P_f}{\partial \alpha} = \sum_{i=1}^{m} \frac{P_f}{P_i} \frac{\partial P_i}{\partial \alpha} \tag{4.5}$$

Reliability sensitivity analysis can reflect the significance of the distributional parameter with respect to the failure probability. According to sample means, reliability sensitivity of Eq. (4.5) for each variable can be obtained using Eqs. (4.6) and (4.7) as follows (Song et al, 2009; Tee et al, 2014a).

$$\frac{\partial(P_1)}{\partial\alpha} = \frac{1}{N_1}\sum_{k=1}^{N_1}\left[\frac{I_{F_1}(\theta_k^{(1)})\partial q(\theta_k^{(1)})}{q(\theta_k^{(1)})\partial\alpha}\right] \tag{4.6}$$

$$\frac{\partial(P_i)}{\partial\alpha} = \frac{1}{N_i}\sum_{k=1}^{N_i}\left\{I_{F_i}(\theta_k^{(i)})\left[\frac{1}{q(\theta_k^{(i)})}\frac{\partial q(\theta_k^{(i)})}{\partial\alpha} - \sum_{j=1}^{i-1}\frac{1}{P_j}\frac{\partial P_j}{\partial\alpha}\right]\right\} \tag{4.7}$$

4.2.2 Methodology

Subset Simulation expresses the failure probability as a product of larger conditional failure probabilities for a sequence of intermediate failure events, thereby converting a rare event simulation problem into a sequence of more frequent ones (Au et al, 2007). During the simulation process, the conditional samples are generated from specially designed Markov chains (MC), so that they gradually populate each intermediate failure region until they reach the final target failure region (Au and Beck, 2001). In this study, the intermediate threshold values are chosen adaptively in such a way that the estimated conditional probabilities are equal to a fixed value which is $p_0 = 0.1$ (Au and Beck, 2001; Au and Beck, 2003; Zio and Pedroni, 2008).

Procedure of SS algorithm for adaptively generating samples corresponding to specified target probabilities can be summarised as flow diagram as shown follows:

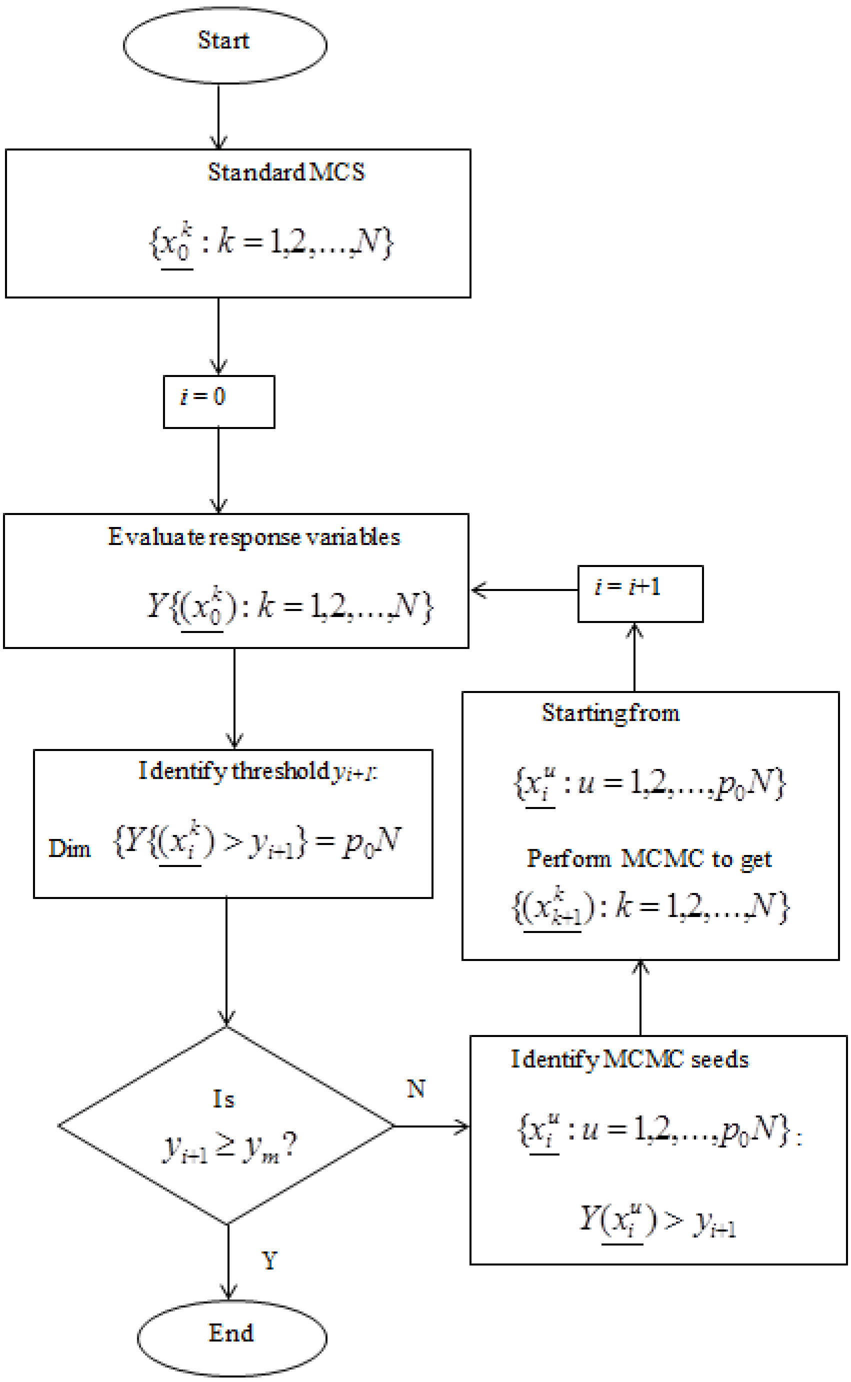


Figure 4.2: Flow diagram for SS method

4.2.3 Advantages of Subset Simulation

Estimating small failure probabilities to precisely assess the risk involved in a system remains quite a challenging task in structural reliability engineering. FORM, SORM or PEM are suitable solutions to estimate reliability of large-scale systems (Tee et al, 2013b). Due to their inherent assumptions, these methodologies are sometimes lead to incorrect results which are involved with multiple design points and/or non-smooth failure domains. On the other hand, MCS is a traditional simulation algorithm to compute failure probabilities in structural systems, which in spite of being robust to solve the problem; it becomes computationally expensive where small failure probabilities to be calculated, since it requires a large number of evaluations of the system to achieve a suitable accuracy.

SS requires much less samples to achieve a given accuracy. It can be used to obtain conditional samples in each simulation level to compute efficiently the probabilities related to rare events in reliability problems with complex system characteristics and with a large number of uncertain or random variables in failure events. Choosing the intermediate failure events $F_i (i = 1,2,3,...,m)$ appropriately, the conditional probabilities involved in Eq. (4.1) can be made sufficiently by subset simulation process (Ching et al, 2005). For example, probability of failure $P_f = 10^{-4}$ is too small for efficient estimation by direct Monte Carlo simulation. However, the conditional probabilities, which are the order of 0.1, can be evaluated efficiently by simulation because the failure events are more frequent as supported by the results in Figure 4.8. The problem of simulating the rare events in the original probability space is thus replaced by a sequence of simulations of more frequent events in the conditional probability spaces.

4.3 NUMERICAL EXAMPLE

The time-dependent structural reliability for an underground flexible metal pipe has been predicted in this example, where pipe failure probability, sensitivity and Cov analysis are conducted by applying SS and MCS. Calculations are presented for a buried steel pipe under a heavy roadway subject to corrosion and external loadings. A typical pipe section is shown in Figure 3.13 (Chapter Three). Numerical values are based on industrial practice and have been obtained from the literature (Ahammed and Melchers, 1997; Sadiq et al, 2004). The materials properties and parameters are listed in Table 3.1. There are 9 random variables where the means and Covs are listed in Table 3.2.

The pipe corrosion rate is modelled using Eq. (3.1). Assuming the change of pipe surface due to corrosion is uniform over the entire surface area. It is assumed that the pipe is thin-walled circular (plain) and placed above ground water level, i.e. H_w = 0. According to the references by Babu and Rao (2005) and Riha and Manteufel (2001), most of the random variables in Table 3.2 are normally distributed as these variables are found symmetric around their mean. However, the deflection coefficient (K_b) accounts for the bedding support which varies with the bedding angle and this variable's logarithm is found normally distributed.

4.3.1 RESULTS AND DISCUSSION

In the case of buried pipes, the assessment of P_f on yearly basis is useful because it enables calculation of reliability over time using the MATLAB software. The P_f for corrosion induced excessive deflection, buckling, wall thrust and bending stress with respect to time have been estimated using SS and MCS with material properties and random variables presented in Tables 3.1 and 3.2. In SS, the P_f is predicted as a sum of the sub failure events within each failure mode. The simple but pivotal idea behind SS is that a small failure probability can be expressed as a product of larger conditional failure probabilities for some intermediate failure events, suggesting the possibility of converting a problem involving rare events simulation into a sequence of problems involving more frequent events. SS is applied in this study with a conditional failure probability at each level equal to $p_0 = 0.1$. The total number of samples, N used in MCS is 10^6 for all the failure modes whereas SS needs 500 samples to achieve the similar accuracy of the results. The results presented in Figures 4.3 to 4.8 are in log scale of P_f to scrutinise the effectiveness of SS method in the region of small failure probability (< 0.1).

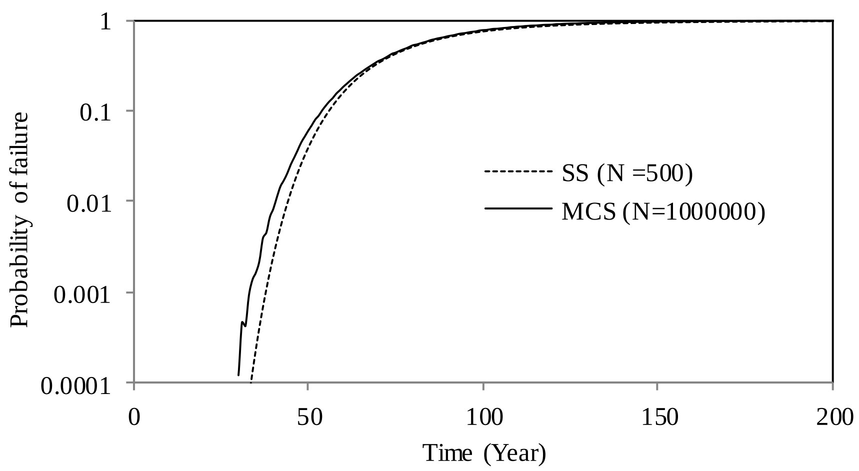


Figure 4.3: Probability of failure due to corrosion induced deflection using SS and MCS

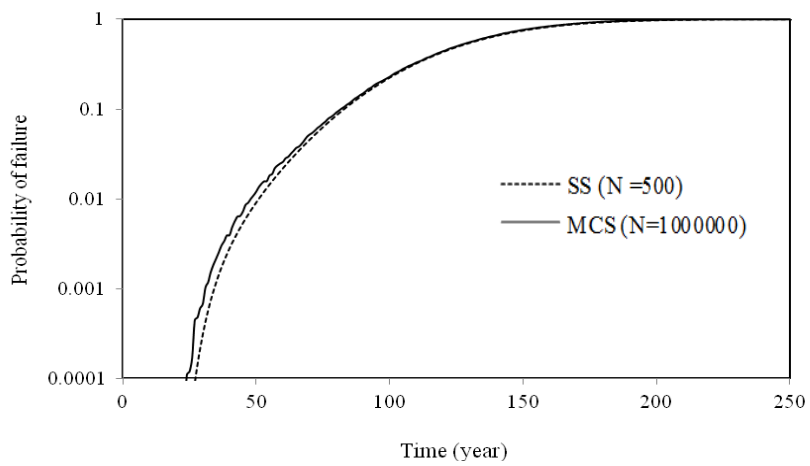


Figure 4.4: Probability of failure due to corrosion induced buckling using SS and MCS

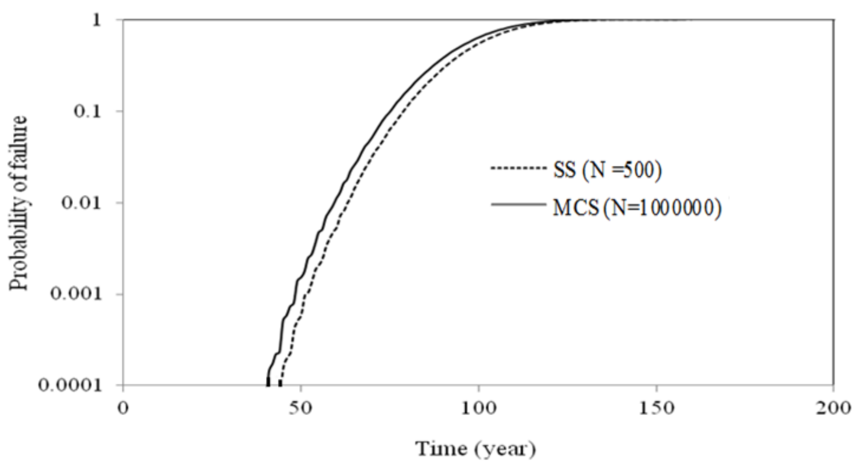


Figure 4.5: Probability of failure due corrosion induced wall thrust using SS and MCS

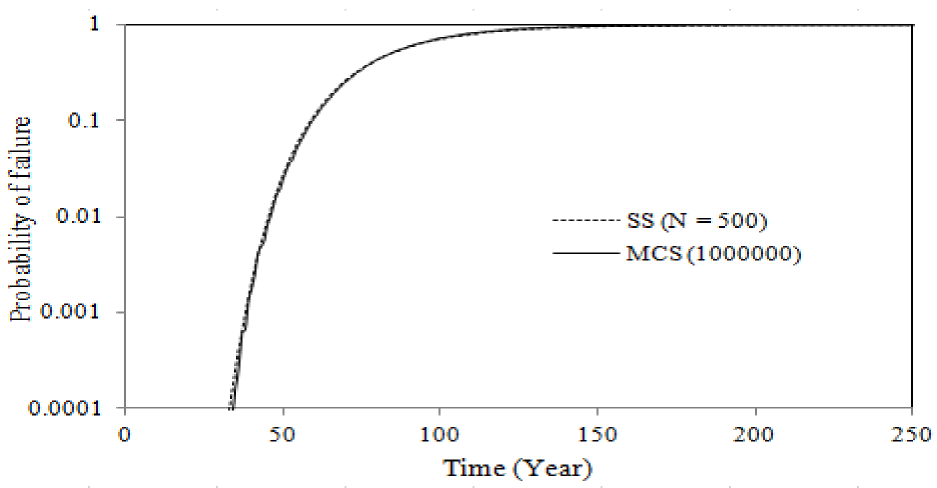


Figure 4.6: Probability of failure due corrosion induced bending stress or strain using SS and MCS

As shown in Figures 4.3 to 4.6, the results reveal that corrosion-induced excessive bending stress is the most critical failure event whereas buckling has the lowest P_f during the whole service life of the pipe. Considering the failure probability of 0.1 (10%) as a threshold level for the safe service life (Babu and Srivastava, 2010; Phoon, 2008), the study illustrates that the safe service life in the worst case scenario is about 50 years.

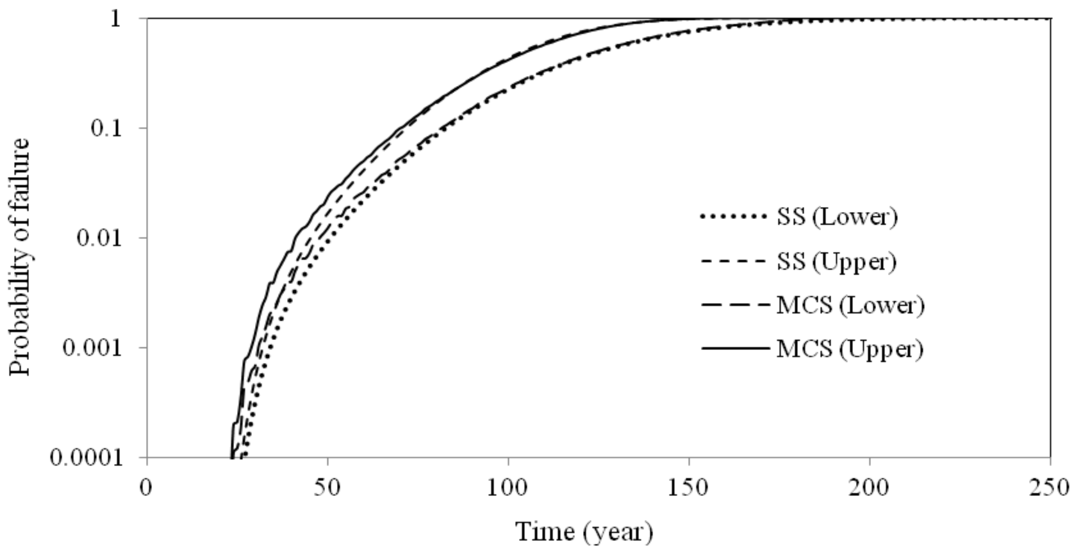


Figure 4.7: Probability of failure in series system due to corrosion induced multi-failure modes using SS and MCS

Pipeline contains multiple failure events in which any of the modes can lead to a system failure. The failure modes are correlated due to common random variables between the failure events. Therefore, a series system is considered for pipe failures prediction. The correlation coefficients between different failure modes show that all the failure modes are strongly correlated positively, i.e., where the failure modes might happen concurrently within a buried pipeline system (Tee and Khan, 2014). Thus, applying the theory of systems reliability, the probability of failure for a series system, P_f can be estimated by Eq. (3.32a) (Fetz and Tonon, 2008).

The expected value of P_f for series system is determined in-between upper and lower bounds and the results are shown in Figure 4.7. The number of conditional levels is chosen to cover the required response level whose failure probability is estimated. The results show that the P_f values using MCS and SS have a good agreement over the pipe service life.

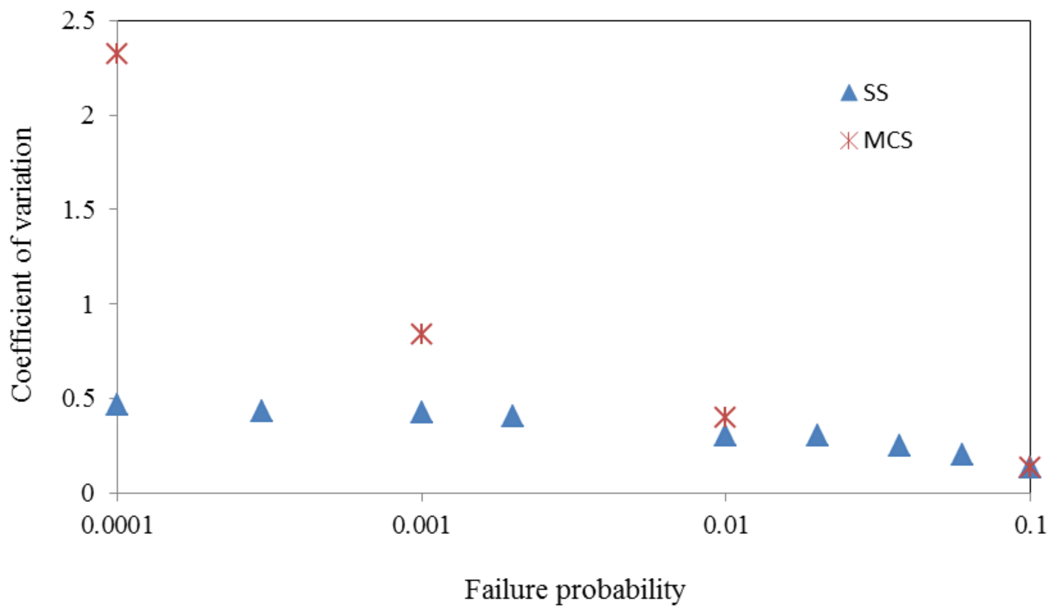


Figure 4.8: Cov of pipe failure probability due to corrosion induced deflection for 50-year of service life

Nevertheless, one of the advantages of SS over MCS is that SS is able to estimate small failure probability more efficiently which is demonstrated in Figure 4.8. In this analysis, the sample average values and Covs of failure probabilities are calculated using 50 independent runs. Coefficients of variation of failure probabilities due to corrosion induced deflection for

50-year of service life is plotted in Figure 4.8 for both SS and MCS. The results show that Covs achieved by SS and MCS are approximately the same in the large probability region. The values of Cov for SS and MCS coincide at $P_f = 0.1$, since according to the SS procedure with $p_0 = 0.1$, this probability is computed based on an initial MCS. The study shows that the Covs are increased with decreasing failure probabilities because it is more difficult to estimate smaller failure probability, which is the main concern of SS. The value of Cov estimated using SS are always less than that using MCS and the difference is larger when the failure probability is getting smaller as shown in Figure 4.8. Thus, it is inefficient to use ordinary MCS when the failure probabilities are small. SS is robust and more accurate and efficient compared to MCS in the prediction of small failure probabilities.

The improvement in accuracy also comes with considerable saving in computational time mainly due to smaller samples involved. The computational speed is measured in terms of Central Processing Unit (CPU) time on a 1.6-GHz Pentium IV personal computer. The study illustrates that SS (with 500 samples) needs 5–6 minutes to obtain the results whereas MCS (with 10^6 samples) spends 15–17 minutes to achieve the similar results. Therefore, on the same computer, the saving in computational time of SS is about 67% as compared to MCS, which indicates the supremacy and accurateness of the proposed SS method. The computational time for MCS is generally higher than SS due to the high number of samples needed.

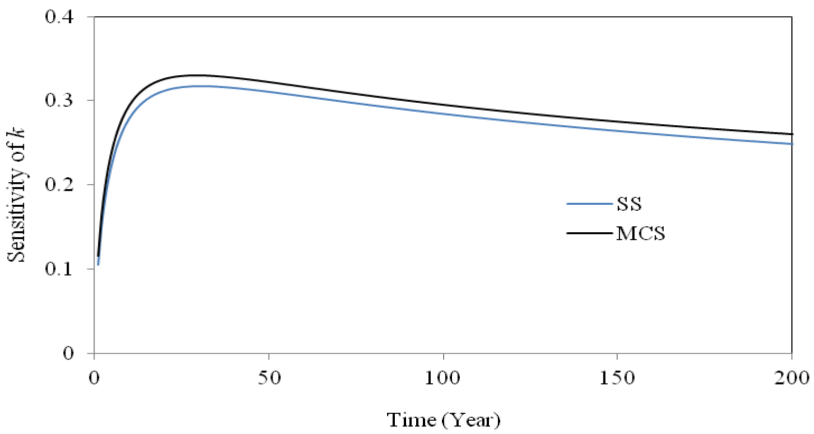


Figure 4.9: Sensitivity of multiplying constant (k) for corrosion induced deflection during pipe service life using SS and MCS

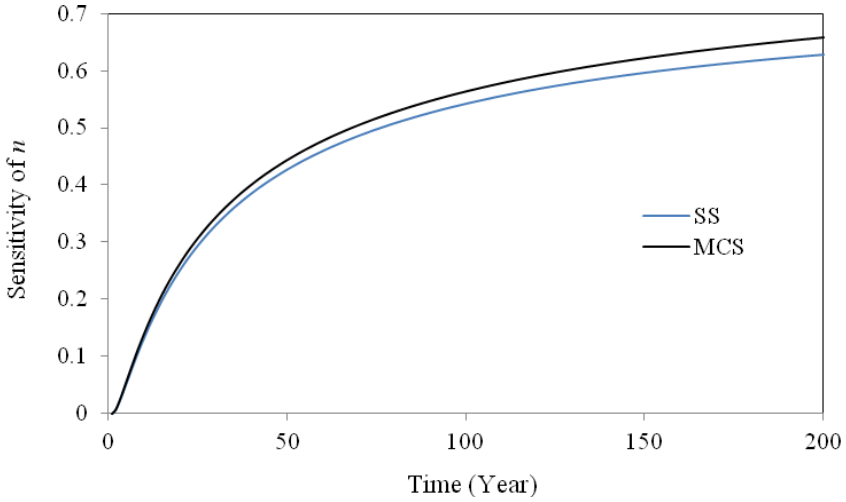


Figure 4.10: Sensitivity of exponential constant (*n*) for corrosion induced deflection during pipe service life using SS and MCS

Finally, two sensitivity analyses based on sample means are selected to evaluate the relative contribution of each random variable in pipe reliability estimation throughout the service life by applying Eqs. (4.5 – 4.7) and the results are shown in Figures 4.9 and 4.10. Note that for simplication, the Cov and sensitivity analyses have been presented only for failure due to corrosion induced deflection. Corrosion constants (multiplying constant, *k* and exponential constant, *n*) in Eq. (3.1) are considered as the dominant influencing parameters in pipe reliability (Tee et al, 2013a; Tee et al, 2014a). The study shows that, at the early stage of pipe service life, multiplying constant (*k*) and exponential constant (*n*) have a negligible effect on pipe reliability but the effect increases significantly with the pipe age as shown in Figures 4.9 and 4.10. The similar trend has been found for other failure criteria, i.e., buckling, wall thrust and bending stress. This is attributed to the fact that corrosion does not cause any problem to new pipes but is mainly the root cause of failure and collapse for aging pipes.

4.4 REAL CASE STUDY

The proposed approach has been applied for time dependent reliability analysis for a real case buried pipeline in Bergenfield, New Jersey, United States. New Jersey is a state in the North-eastern and Middle Atlantic regions of the United States. It is bordered on the north and east by New York State, on the southeast and south by the Atlantic Ocean, on the west by

Pennsylvania, and on the southwest by Delaware. The pipeline was a schedule 40 steel natural gas service line. The outside diameter was 4.24 cm and the inside diameter was 3.52 cm. The operating pressure was 79.3 kPa.

This pipeline was initially buried under asphalt pavement at an average depth of 0.838 m and extended from the gas main along the street to a three-story brick apartment building. Other data needed in the failure analysis that follows are the material properties of the steel pipeline. These properties include its tensile behaviour, on the basis of true stress of 483 MPa. Other parameters are listed in Table 4.1. There are 6 random variables where the mean and coefficient of variation are listed in Table 4.2. All the variables listed in Table 4.2 are normally distributed.

Table 4.1: Parameter values for real case study

Symbol description	Value
Buoyancy factor, R_w	1.00
Outside diameter of pipe, D_o	0.0424m
Inside diameter of pipe, D_i	0.0352 m
Pipe length, (L)	7.32 m
Deflection lag factor, D_L	1
Shape factor, D_f	4.0
Deflection coefficient, K_b	0.11
Capacity modification factor for soil, φ_s	0.90
Capacity modification factor for pipe, ϕ_p	1.00
Initial thickness of pipe, t	0.0036 m
Elastic modulus of pipe, E	207×10^6 kPa
Tensile strength of pipe, F_y	483 MPa
Allowable Strain, ε_{cr}	0.2%

Table 4.2: Statistical properties of random variables for real case study

Material properties	Mean (μ)	Cov (%)
Backfill soil modulus, E_s	2×10^3 kPa	5
Unit weight of soil, γ_s	23.5 kN/m^3	10
Live load, P_s	79.3 kPa	10
Multiplying constant, k	0.8	10
Exponential constant, n	0.5	5
Height of the backfill, H	0.838 m	15

The available data are collected from the National Transportation Safety Board (NTSB) and the U.S. Department of Transportation approached the National Institute of Standards and Technology (NIST) (NBS became NIST in 1988) (Ricker, 2010). In this case, the corrosion empirical constants, k and n are predicted based on available NIST studies conducted in between 1922 to 1940 and relevance to pipeline management in New Jersey, USA. Values for the basic data in the current study are presented in Tables 4.1 and 4.2.

Due to limitation of available real data, some numerical values are assumed, namely, buoyancy factor, deflection lag factor, and capacity modification factor for soil and pipe. These assumed parameter values are commonly used in buried pipeline industry. Due to randomness of the variables, the coefficients of variation are assumed based on engineering practice in real field (Ahammed and Melchers, 1997; Watkins and Anderson, 2000). The pipe is thin walled circular (plain) pipe and placed above ground water table.

4.5 RESULTS FROM REAL CASE STUDY

Three reliability analysis methods, Hasofer-Lind and Rackwitz-Fiessler algorithm, Subset Simulation (with 500 samples) and direct Monte Carlo Simulation (with 10^6 samples) methods are applied to predict the probability of failure over time. The dominating failure criteria of flexible pipes are characterised by corrosion induced excessive deflection, buckling, excessive wall thrust and bending stress. The results of failure probabilities are presented in Figures 4.11 – 4.14 for corrosion induced every failure mode for the above real case study.

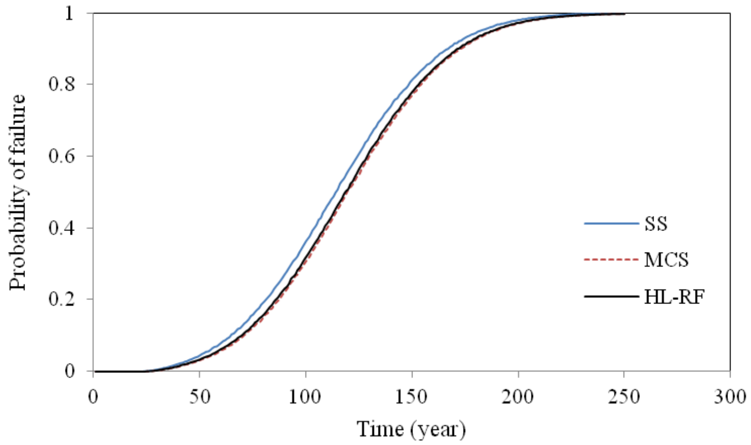


Figure 4.11*:* failure probability with respect to time due to corrosion induced deflection in case study

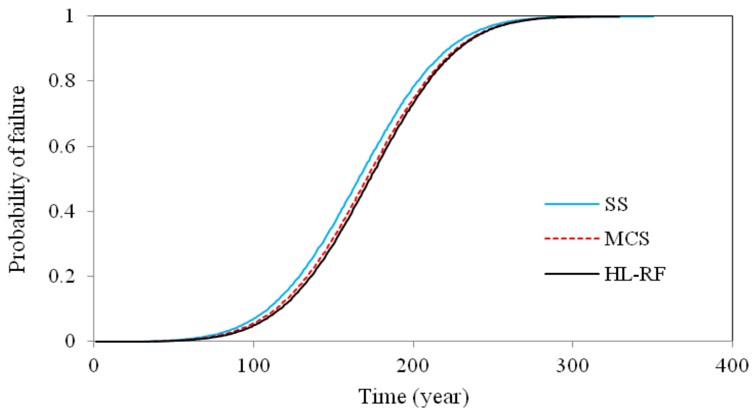


Figure 4.12: failure probability with respect to time due to corrosion induced buckling in case study

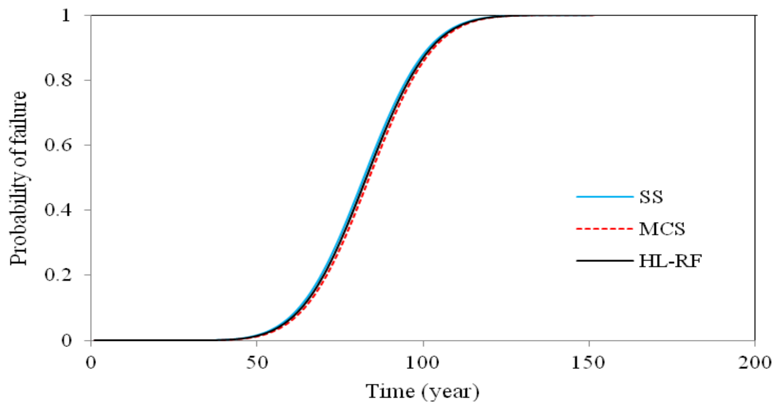


Figure 4.13: failure probability with respect to time due to corrosion induced wall thrust in case study

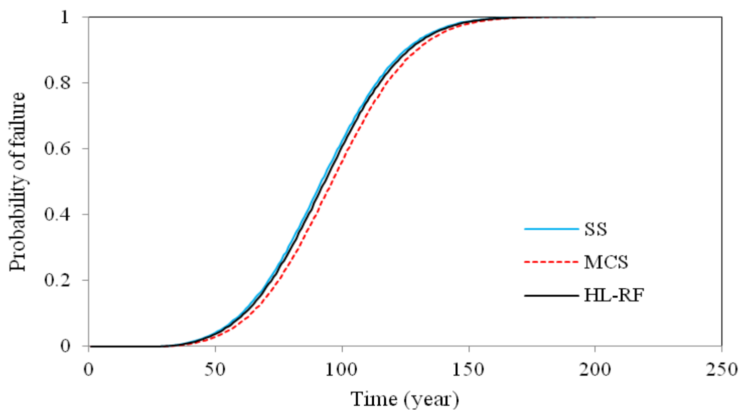


Figure 4.14: failure probability with respect to time due to corrosion induced bending stress in case study

The calculations are performed using the failure mode Equations as discussed in Chapter Three. The results of the probability of failure are presented in Figure 4.11 to 4.14 to compare the results obtained from the three different methods. The results reveal that the probabilities of failure predicted by the three methods (HL-RF, SS and MCS) applying modified failure modes of corrosion induced deflection, buckling, wall thrust and bending stress are in a reasonable good agreement.

The case study shows that corrosion induced excessive deflection is the most critical failure mode whereas wall thrust is the least susceptible failure mode over the whole service life of the pipe. Considering the failure probability of 0.1 (10%) as a threshold level for the safe service life (Tee et al, 2013a), the case study demonstrates that the safe service life in the worst case scenario is about than 60 years with respect to available soil and pipe materials parameters.

4.6 SUMMARY

A Subset Simulation approach is proposed for time-dependent reliability estimation of buried pipeline system subject to corrosion induced failures modes. The results show that this method is robust to the choice of the intermediate failure events. One of the major complications to estimating small failure probabilities is to simulate rare events. SS resolves this by breaking the problem into the estimation of a sequence of larger conditional probabilities. It is found that the reliability analysis calculated by SS is in good agreement with that from MCS, while the efficiency of the SS method, which is indicated by the sample size and computational time, is higher than that of MCS. The study also shows that SS is robust and more accurate than MCS in small failure probability prediction based on Cov analysis. The analysis shows that behaviour of buried pipes is considerably influenced by uncertainties due to external loads, corrosion parameters, pipe materials and surrounding soil properties etc. where excessive bending is the most critical failure mode whereas buckling is the least susceptible during the whole service life of the pipe. At the end, a real case study on pipeline reliability analysis also been conducted where probability of failure with respect to time is predicted using HL-RF, MCS and SS methods. The results show that there is a good agreement among the applied methods. In real case study the most dominating failure mode is excessive deflection and least is wall thrust during the service life. This demonstrates that the pipes dominating failure mode is not constant and it depends on the random variables and properties of pipe materials, soil properties and pipe thickness, etc.   The estimation of failure probability can be utilised to form a maintenance strategy and to avoid unexpected failure of pipeline networks during service life.

CHAPTER FIVE

APPLICATION OF *ROC* CURVE FOR PIPELINE RELIABILITY ANALYSIS

5.1 INTRODUCTION

Measuring the accuracy of a reliability analysis is an effective approach for enhancing the applicability and management process. Good methods for determining the threshold value for a pipe failure state provide a useful guidance on selection of the reliability prediction methods and compare different analysis techniques. Classical reliability theory and methodologies are rarely considered in the actual state of a system and therefore, these are not capable to reflect the dynamics of runtime systems and failure processes. Conventional methods are typically useful in design for long term or average behaviour predictions and comparative studies (Tee and Khan, 2013). But these are not good enough in the evaluation of the good accuracy in any crucial research and application areas, such as medicine, engineering construction, maintenance and data mining. Good accuracy provides useful guidance on selection of reliability assessment which has a direct impact on quality of care. One of the accuracy measurements of assessment methods is ‘Receiver Operating Characteristic (*ROC*) curve’ which is a statistical method applied for ordinal or continuous data, tends to use concepts like sensitivity and specificity to express the accuracy. If an analysis results have only two values, such as yes or no, plus or minus, 1or 0 etc., then these are called binary data. If the values are in a finite number of ordered, such as 1, 2, 3... or low, medium, large etc., are called ordinal data and if values are real data which are called continuous data.

ROC curve has been commonly used for describing the performance of medical tests for parametric (data rely on particular distribution, such as mean and standard deviation) and non-parametric (not rely on data belonging to any particular distribution) analysis. The *ROC* curve has also been used in many other areas, such as signal detection, radiology, machine learning, data mining and credit scoring. The authors Debon et al (2010) and Arian et al (1998) conclude by identifying a knowledge gap and research possibilities, mainly relating to data collection and how to best use the existing data for the development and calibration of predictive deterioration models, risk assessment methods, etc. However, no such works have been found on buried pipeline reliability analysis in literature, where time dependent multi-failure modes are considered. In this research, a *ROC* curve has been applied in buried flexible (steel) metal pipeline network where classical (or empirical) and Nonparametric Predictive Inference (*NPI*) technique are used for describing the performance of the reliability analysis for pipe failure due to corrosion induced deflection, buckling, wall thrust and bending stress.

In recent years, *NPI* has been developed as an alternative and frequent statistical framework method based on few modelling assumptions and considers one or more future observations instead of a population (Augustin and Coolen, 2004). It is a statistical method based on Hill'sassumption (Hill, 1968), which gives direct probabilities for a future observable random quantity, given observed values of related random quantities (Coolen-Maturi et al, 2011). *NPI* uses lower and upper probabilities for uncertainty quantification and has strong consistency properties within theory of interval probability (Augustin and Coolen 2004). From a statistics perspective, *NPI* is defined as a plot of analysis results as true positive fraction (*TPF*) or sensitivity along *y* coordinate versus false positive fraction (*FPF*) or its 1-specificity along *x* coordinate. Normally, *ROC* curve is useful in evaluating the discriminatory ability of an analysis, finding optimal cut-off point and comparing efficacy of two or more assessment or tests results.

The multiple time-dependent failure conditions for underground flexible metal pipelines, namely, corrosion induced deflection, buckling, wall thrust and bending are considered in this study. The formulations for pipeline failure are presented in Chapter Three. The loss of structural strength is due to corrosion through reduction of pipe wall thickness which then leads to pipe failure. Pipe wall thickness is considered as a key random variable and Monte Carlo simulation has been applied to generate the thickness data based on pipe material and soil parameters. Due to lack of real case data, the Monte Carlo simulation has been applied to generate pipe thickness data for deflection, buckling, wall stress or thrust and bending stress, using Eqs. (3.7) to (3.15), based on pipe material and soil parameters in Table 3.1 and 3.2. In this analysis, 100 years of service life has been chosen for the study. However, any service life time can be chosen in this analysis. When the results of the actual value of the pipe condition (deflection, buckling, bending, etc.) are greater than threshold value or allowable limit, then this indicates failure condition and if the actual value is smaller than the allowable limit, then it indicates non-failure condition. However, in reality, pipelines may not follow the predicted pipe conditions which are estimated according to the applied formulas as mentioned in Chapter Three. Different researchers, such as Gustafson and Clancy (1999), Kettler and Goulter (1985), Mailhot et al (2000) showed that there were 10% to 20% discrepancies in the actual and the estimated pipe conditions measured by available models (Cox's proportional hazards model, Weibull and exponential distributions, etc.). Therefore, it is assumed that, these estimated data are not 100% accurate and there are up to 30% failure and non-failure condition data are incorrect in this analysis (for worst case scenario). According to these considerations the aim of this Chapter can be summarised as follows:

(a) To assess the accuracy of the buried pipeline reliability estimation for pipe condition data due to corrosion induced deflection, buckling, wall thrust and bending stress using *ROC* curve.

(b) To identify the underground pipeline failure-prone situations, i.e. the threshold value for different failure modes.

The contents of this Chapter are structured as follows. The basics of receiver operating characteristics (*ROC*) curve are studied in Section 5.2, where classical *ROC* and *NPI* for *ROC* curve are briefly discussed. In Section 5.3, a numerical example is considered for pipeline reliability accuracy prediction in *ROC* curve. The results and discussion are presented for different failure modes in Section 5.4. Finally, conclusions are made on basis of outcomes in this study in Section 5.5.

5.2 BASIC OF *ROC* CURVE

ROC curves are two-dimensional graphs that visually depict the performance and performance trade-off of a classification model (Zhou et al, 2002). *ROC* curves are originally designed as a tool to distinguish between the actual results and analytical results. Sensitivity and specificity, which are defined as the number of true positive decisions (the number of actually positive cases) and the number of true negative decisions (the number of actually negative cases), respectively, constitute the basic measures of performance of *ROC* curve. A *ROC* curve displays the full picture of trade-off between the true positive fraction (*TPF*) or sensitivity and false positive fraction (*FPF*) or 1 – specificity across a series of cut-off points. Area under the curve is considered as an effective measure of inherent validity of an analysis or experimental result. It is a very powerful tool to measure the accuracy of analysis results and commonly used in medical field but currently *ROC* curves are also using in other fields, such as engineering and agricultures.

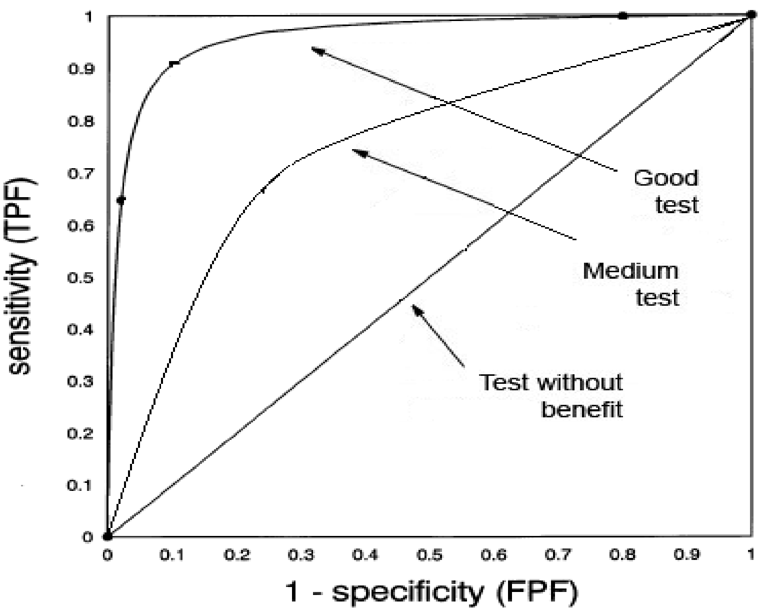


Figure 5.1: Basic of a typical *ROC* Curve (Arian et al, 1998)

A *ROC* curve is applicable only for continuous data or at least ordinal data. A classification model classifies each instance into one of two classes; say a true and a false class. This rise to four possible classifications for each instance: (1) a true positive, (2) a true negative, (3) a false positive, and (4) a false negative. The classifications that lie along the major axis *x* and *y* of the curve are the 100% correct classifications, that is, the true positives and the true negatives, respectively (Figure 5.1). For a perfect model, only the true positive and true negative fields are filled out, the other fields would be zero. A number of regions of interest can be identified in a *ROC* graph. The *ROC* curve illustrates the relationship between *TPF* and *FPF* at all possible cut-off levels; therefore, it can be used to assess the performance of an analysis results independently with respect to the decision threshold. Area under *ROC* curve and the threshold value of the reliability assessment can be predicted from *ROC* curve which are main concerned in this study. Let D_c be a variable describing the pipeline condition, where $D_c = 1$ for pipe failure and $D_c = 0$ for non-failure condition. Suppose that *Y* is a continuous random quantity of a condition result and that large values of *Y* which are greater than threshold or allowable limit is a failure state. Using a threshold, for example c, the result is called positive if $Y > c$, so it indicates the failure condition and if $Y < c$, i.e., negative, pipe condition is non-fail condition, where $c \in (-\propto, \propto)$. Obviously, an accurate assessment will have both sensitivity and specificity close to 1. Based on the above conceptions, *FPF*, *TPF* and *ROC* curve can be estimated as below Eqs. (5.1) – (5.3) (Coolen-Maturi et al, 2011)

$$FPF = P(Y^0 > \text{c} \mid D_c = 0) = S_0(c) \tag{5.1}$$

$$TPF = P(Y^1 > \text{c} \mid D_c = 1) = S_1(c) \tag{5.2}$$

$$ROC = \{(FPF(c), TPF(c),\ c \in (-\infty, \infty)\} \tag{5.3}$$

Throughout this Chapter it is assumed that the two groups (failure and non-failure) are fully independent, i.e., no information about any aspect related to one group contains information about any aspect of the other group. If there are n_1 conditions data from a failure group and n_0 data from non-failure group, then these can be denoted by $\{y_i^1, i = 1,2,....,n_1\}$ and $\{y_j^0, j = 1,2,....,n_0\}$, respectively. For the classical (empirical) method, these observations per group are assumed to be realisations of random quantities that are identically distributed as Y^1 and Y^0 with corresponding survival functions $S_1(y) = P[Y^1 > y]$ and $S_0(y) = P[Y^0 > y]$. According to Pepe (2003), the empirical estimator of the *ROC* can be estimated as below:

$$\hat{ROC} = \{(\hat{FPF}(c), \hat{TPF}(c)), c \in (-\infty, \infty)\} \tag{5.4}$$

where

$$\hat{TPF}(c) = \hat{S}_1(c) = \frac{1}{n_1}\sum_{i=1}^{n_1} 1\{y_i^1 > c\} \tag{5.5}$$

$$\hat{FPF}(c) = \hat{S}_0(c) = \frac{1}{n_0}\sum_{i=1}^{n_0} 1\{y_j^0 > c\} \tag{5.6}$$

where 1{A} is the indicator function which is equal to1 if A is true and 0 else and where $\hat{S}_1$ and $\hat{S}_0$ are the empirical survival functions for Y^1 and Y^0, respectively. The empirical estimator of the *ROC* can also be written as below Eq. (5.7)

$$\hat{ROC} = \hat{S}_1(\hat{S}_0^{-1}(c)) \tag{5.7}$$

5.2.1 *Area under ROC* curve

One of the very important factors of *ROC* curve analysis is the area under the *ROC* curve, denoted as *AUC*. *AUC* can be estimated both parametrically and non-parametrically. The parametric estimation of *AUC* under the empirical *ROC* curve is the area under the curvature. On the other hand, the nonparametric estimation of the area under the empirical *ROC* curve is the summation of the areas of the trapezoids formed by connecting the points on the *ROC* curve. The nonparametric estimate of the area under the empirical *ROC* curve tends to underestimate *AUC* when discrete rating data are collected, whereas the parametric estimate of *AUC* has negligible bias except when extremely small case samples are employed. Therefore, for discrete rating data, the parametric method is preferred. For continuous or quasi-continuous data (e.g., a per cent confidence scale from 0% to 100%), the parametric and nonparametric estimates of *AUC* will have very similar values and the bias is negligible (Zhou et al, 2002). A useful way to estimate the area under the *ROC* curve, *AUC*, which can be expressed as below Eq. (5.8) (Coolen, 1996)

$$AUC = \int_0^1 ROC(t)dt \tag{5.8}$$

According to Zhou et al (2002), the *AUC* is equal to the probability that the analysis results from a randomly selected pair of fail and non-fail group, as shown in Eq. (5.9)

$$AUC = P[Y^1 - Y^0] \tag{5.9}$$

The *AUC* measures the overall performance of the assessment. Higher *AUC* values indicate more accurate results, where *AUC* = 1 for perfect or ideal results and *AUC* = 0.5 for uninform results. So the *AUC* represents the analysis ability to correctly classify a randomly selected individual as being from either the failure group or the non-failure group. The empirical estimator of the *AUC* is the well-known Mann–Whitney U statistic can be presented as below Eq. (5.10) (Coolen-Maturi et al, 2011),

$$\hat{AUC} = \frac{1}{n_1 n_0} \sum_{j=1}^{n_0} \sum_{i=1}^{n_1} \psi(y_i^1 y_j^0) \tag{5.10}$$

where

$$\psi(y_i^1 y_j^0) = \begin{cases} 1 & if \quad y_i^1 > y_j^0 \\ 0.5 & if \quad y_i^1 = y_j^0 \\ 0 & if \quad y_i^1 < y_j^0 \end{cases}$$

Sometimes, it may be of interest to use the area under *ROC* curve between two values of *FPF*, say t_0 and t_1. This is known as the partial area under the *ROC* curve, called *pAUC* can be expressed as below Eq. (5.11)

$$pAUC(t_{0,}t_1) = pAUC(t_0 \le FPF \le t_1) = \int_{t_0}^{t_1} ROC(t)dt \tag{5.11}$$

The *pAUC* can also be written as (Dodd and Pepe, 2003),

$$pAUC(t_{0,}t_1) = P[Y^1 > Y^0, Y^0 \in (S_0^{-1}(t_1), S_0^{-1}(t_0))] \tag{5.12}$$

Note that Eq. (5.12) will also be used as partial area under the *ROC* curve to introduce *NPI* in the Section (5.2.3). The empirical estimator of *pAUC* (Dodd and Pepe, 2003) can be given by below Eq. (5.13)

$$p\,\hat{AUC}(t_{0,}t_1) = \frac{1}{n_1 n_0} \sum_{j=1}^{n_0} \sum_{i=1}^{n_1} \psi^*(y_i^1 y_j^0) \tag{5.13}$$

where

$$\psi^*(y_i^1 y_j^0) = \begin{cases} \psi(y_i^1 y_j^0) & if \quad y_j^0 \in (\hat{S}_0^{-1}(t_1), \hat{S}_0^{-1}(t_0)) \\ 0 & else \end{cases}$$

The *AUC* value 0.50 to 0.75 is fair, 0.75 to 0.92 is good, 0.92 to 0.97 is very good and 0.97 to 1.00 is considered as excellent result of an analysis (Huguet et al, 1994).

5.2.2 *Optimum threshold value in ROC curve*

Another potential uses of the *ROC* curve is in optimising the threshold value of an assessment. The *ROC* curve comprises all possible combinations of sensitivity and specificity at all possible threshold values. This offers the opportunity to assess the optimal threshold value to be used in critical decision practice.

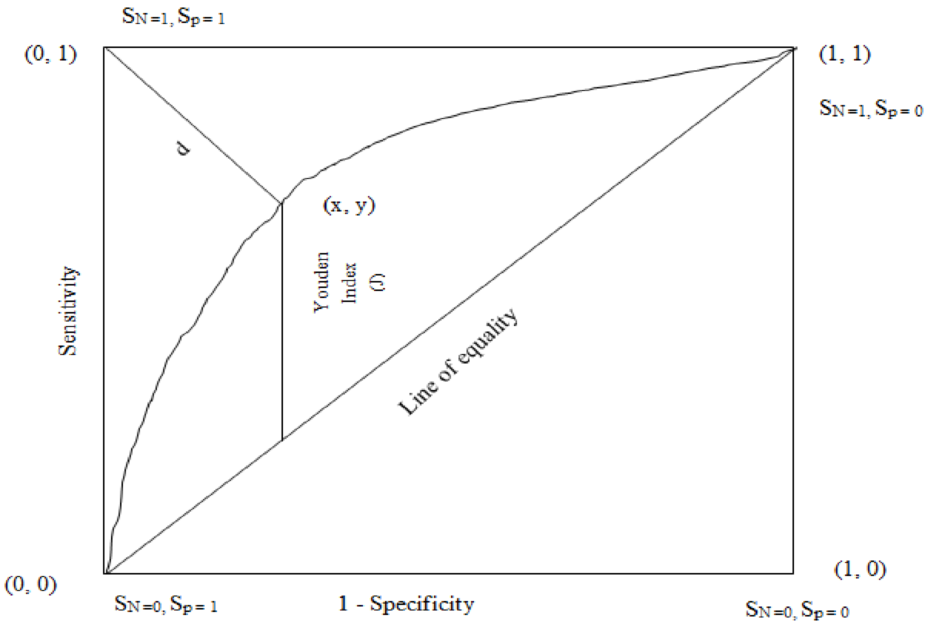


Figure 5.2: A typical best cut-off or threshold value in the *ROC* curve (Indrayan, 2012)

In practice, choosing an optimal threshold value based on *ROC* analysis is practicable only for continuous data. For continuous data, all operating points on the curve correspond to realistic threshold values are considered. Different criteria are used to find optimal threshold point from *ROC* curve, such as points on curve closest to the (0, 1) and Youden index (*J*) etc, (Indrayan, 2012) based on number of observed operating points (Figure 5.2). Most of the operating points on the *ROC* curve consist of sensitivity and specificity combinations that do not correspond to realistic threshold values. Naturally, one would identify the 'optimal' operating point as the point on the *ROC* curve that is closest to the ideal upper left-hand corner. The optimal range of the operating point will thus, shift towards the lower left hand corner of the *ROC* graph. Ideally, such decisions should be made by linking the constructed *ROC* curve in explicit decision analysis. If S_N and S_p denote sensitivity and specificity respectively, the distance between the point (0, 1) and any point on the *ROC* curve can be predicted applying Eq. (5.14) as follows (Indrayan, 2012)

$$d = \sqrt{[(1-S_N)^2 + (1-S_p)^2]} \tag{5.14}$$

where *d* is the distance from top point (0, 1) to any point on curve. To obtain the optimal cut-off point, it is necessary to calculate this distance for each observed cut-off point and locate the point where distance is found minimum.

The Youden index (*J*) is the point on the *ROC* curve which is farthest from line of equality. The main aim of Youden index is to maximise the difference between *TPF* (S_N) and *FPF* $(1-S_p)$ and little algebra yields $J = Max[S_N + S_p]$. The value of *J* can be located by doing a search of plausible value where sum of sensitivity and specificity is maximum value (Indrayan, 2012).

5.2.3 *NPI for ROC curve*

In *NPI*, the uncertainty is quantified by lower and upper probabilities for events of interest. In effect, the optimal lower and upper bounds for the *ROC*, *AUC* and *pAUC* can be derived. Suppose that $\{Y_i^1, i = 1,2,....,n_1, n_1+1\}$ are continuous and exchangeable random quantities from the failure group and $\{Y_j^1, j = 1,2,....n_0, n_0+1\}$ are continuous and exchangeable random quantities from the non-failure group, where $Y_{n_1+1}^1$ and $Y_{n_0+1}^0$ are the next observations from the failure and non-failure groups following n_1 and n_0 observations, respectively. Let $y_1^1 < .... < y_{n_1}^1$ is the ordered observed values for the first n_1 pipes data from the failure group and $y_0^1 < .... < y_{n_0}^1$ the ordered observed values for the first n_0 pipes data from the non-failure group. For ease of notation, let $y_0^1 = y_0^0 = -\propto$ and $y_{n_1+1}^1 = y_{n_0+1}^0 = +\propto$. Thus *NPI* can be used for reliability applications when the data represent failure and non-failure event which are non-negative. The *NPI* lower and upper survival functions for $Y_{n_1+1}^1$ and $Y_{n_0+1}^{01}$ can be determined as follows (Coolen-Maturi et al, 2012; Augustin and Coolen, 2004):

$$\underline{S}_1(c) = \underline{TPF}(c) = \underline{P}(Y_{n_1+1}^1 > c) = \frac{\sum_{i=1}^{n_1} 1\{y_i^1 > c\}}{n_1+1} \tag{5.15}$$

$$\overline{S}_1(c) = \overline{FPF}(c) = \overline{P}(Y^1_{n_1+1} > c) = \frac{\sum_{i=1}^{n_1} 1\{y_i^1 > c\} + 1}{n_1 + 1} \tag{5.16}$$

$$\underline{S}_0(c) = \underline{FPF}(c) = \underline{P}(Y^0_{n_0+1} > c) = \frac{\sum_{j=1}^{n_0} 1\{y_j^0 > c\}}{n_0 + 1} \tag{5.17}$$

$$\overline{S}_0(c) = \overline{FPF}(c) = \overline{P}(Y^0_{n_0+1} > c) = \frac{\sum_{j=1}^{n_0} 1\{y_j^0 > c\} + 1}{n_0 + 1} \tag{5.18}$$

where $\underline{P}$ and $\overline{P}$ are *NPI* lower and upper probabilities. As the *ROC* curve clearly depends monotonously on the survival functions, therefore, it is easily seen that the optimal bounds, which is defined to be the *NPI* lower and upper *ROC* curves areas are as follows (Coolen, 1996):

$$\underline{AUC} = \underline{P}(Y^1_{n_1+1} > Y^0_{n_0+1}) = \frac{1}{(n_1+1)(n_0+1)} \sum_{j=1}^{n_0} \sum_{i=1}^{n_1} 1\{y_i^1 > y_j^0\} \tag{5.19}$$

$$\overline{AUC} = \overline{P}(Y^1_{n_1+1} > Y^0_{n_0+1}) = \frac{1}{(n_1+1)(n_0+1)} [\sum_{j=1}^{n_0} \sum_{i=1}^{n_1} 1\{y_i^1 > y_j^0\} + n_1 + n_0 + 1] \tag{5.20}$$

Based on Eqs. (5.19) and (5.20) it is evident that the difference between upper and lower *AUC* can be expressed as follows (Coolen Maturi et al, 2012):

$$\overline{AUC} - \underline{AUC} = \frac{n_1 + n_0 + 1}{(n_1+1)(n_0+1)} \tag{5.21}$$

Eq. (5.21) indicates that it depends on the two sample sizes n_0 and n_1 only. Similarly for the partial area under *ROC* curve can estimated using Eqs. (5.19) and (5.20) for any specific point of interest.

5.3 NUMERICAL EXAMPLE

The proposed *ROC* approach has been applied to a steel buried pipe under a heavy roadway subject to external loading and corrosion. Four underground pipeline failure modes, namely corrosion induced deflection, buckling, wall thrust and bending stress have been used to illustrate the application of *ROC* curve in reliability accuracy estimation and failure threshold value prediction. The loss of structural strength is due to corrosion through reduction of pipe wall thickness which then leads to pipe failure. In this study, a 100-year of service life of the buried pipe has been chosen. Pipe wall thickness is considered as a classifier to distinguish between the failure and non-failure conditions. Due to lack of real data, 100 pipe wall thicknesses have been simulated at 100-year of service life using Monte Carlo method for each failure criterion based on soil and pipe material listed in Table 3.1 (Ahammed and Melchers, 1997; Sadiq et al, 2004; Babu et al, 2006).

It is assumed that when actual pipe behaviour or pipe wall thickness exceeds the threshold value or allowable limit ($Y > c$), the result is positive (D = 1), i.e. failure condition; and when $Y < c$, the result is negative (D = 0), i.e. non-failure condition. However, there are 10% to 20% discrepancies in the actual and the estimated pipe conditions (Mailhot et al, 2000). Therefore, it is assumed that, the predictions of pipe failure and non-failure conditions are not 100% accurate. The empirical and *NPI* lower and upper *ROC* curves have been applied for different failure modes with 10%, 20% and 30% inaccurate pipe reliability prediction. Tables 5.1 to 5.4 show the pipe wall thickness with 10% inaccurate prediction for the case of corrosion induced deflection, buckling, wall thrust and bending stress, respectively.

Table 5.1: Pipe wall thickness (m) with 10% inaccurate prediction for the case of deflection

Failure group									
0.013711	0.013717	0.013638	0.01367	0.012256	0.013659	0.013754	0.013056	0.014336	0.013639
0.013621	0.013749	0.013913	0.012942	0.013693	0.01367	0.01365	0.01395	0.013921	0.0138
0.013989	0.01699	0.013639	0.012865	0.0138	0.01376	0.0139	0.01361	0.013821	0.013755
0.013976	0.013431	0.014138	0.013709	0.013895	0.013147	0.013159	0.012774	0.012002	0.012245
0.013983	0.013866	0.013934	0.017792	0.01386	0.016665	0.012867	0.01744	0.013876	0.016101
Non-failure group									
0.011358	0.011579	0.0131	0.013198	0.013332	0.012482	0.012303	0.013431	0.012126	0.013077
0.012755	0.013135	0.012934	0.011323	0.012859	0.012523	0.01289	0.013035	0.013332	0.013018
0.012963	0.013181	0.013824	0.012724	0.012456	0.012408	0.012732	0.012675	0.014351	0.012753
0.014237	0.013091	0.012728	0.011857	0.013177	0.013711	0.013231	0.013534	0.012028	0.014094
0.013576	0.01348	0.013257	0.013538	0.014696	0.012475	0.013428	0.012847	0.012283	0.011654

Table 5.2: Pipe wall thickness (m) with 10% inaccurate prediction for the case of buckling

Failure group									
0.016711	0.016717	0.016638	0.016621	0.016749	0.016913	0.012942	0.016693	0.01667	0.01665
0.016989	0.01699	0.016639	0.012865	0.0168	0.01676	0.0169	0.01695	0.016921	0.0138
0.016976	0.016431	0.016738	0.016709	0.013895	0.016847	0.016859	0.01661	0.013821	0.016755
Non-failure group									
0.011358	0.011579	0.0131	0.013198	0.013332	0.012482	0.012303	0.013431	0.012126	0.013077
0.012755	0.013135	0.012934	0.011323	0.012859	0.012523	0.01289	0.013035	0.013332	0.013018
0.012963	0.013181	0.016824	0.012724	0.012456	0.012408	0.012732	0.012675	0.014351	0.012753
0.014237	0.013091	0.012728	0.011857	0.013177	0.016711	0.013231	0.013534	0.012028	0.017094
0.013576	0.01348	0.013257	0.013538	0.016696	0.012475	0.013428	0.012847	0.012283	0.011654
0.01367	0.012256	0.013659	0.013754	0.013056	0.014336	0.013639	0.013983	0.013866	0.013934
0.01744	0.013876	0.016101	0.013792	0.01386	0.013665	0.016867	0.012774	0.012002	0.012245

Table 5.3: Pipe wall thickness (m) with 10% inaccurate prediction for the case of wall thrust

Failure group									
0.013711	0.013717	0.013638	0.01367	0.012256	0.013659	0.013754	0.012056	0.014336	0.013639
0.013621	0.013749	0.013913	0.012942	0.013693	0.01367	0.01365	0.01395	0.013921	0.0138
0.013989	0.01699	0.013639	0.012865	0.0138	0.01376	0.0139	0.01361	0.013821	0.013755
0.013976	0.013431	0.014138	0.013709	0.013895	0.013147	0.013159	0.012774	0.012002	0.012245
0.013983	0.013866	0.013934	0.017792	0.01386	0.016665	0.012867	0.01744	0.013876	0.016101
0.014237	0.013091	0.012728	0.011857	0.013177	0.013711	0.013231	0.013534	0.012028	0.014094
0.013576	0.01348	0.013257	0.013538	0.014696	0.012475	0.013428	0.012847	0.012283	0.011654
0.014351	0.013824								
Non-failure group									
0.011358	0.011579	0.0129	0.012198	0.013332	0.012482	0.012303	0.013431	0.012126	0.013077
0.012755	0.013135	0.012934	0.011323	0.012859	0.012523	0.01289	0.012035	0.012332	0.013018
0.012963	0.013181	0.012724	0.012456	0.012408	0.012732	0.012675	0.012753		

Table 5.4: Pipe wall thickness (m) with 10% inaccurate prediction for the case of bending stress

Failure group									
0.013711	0.013717	0.013638	0.01367	0.011256	0.013659	0.013754	0.011056	0.014336	0.013639
0.013621	0.013749	0.013913	0.01142	0.013693	0.01367	0.01365	0.01395	0.013921	0.0138
0.013989	0.01699	0.013639	0.01165	0.0138	0.01376	0.0139	0.01361	0.013821	0.013755
0.013976	0.013431	0.014138	0.013709	0.01125	0.013147	0.013159	0.012774	0.012002	0.012245
0.013983	0.013866	0.013934	0.017792	0.01386	0.016665	0.012867	0.01744	0.013876	0.016101
0.014237	0.013091	0.012728	0.011857	0.013177	0.013711	0.013231	0.013534	0.012028	0.014094
0.013576	0.01348	0.013257	0.013538	0.014696	0.012475	0.013428	0.012847	0.012283	0.011654
0.012408	0.012732	0.012675	0.014351	0.012753	0.012963	0.013181	0.013035	0.013332	
Non-failure group									
0.011358	0.011579	0.0131	0.011198	0.013332	0.011482	0.011303	0.011431	0.011126	0.011077
0.011755	0.011135	0.011934	0.011323	0.010859	0.011523	0.01189	0.013824	0.012724	0.012456

5.4 RESULTS AND DISCUSSION

The empirical *ROC* curves are applied for prediction of *AUC* and threshold value of pipe failure condition with 10%, 20% and 30% inaccurate reliability prediction for different corrosion induced pipe failure modes. The performance of the *ROC* curve analysis is computed in terms of the true positive and false positive rates. This traces the curve from left to right (maximum ranking to minimum ranking) in the *ROC* graph. That means that the left part of the curve represents the behaviour of the model under high decision thresholds (conservative) and the right part of the curve represents the behaviour of the model under lower decision thresholds.

Empirical *AUC*, which is interpreted as the average value of sensitivity for all possible values of specificity, is a measure of the overall performance of the analysis for every failure case. The area under empirical *ROC* curve (*AUC*) is estimated using Eq. (18). *AUC* can take any value between 0 and 1, where a bigger value suggests the better overall performance of an analysis with 95% confidence level. Figures 3 to 6 show that *AUC* is higher for the case of 10% than that for 20% inaccurate prediction. Similarly, the case for 20% inaccurate prediction shows higher *AUC* than that for 30%. This indicates that the area under empirical *ROC* curve can be used to predict the reliability accuracy for different failure modes.

Table 6 indicates that different failure modes have different *AUC* for the same percentage of inaccurate prediction due to randomness of the data. The analysis shows that if simulated inaccurate prediction is 10%, the accuracy of the results is still fair enough for all the failure modes (*AUC* > 0.75). However if it is more than 10%, the accuracy of the results falls below the acceptable value (*AUC* < 0.75) which is implemented in practice as suggested by Huguet et al (1994).

The allowable limit and the corresponding threshold pipe wall thickness for each corrosion induced failure modes, namely deflection, buckling, wall thrust and bending stress can be calculated using pipeline design formula as discussed in Section 2. For example, in the case of corrosion induced deflection, the allowable limit of deflection is estimated as 5% of initial inside diameter of pipe. Then, the corresponding threshold pipe wall thickness is calculated using Eq. (3.7). Similarly, in the case of corrosion induced buckling, the allowable limit is estimated using Eq. (3.10) based on the assumption that the pipe fails when the actual buckling pressure is equal to the allowable buckling pressure and then the corresponding pipe wall thickness is calculated using Eq. (3.11). The same procedure is followed for other failure modes.

Besides that, empirical *ROC* can also be used to determine the optimum threshold value of pipe failure condition. The threshold pipe wall thickness values are predicted for the failure modes of deflection, buckling, wall thrust and bending stress. This methodology has allowed establishing a threshold at which a pipe can be considered in high-risk condition. The optimum threshold value for each failure criteria predicted from the empirical *ROC* curve is obtained from Eq. (5.10) and the results are shown in Table 5.5 for comparison with the values obtained from pipeline design formula. Both results are reasonably close in which the optimum threshold pipe wall thickness obtained from empirical *ROC* curve is more conservative. The results show that the corrosion induced bending stress is the most dominating failure mode whereas buckling is the least susceptible failure mode.

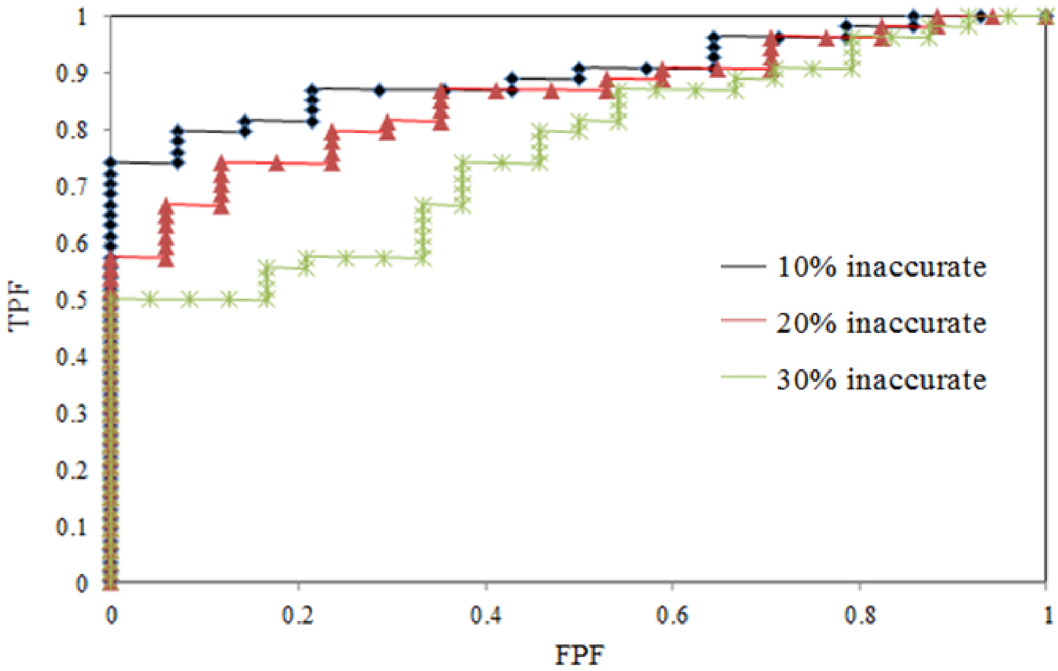


Figure 5.3: Empirical *ROC* curve for pipe failure due to corrosion induced deflection for different percentages of inaccurate prediction

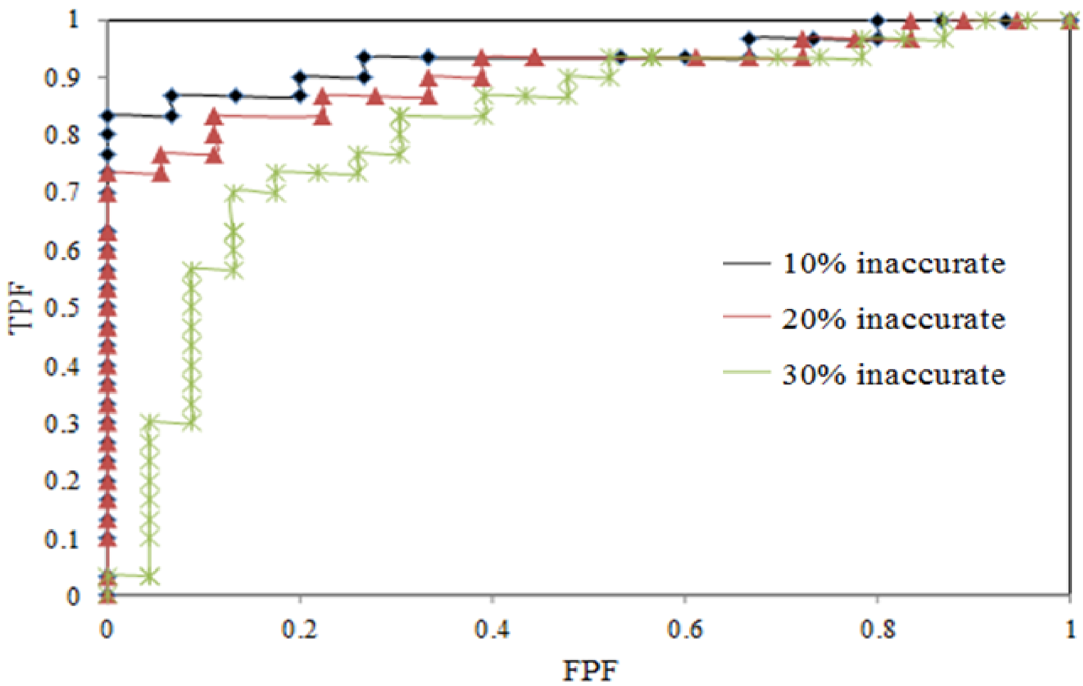


Figure 5.4: Empirical *ROC* curve for pipe failure due to corrosion induced buckling for different percentages of inaccurate prediction

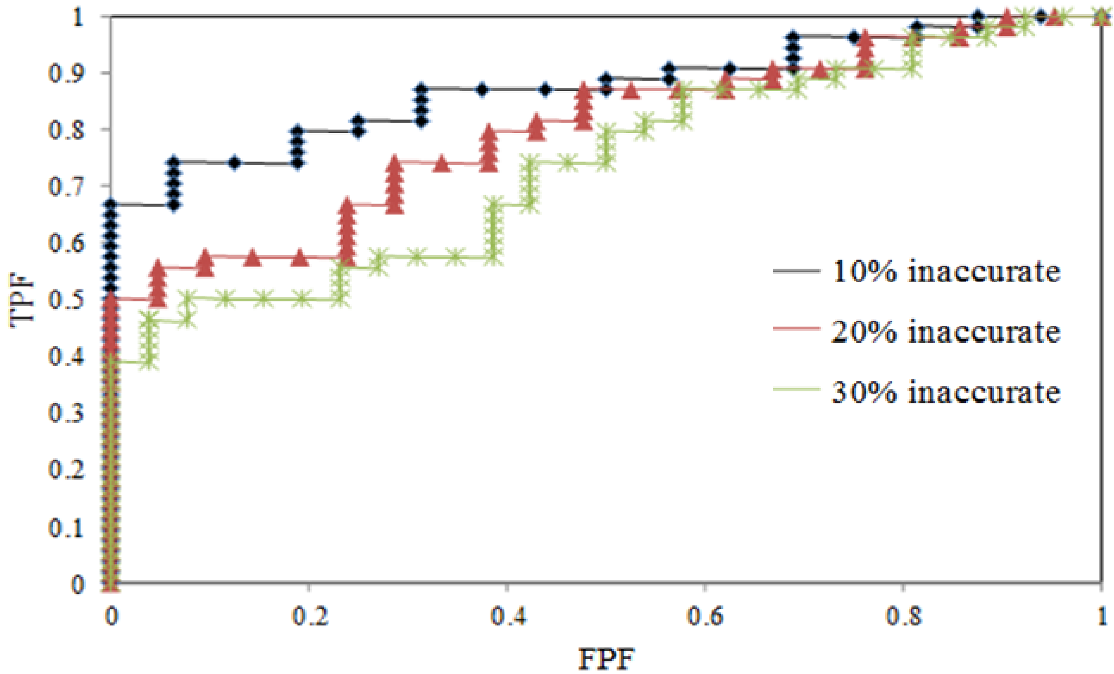


Figure 5.5: Empirical *ROC* curves for pipe failure due to corrosion induced wall thrust for different percentages of inaccurate prediction

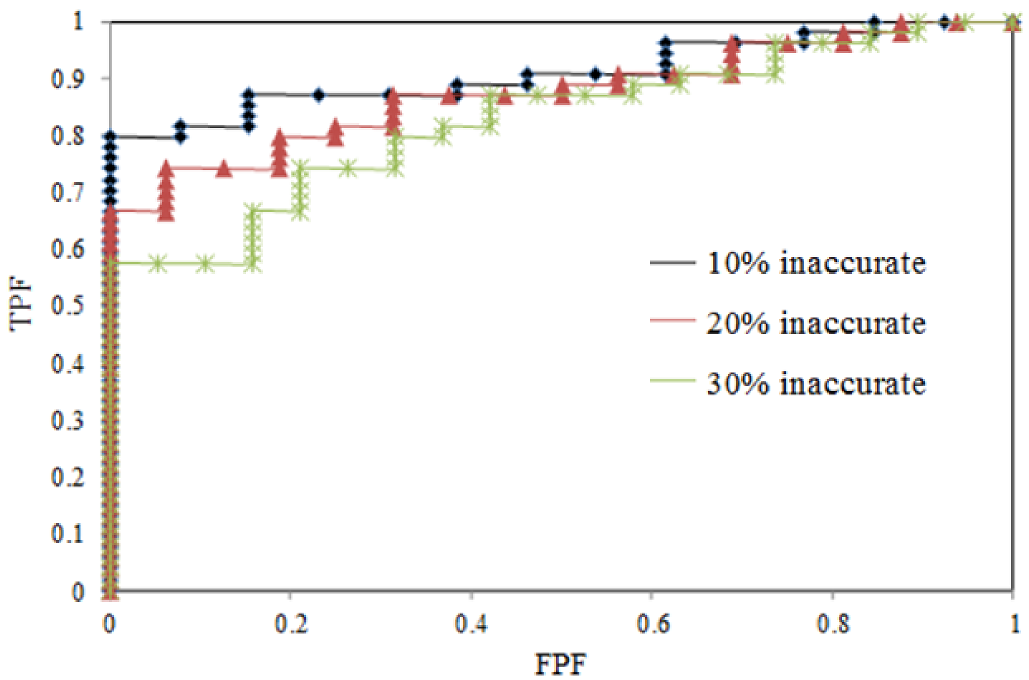


Figure 5.6: Empirical *ROC* curves for pipe failure due to corrosion induced bending stress for different percentages of inaccurate prediction

Table 5.5: Threshold values and area under empirical *ROC* curves

		Failure modes			
		Deflection	Buckling	Wall thrust	Bending stress
Allowable limit using pipeline design formula		0.0605 m	1023.8 kPa	5867 kPa	450000 kPa
Threshold wall thickness using pipeline design formula		0.0137 m	0.0171 m	0.0136 m	0.0132 m
Optimum threshold wall thickness from empirical *ROC* curve		0.01357 m	0.0166 m	0.013 m	0.0128 m
Area under empirical *ROC* curve with inaccurate prediction	10%	0.89	0.78	0.80	0.76
	20%	0.68	0.67	0.68	0.70
	30%	0.55	0.63	0.58	0.56

Next, *NPI ROC* curves are applied to estimate the lower and upper bounds of *AUC* for all the failure modes and the results are shown in Figures 5.7 – 5.10 and Table 5.6 with different percentages of inaccurate prediction. The *NPI* lower and upper areas under the *ROC* curves are calculated from Eqs. (5.19) and (5.20), respectively. As shown in Tables 5.5 and 5.6, the area under the upper bound of *NPI AUC* is always larger than empirical *AUC* for all the failure modes. It is clear that with increasing the percentage of inaccurate prediction, the areas under the upper and lower bounds of *NPI* are decreased. Therefore, the accurateness of the reliability prediction is decreased as shown in Figures 5.7 to 5.10 and Table 5.6.

The performance of a prediction analysis should be judged in the context of the situation to which the data is applied. It can be seen that *AUC* for *NPI* is given in terms of upper and lower limits instead of a single curve. In this way it provides an interval of accuracy prediction which is more reasonable compared to classical *ROC*. Alternatively, the partial area estimation, where only a portion of the entire *ROC* curve needs to be considered, can also be used to predict the accuracy of an analysis when a particular *FPF* is useful indicator.

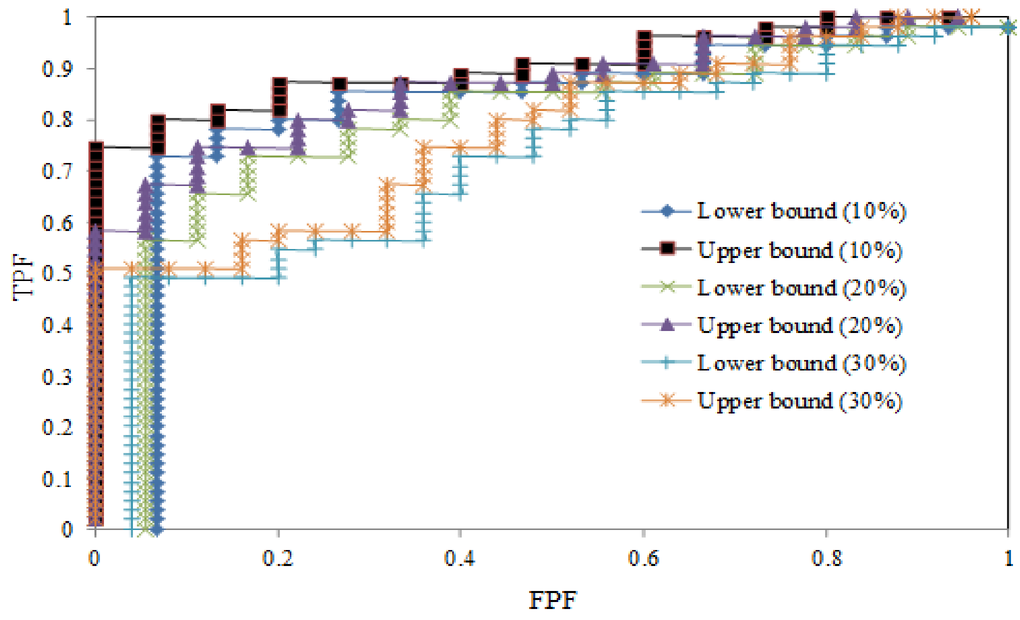


Figure 5.7: *NPI* lower and upper *ROC* curves for pipe failure due to corrosion induced deflection for different percentages of inaccurate prediction

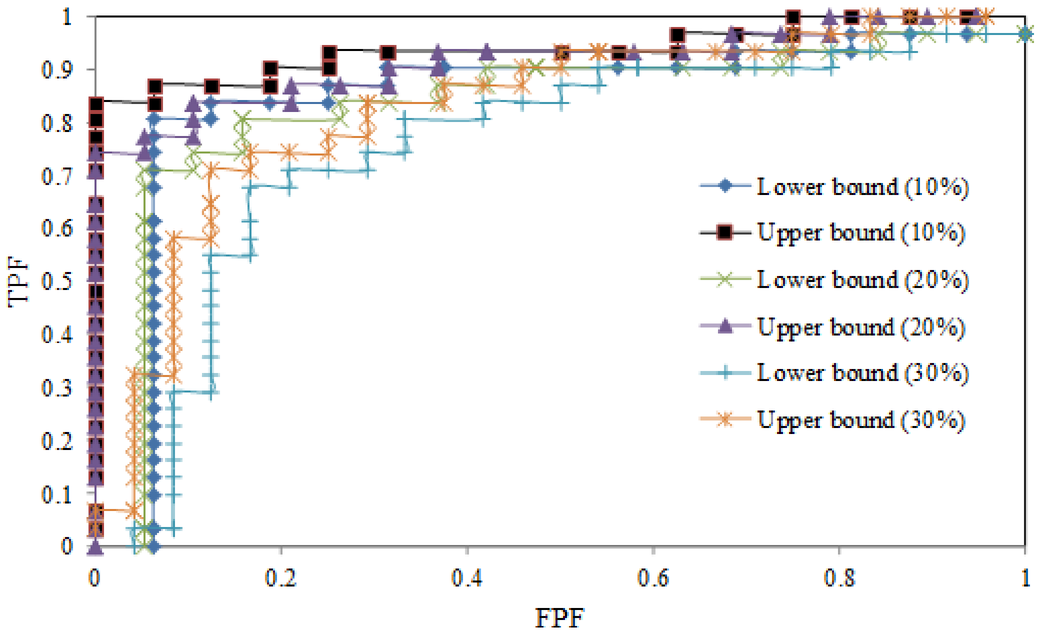


Figure 5.8: *NPI* lower and upper *ROC* curves for pipe failure due to corrosion induced buckling for different percentages of inaccurate prediction

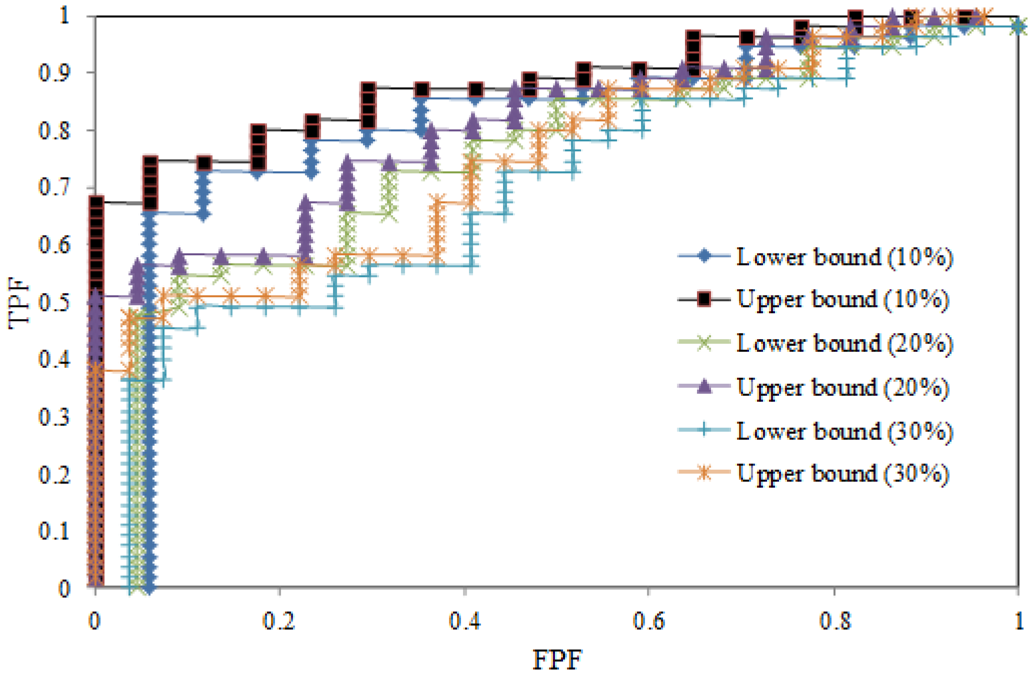


Figure 5.9: *NPI* lower and upper *ROC* curves for pipe failure due to corrosion induced wall thrust for different percentages of inaccurate prediction

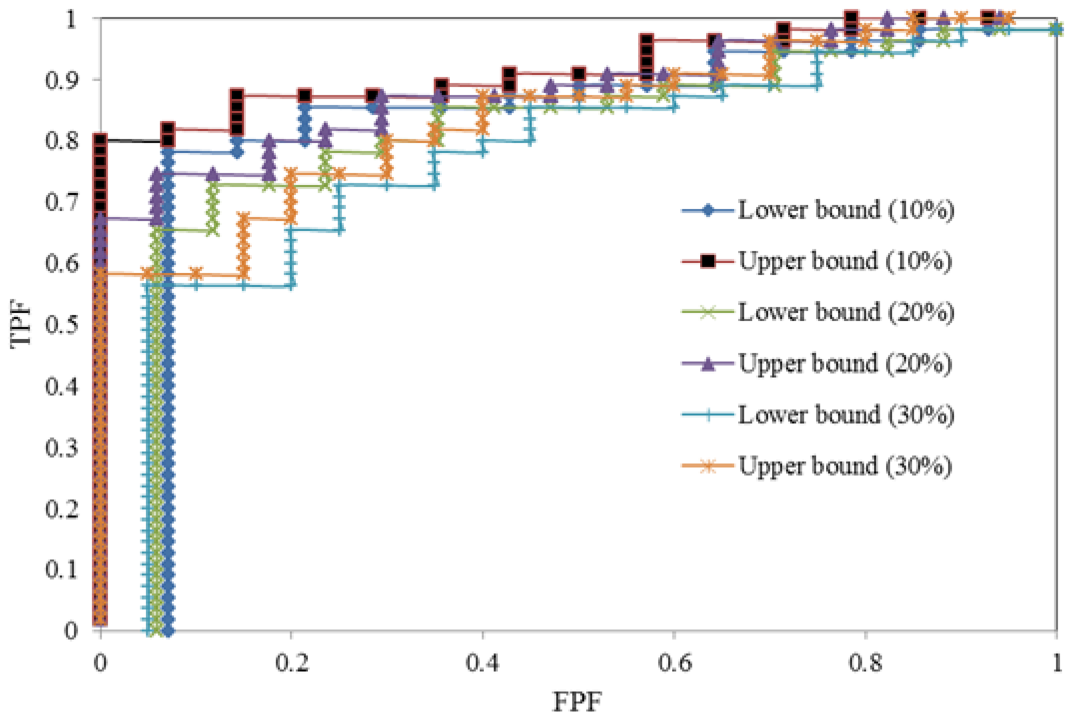


Figure 5.10: *NPI* lower and upper *ROC* curves for pipe failure due to corrosion induced bending stress for different percentages of inaccurate prediction

Table 5.6: Area under *NPI ROC* curves

% of inaccurate prediction	*NPI* Area	Failure modes			
		Deflection	Buckling	Wall thrust	Bending stress
10%	$\overline{AUC}$	0.92	0.86	0.87	0.90
	$\underline{AUC}$	0.88	0.81	0.78	0.87
20%	$\overline{AUC}$	0.73	0.70	0.71	0.72
	$\underline{AUC}$	0.67	0.64	0.66	0.65
30%	$\overline{AUC}$	0.60	0.61	0.60	0.59
	$\underline{AUC}$	0.54	0.58	0.56	0.54

Similar to empirical and *NPI* upper and lower bound *AUC*, the partial *ROC* area estimation also can be used to predict the accuracy of an analysis when a particular *FPF* is useful indicator, then only a portion of the entire *ROC* curve needs to be considered as briefly discussed in Section 5.2.1.

5.5 SUMMARY

In this Chapter, *ROC* curve has been applied in reliability analysis for underground pipelines due to corrosion induced deflection, buckling, wall thrust and bending stress. The *ROC* curve provides a performance assessment model for reliability prediction of pipe failure state function. The analysis shows that *ROC* curve is a useful technique to predict the optimum threshold value and the accuracy of the results. The area under the curve provides an objective valuation for the accuracy of an analysis with combinations of sensitivity and specificity values. Thus two or more reliability prediction methods can also be compared using *ROC* curve. The results demonstrate that with increasing inaccurateness of reliability prediction, the areas of the *ROC* curves (both classical and *NPI*) are decreased. Choosing the optimal operating point on the *ROC* curve which involves both maintenance and financial issues, can be ideally implemented in a formal risk-cost management process of buried pipeline network.

CHAPTER SIX

RISK-COST OPTIMISATION USING GENETIC ALGORITHM

6.1 INTRODUCTION

The world is moving towards adopting more proactive and optimised approaches to manage underground pipeline systems in a more sustainable way. These approaches mostly aim to maximise the return on investment by optimising the allocated budgets. Return on investment of such systems comprises of higher asset performance, lower risk of failure and lower life cycle costs, based on the proper decisions. Such decisions can range from determining the optimal maintenance or inspection interval to evaluate a proposed design changes and deliberate expenditure in order to achieve the reliability, performance and other benefits. These decision elements are inherently conflicting, so an integrated multi-objective approach is needed to develop a careful plan to satisfy these criteria in a balanced and optimised manner. The concept that needs to clarify is the meaning of ‘optimum’. The word is often used in phrases such as the optimum maintenance strategy or the optimum performance. Woodhouse (2001) stated that in areas where there are conflicting interests, such as pressures to reduce costs at the same time as the desire to increase reliability or performance or safety, an optimum represents some sort of compromise between the demand and performance. It is quite impossible to achieve the ideals - zero costs and at the same time total 100% reliability or safety etc. Till now the managing plans are typically performed in a manual and subjective manner with limited or no software support (Halfawy et al, 2008). Different research show that the vast majority of existing underground pipeline systems focus primarily on managing day-to-day operational activities, such as issuing and tracking work orders, mapping and data management, logging service requests, cost estimating, etc. But the optimum long-term management planning for the pipeline network is very limited. This scarcity is mainly attributed to the lack of systematised, standardised and quantitative models, e.g., deterioration, risk, prioritisation and optimisation models as well as the lack of adequate reliable data to support the application of such models. Finding the optimal strategy is not easy and the wrong maintenance strategy may result in excessive risks, costs and losses. Optimisation models for pipeline maintenance methodologies are still in their infancy condition compared to those in bridges, buildings and other civil engineering structures, although optimum design approaches for pipe structural systems are continuously evolving and improving (McDonald and Zhao, 2001).

To address these problems, several countries have developed or initiated the development of pipe management systems to optimise the inspection and maintenance of deteriorated pipe structures. Different optimisation approaches have been implemented in the different buried pipe management systems ranging from simplified economic models to advanced Markovian decision processes (Lounis, 2006). In the last decade, the reliability based optimal design of buried pipe distribution systems problem studied by several researchers and resulted in the development of a number of reliability models and the application of optimisation techniques (Rahman and Vanier, 2004). But the design of these models is based on future predefined and perfectly known working conditions, a premise that directly impacts the optimisation process. The imposed scenario may perform badly if the reality turns out significantly different. In the context of a proactive attitude toward these risks, it is important to consider these aspects at the beginning of the design phase. Arranging these activities in a proper time scale is also a difficult task. Different pipeline project requires different timetable to complete. The shorter project duration may leads to higher direct costs. In contrast, longer project duration may leads to lower direct and indirect costs. In such situations, it is important to study the trade-off between completion time, risk involved in each resource option and the cost of the project. Trade-off between these conflicting aspects of a project is a challenging job and such cases, planners are faced with numerous possible combinations for project delivery. If durations of the activities are crashed, the cost may show an increasing trend due to more resources being allocated for its rapid accomplishment (Tee et al, 2014b; Khan et al, 2013; Ambrose et al, 2008).

To overcome the above drawbacks and difficulties of the existing methods, the current research proposes a new step-wise integrated approach in developing optimisation plan using Genetic Algorithm (GA) that would identify the most appropriate compromise of renewal solutions while simultaneously optimising the renewal costs, condition state and risk of failure of the underground pipeline network. Life cycle cost (LCC) of pipeline network has been used as an objective function in the procedure. The LCC of a pipeline structure includes the initial costs or capital cost, including costs of design and construction plus costs of utilities, maintenance cost and failure risk cost over the lifetime of the structure.

Due to uncertainty associated with the rate of failure and behaviour of buried pipeline system, the probabilistic pipe reliability methodology has been applied in optimisation process. The approach has been applied for flexible buried metal pipeline system which is involved in corrosion induced failure modes of deflection, buckling, wall thrust or stress and bending as mentioned earlier in Chapter Three. According to Sarma and Hojjat (2002), a few researchers have presented probabilistic reliability models for life cycle risk and cost optimisation of buried pipeline structures. The propose management option has yield a performance according to the risk involved and cost of the activities through service life. The proposed maintenance strategy enables decision maker to decide when and how to renew the pipes (i.e. the most effective maintenance strategy, which could be replacement, structural, semi structural and non-structural lining methods) at the minimum cost (Tee et al, 2014c).

The contents of this Chapter are structured as follows. A brief description on the optimisation algorithm, GA has been presented in Section 6.2. In Section 6.3, problem formulation for LCC is presented. The parameters of LCC including capital cost, maintenance cost and failure risk cost are discussed in Section 6.4. In Section 6.5, the renewal methods are presented where condition index, impact assessment and priority are discussed for buried pipeline network. A numerical example is conducted to validate the proposed risk-cost optimisation process in Section 6.6. The results and discussion are presented in Section 6.7 where pipe reliability, renewal time and methodologies, renewal priority and some parametric studies are presented. Finally, some concluding remarks are made based on the outcomes of the study in Section 6.8.

6.2 OPTIMISATION ALGORITHMS

Many optimisation techniques have been developed and used for the optimal design and management of underground pipeline network, such as Genetic Algorithm (GA), Deterministic Dynamic Programming Optimisation (DDPO), Fuzzy Set Method (FSM), Linear Programming (LP) and Discrete Differential Dynamic Programming (DDDP), etc. Some researchers, such as Berardi et al (2009), Rasekh et al (2010), Pan and Kao (2009), Abraham et al (1998), Stansbury et al (1999) and Li & Matthew (1990) adopted experimental approaches for simplicity and used for buried pipe network design problems. As GA is a powerful evolutionary and robust optimisation technique and can solve difficult distribution network design problems, GA has been applied in the current underground pipeline risk and cost optimisation process. It is very effective in finding the near optimal solutions and discrete pipe elements. A brief description of GA can be presented as follows:

6.2.1 Genetic algorithm

The genetic algorithm owes its credit to the claim of simulating the real world evolutionary process, engineered by nature. It is mainly applied in the optimisation of tasks, scheduling and project planning. Three basic GA operators, such as selection and mating, crossover and mutation are used in designed process to mimic the nature as closely as possible. The principal purpose of this algorithm is to program a character, property or variable using a sequence of codes. With the help of stochastic generations, GA can form a set of initial possible solutions using the codes, called population. From this initial population, the algorithm explores the solution space and creates a new set of solutions by means of the genetic operators of crossover and mutation and selects the best optimal solutions. The main components, namely, selection, crossover and mutation are briefly described as below (Nafi et al, 2008; Prasad et al, 2003):

a) Selection: Selection is used to apply upon the population in a manner similar to that natural selection found in biological systems. Poorer performing individuals are disappeared or out of the process and the better are survived. Better individuals are then having greater chance of performing new fitter genes.

b) Crossover: This operator allows solutions to exchange information in a way similar to that used by natural organism undergoing sexual reproduction. Information can be totally or partially changed by fixed point crossover (constant percentage crossover) or variable point crossover (non-constant percentage crossover).

c) Mutation: Mutation is used to randomly change the value of single bits within individual strings. The importance of mutation operator is securing evolving of string that includes the global optimum as the mutation allows the population to "leapfrog" over the global optimum.

With referring to accurate definition of each variable and objective function, GA has been applied in flexible underground metal pipeline network management approach. The problem is considered as an unconstraint problem. In this research, the optimal management strategy has been performed through risk-cost optimisation. The whole life cycle cost has been used as an objective function in optimisation process where optimum cost and time need to be estimated with respect to optimum risk. Different pipeline network intervention alternatives and several environmental and physical variables (loading, corrosion, soil density and modulus, pipe material, length, diameter, soil height etc.) are used as the structural deterioration of pipes which are used in the statistical model. The concatenation of these design variables defines a renewal policy that takes into account a string of codes, called chromosomes. The problem is treated as a multi-objective problem characterised by a technical objective defined by a risk measure and an economic objective defined by a total life cycle cost. For this study, GA has been selected as an optimisation search technique in the LCC analysis because (a) GA has no mathematical limitations on the type and number of decision variables, formulations of objective function or the formulation of the constraints, which is an important factor considering the complexity for driving the optimisation trade-off process and (b) GA has been proven to be robust and powerful algorithm for arriving at the global optimum in the vicinity of the local optima. The design variables for the problem studied are the possible alternatives for interventions on the pipeline network.

6.3 PROBLEM FORMULATION

The implementation of a quantitative assessment and risk-based life cycle management is a very complex task due to the difficulties of assessing quantitatively the probability of failure and the consequences of failure, especially for a large network of pipe structures. For a given pipeline distribution network, huge number of solutions can be selected through a range of decision variables and in such cases, probabilistic methods are used instead of mathematical models to search for the best solution. Life cycle cost (LCC) of pipeline network has been used as an objective function in the procedure. The LCC of a pipeline structure includes the initial costs or capital cost, including costs of design and construction plus costs of utilities, maintenance cost and failure risk cost over the lifetime of the structure. While project level or short-term planning would require more accurate assessment of direct, indirect, social, environmental costs, network level. For long-term planning could be reasonably conducted using approximate total cost figures as those compiled or estimated from the literature.

The total life cycle cost, C_{LCC} can be presented as follows (Khan et al, 2013; Hinow et al, 2008; Sarma and Hojjat, 2002):

$$C_{LCC} = C_A + \sum_{i=1}^{T} C_o(i) \tag{6.1}$$

where C_A = The capital cost; C_o = Operation cost; i = 1, 2, 3,..., T years.

The operation cost, C_o can be calculated by Eq. (6.2) as below:

$$\sum_{i=1}^{T} C_O(i) = \sum_{i=1}^{T} C_M(i) + \sum_{i=1}^{T} C_R(i) \tag{6.2}$$

where C_M the maintenance cost and C_R is the failure risk cost.

The failure risk cost, C_R is influenced by the failure cost, C_f and the failure probability as a series system, P_f (determined by Eqs. (3.32)), the failure risk cost can be estimated as follows:

$$\sum_{i=1}^{T} C_R(i) = \sum_{i=1}^{T} C_f(i) \times P_f \tag{6.3}$$

Therefore, based on Eqs. (6.2) and (6.3), Eq. (6.1) can be rewritten as below:

The life cycle cost,

$$C_{LCC}(T) = C_A + \sum_{i=1}^{T} C_M(i) + \sum_{i=1}^{T} C_f(i) \times P_f \tag{6.4}$$

The cost terms in the right-hand side of the Eq. (6.4) are the costs in the year they actually occur. The $(1+r)^T$ factor is used to convert the cost into its present value discounted by the discount rate of r, for the T years period. The discount rate depends on the prevailing interest rate and the depreciation of the currency or inflation rate. This rate is not a constant term and may vary over the life of the pipeline structure. From an economical point of view, the ideal goal of risk and cost management of pipeline network should be minimising the total LCC of the network. In this study, the problem of identifying the optimal intervention year is transformed into minimisation of total LCC (Eq. (6.4)). A poor maintenance policy often leads to early failure. On the other hand, a conservative maintenance policy may result in excessive costs. Therefore, underground pipeline network will require rehabilitation or replacement several times during the system design life.

6.4 PARAMETERS ANALYSIS

6.4.1 Life cycle cost

Life-cycle cost is the total cost of structure during its lifetime. The life-cycle cost is an important issue in the engineering design, especially for managing the large engineering construction works. LCC for buried pipelines includes all associated cost in the service life of a pipeline structure. Economical design and management is main goal of LCC analysis. If the initial cost of a pipeline structure is low but the utilities and maintenance costs are high, then the structure may not be considered as an economical design. Only a small fraction of the papers published in the area of structural optimisation deal with cost optimisation of pipeline structures where the cost calculations include capital cost, maintenance cost and failure risk cost (Ambrose et al, 2008). LCC normally does not include of penalty payments to customers, traffic disruption and other costs that utilities may encounter when a pipe fails and these would need to be examined on a case by case based on local conditions. For a cost-effective approach, the ideal goal of the risk and cost management of the buried pipe network should be minimising the total life cycle cost of the network at an optimal time. Different features of typical buried pipelines life cycle costs are presented as follows:

6.4.1.1 Capital cost

The capital cost normally includes material and installation costs for pipelines and is a vital part of the LCC. According to Vipulanandan and Pressari (2003), the capital cost model for an underground pipeline network can be developed by breaking down the cost of construction into below major component:

a) Cost of pipe material;
b) Cost of installation;
c) Cost of manhole material and installation (in case of sewer);
d) Cost of wastewater treatment plant (in case of treatment plant); and
e) Pump station cost (in case of pressure pipeline).

6.4.1.2 Maintenance cost

Maintenance cost is calculated for a buried pipeline by determining the future value of each cost occurrence of a maintenance activity (routine maintenance), discounting each to a present value and then summing up all the cost values. Maintenance cost is estimated on an annual basis. The life expectancy as well as maintenance cost depends on the type of material used in the pipe structure. Frequent changes in weather, cracks, shrinkage and corrosion may reduce the life of an underground pipe structure. Moreover, in an exposed soil conditions, the pipe joints may accumulate dirt and debris and if proper maintenance is not done, this may lead to failure and incur cost.

Apart from aforementioned reasons, geographic location also influences the maintenance costs. For example, a place with abundance of skilled labour force costs less than a place where labour force is scarce. The maintenance costs of structures in a difficult terrain are often expensive. Time is also an important matter in maintenance policy. If maintenance time is delayed, it may lead to excessive cost. On the other hand, a conservative maintenance policy (early maintenance) may save extra costs.

6.4.1.3 Risk of failure cost

A number of planning models are currently available to allow the future costs of pipeline failures for buried pipeline networks (Ambrose et al, 2008). However, these models are required detailed analysis of the failure data for all pipe assets and some required specific failure curves for each class (sewer, water, etc.). Ambrose et al (2008) stated that database on pipe failure statistics are often incomplete and/or limited and in many cases it is difficult to ascertain whether a failure resulted from the pipe replacement (if the pipe was replaced at the end of its economic life) or newly installed pipe. In the context of reliability engineering and risk management, the failure risk depends on the type of pipeline (steel, ductile iron, concrete pipes etc.). For underground pipelines, the consequence of failure cost is measured based on the consequences of failure rehabilitation or remediation costs, social and environmental costs multiplied by the probability of failure (Rajani and Kleiner, 2004). In other way, the risk of failure cost can be expressed as Eq. (6.5):

$$\text{Risk of failure cost} = E\,(\text{failure consequence}) = f\,(\text{probability of failure, failure costs}) \tag{6.5}$$

The direct costs are those costs related to the failure cost paid either "out of pocket" by the utility or through the utility's insurance carrier. Examples of common direct costs are as below (Peter et al, 2007):

a) Landscaping/restoration costs;
b) Attorney fees and other legal costs;
c) Utility construction staff labours;
d) Cost of repair materials taken from stock; and
e) Claims paid by utility or utility's insurance.

Indirect costs, on the other hand, are costs not paid out of pocket by the utility authority or their insurance carrier. Indirect costs are paid, either in terms of actual expenditures by others or in terms of the value of lost wages and lost productivity of others. Some common costs that are identified as indirect cost are as below (Peter et al, 2007):

a) Value of people's time delayed in traffic/detours;
b) Lost production of commercial/industrial work;
c) Cost of illness and injury;
d) Cost of flooding damage to structures and cars;
e) Damage to parallel utilities (not reimbursed by the utility authority);
f) Cost of police, fire and emergency services (not reimbursed by the utility authority); and
g) Damage to transportation systems (cost for damages to trains, subways, state roads / bridges and parking facilities, not reimbursed by the utility authority).

Furthermore, indirect costs are classified as hard and soft indirect cost. Hard indirect costs are those costs which are sometimes paid by utilities, such as property damage (typically flooding damage), parallel utility damage, costs for emergency services and damage to public transportation systems, etc. Soft indirect costs are those costs which are never paid by water or wastewater, such as costs for traffic delays, water outage, lost productivity, reduced fire fighting capability, injury and illness (medical bills), etc.

Typically, with respect to time, buried metal pipe components deteriorate and the probability of failure increase due to different loadings and corrosion. As long as the pipe continues to age and deteriorate without renewal, the risk increases as well as cost. Like maintenance cost, the failure cost is also increased if pipe renewal is delayed. In some cases, the risk of failure cost of also likely to increase with respect to location. For example, when a pipe is located in a rapidly developing area, there is more chance to pipe fail than a less developed area.

6.5 SELECTION OF RENEWAL METHODS

The underground pipeline renewal technologies are growing rapidly and becoming more efficient and cost-effective for underground pipeline network. Different renewal methods exhibit different capabilities, limitations, costs and benefits. The particular characteristics of the buried pipes (e.g., material, diameter, etc.) and site conditions (e.g., soil, water table, traffic etc.), along with other operational, social and environmental factors determine the applicability of different renewal methods in a particular situation. Based on pipe and site conditions, Water Resource centre (WRc, 2001) presented a simple procedure for renewal of buried pipes for possibility of soil loss based on soil type and groundwater level; and renewal categories based on the condition index and the possibility of surrounding soil loss as shown in Table 6.1 and Table 6.2. In this research, the underground pipeline management strategy complements the aforementioned risk-cost optimisation by identifying applicable renewal categories based on the condition index and the possibility of surrounding soil loss. In any given scenario, some renewal methods are more applicable and cost effective than others and therefore, a systematic procedure for selecting feasible methods is needed.

Table 6.1: Selection of renewal categories based on condition index and soil loss possibility

Cond. Index	Possibility of soil loss		
	Low	Medium	High
2	Non-structural or semi-structural	Non-structural or semi- structural	Semi- structural, structural or replacement
3	Non-structural or semi-structural	Semi- structural or structural	Semi- structural, structural or replacement
4 and 5	Structural or replacement	Structural or replacement	Structural or replacement

Table 6.2**:** Possibility of soil loss based on soil type and groundwater level

Soil Type	Groundwater level		
	Below pipe	Same line with pipe	Above pipe
Clay	Low	Medium	High
Gravels and low plasticity clay	Low	Medium	High
Silt and sand	High	High	High

The renewal methods are grouped into four main categories in this study: replacement, structural, semi structural and non-structural lining methods. Generally, replacement is normally recommended when the pipes are collapsed or out of work and cannot be repaired. If the pipe repair cost is high compare to a new pipe, also replacement is recommended instead of repair. Structural liners are defined to be capable of carrying hydrostatic, soil and live loads. Structural liners are expected to be independent i.e., bonding with original pipelines is not required. Semi structural liners are designed to withstand hydrostatic pressure or perform as a composite with the existing pipelines. Semi structural liners could be designed as interactive or independent and typically are not used for gravity pipelines (Halfawy et al, 2008). On the other hand, non-structural liners are used mainly for gravity pipelines system to improve flow, resist corrosion, or to seal minor cracks on pipe surface (Heavens, 1997).

6.5.1 Condition index

The maintenance strategy can be implemented by identifying applicable renewal categories based on the underground pipeline condition which is called condition index or mean structural pipe grade. The purpose of the condition index is to objectively rate or scale the current condition of buried pipes based on several physical, environmental, and operational factors, which provide the basic terminology and framework .The condition index (*CI*) can be calculated from the regression model (Newton and Vanier, 2006; Khan et al, 2013; Tee et al, 2014b) as Eq. (6.6) (Figure 6.1):

$$CI = 0.0003T^2 - 0.0003T + 1 \tag{6.6}$$

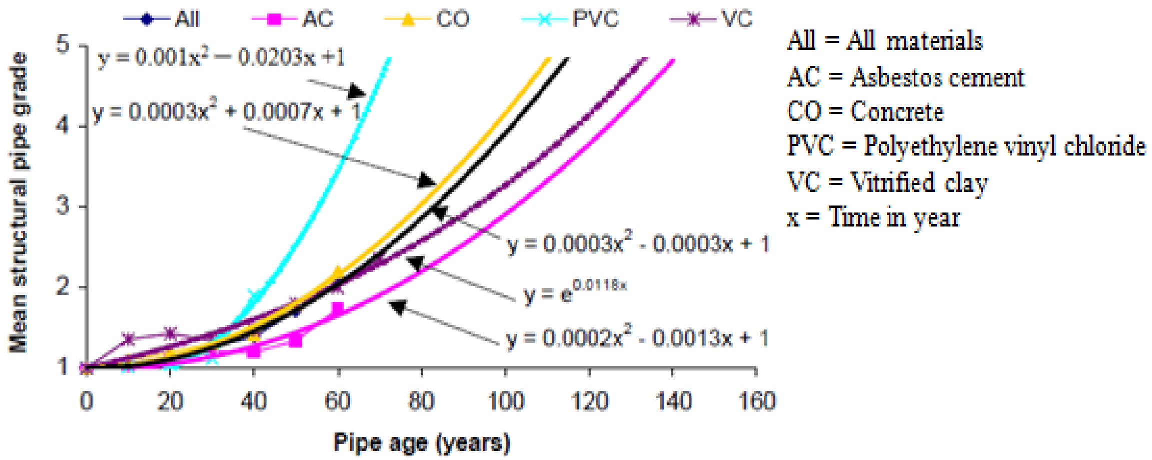


Figure 6.1: Underground pipeline deterioration models using MIIP dataset

where T = age of the pipe (in year) which corresponds to the intervention year obtained from the risk-cost optimisation. The renewal methods are selected based on detailed analysis of possible defects, as indicated by the condition index and the possible scenarios of soil loss. For example, a pipe with condition index 3 and high possibility of soil loss will need replacement or the use of a structural liner to carry loads and stabilise deformation. At a minimum, a semi structural liner that can withstand hydrostatic pressure is required.

6.5.2 Impact assessment

The criterion used to renewal of pipes is the degree of impact of an underground pipeline failure. The impact assessment ranks the pipe segments in unit length in terms of six major factors, namely, location, embedment soil, pipe size, burial depth, functionality and seismic zone. The assessment generates a rank of impact for the underground pipeline system. The premise for an impact factor follows from the fact that not all pipe segments in a network have the same likelihood of failure or the same consequence of failure.

Each of the six factors is assigned a degree of impact defined by low, medium or high. How each factor is assessed is explained below (McDonald and Zhao, 2001):

1. Location: The impact based on pipe location is assessed on how the public and environment will be affected if failure occurs. The contributing aspects include land

use, traffic intensity, access for repair, location under or adjacent to critical establishments and environmental classifications. For example a segment of pipe within an airport perimeter or under 6 lanes of traffic or in a commercial area will have a high degree of impact (rating of 3). On the other hand, a pipe in an industrial park or under 1 or 2 lanes of traffic will have a low degree of impact (rating 1).

2. Soil: Soil support is an integral component of the pipe-soil system. Void formation and loss of soil support resulting from fractures and open joints in the presence of sufficient hydrostatic head can contribute to premature pipe failures. The types of supporting material that pose the greatest threat are silts and sands (rating of 3), while medium to high plasticity clays have the lowest degree of impact (rating 1).

3. Pipe size: The magnitude of repair work and the selection of rehabilitation methods are dependent on pipe size. If a failure occurs, the size of the pipe will have an impact on the amount of contamination to the surrounding environment. As a result, a pipe with a diameter (or vertical size) of less than 900 mm is given a low rating (1) while those with diameters greater than 1800 mm are given a high rating (3).

4. Burial depth: The deeper a pipe is buried, the greater the degree of difficulty in accessing it for repair and inspection. The burial depth rating will be low (1) for pipe buried less than 3 m and high (3) for a burial depth greater than 10 m.

5. Functionality: The function of the underground pipeline includes both the types of liquid carried and the location of the segment of the system. For example, the environmental consequences will be more severe for a sanitary underground pipeline failure than a storm underground pipeline failure. Also, the failure of a pipe segment entering the treatment plant will be more severe than that of a collector pipe. The rating for a high degree of impact is 3 (pipe entering/ exiting a treatment plant) and 1 for a low degree of impact (collector pipe).

6. Seismic zone: Areas prone to seismic activity based on velocity or acceleration are assigned a rating of 1 for a low seismic (zone velocity or acceleration between 0 and 2), and 3 for a high seismic zone (zone velocity or acceleration between 5 and 6).

For all of the factors listed above, the medium degree of impact falls between the high and low extremes and is assigned a value of 1.5. A weighted impact factor (I_w) is used to combine the influence of each of the six factors described above for each pipe segment within the system as below Eq. (6.7)

$$I_w = 0.2 f_l + 0.16(f_s + f_z + f_d + f_f + f_q) \tag{6.7}$$

where f_l = location factor, f_s = embedment soil factor, f_z = size factor, f_d = burial depth factor, f_f = underground pipeline function factor and f_q = seismic factor. Although these factors do not change dramatically from year to year, periodic updating may be necessary. The failure impact rating can be assessed based on Table 6.3 (WRc, 2001).

Table 6.3: Failure impact rating

Weighted impact factor, I_w	Failure impact rating, R_{imp}
1.00	1
1.01 – 1.60	2
1.61 – 2.20	3
2.21 – 2.80	4
>2.81	5

6.5.3 Prioritisation

Once the weighted impact rating is determined for individual pipe segment, the impact assessment can then be used in a number of ways in the decision-making process. The impact ratings can be used in combination with the physical condition rating of a pipe to prioritise rehabilitation or replacement work and the future inspection frequencies (Table 6.4) (WRc, 2001). For instance, among the pipe segments with the same physical condition rating, those with higher impact ratings would be considered first for rehabilitation. Finally, in high seismic areas, those pipe segments surrounded by soils with high liquefaction potentials should be identified.

Table 6.4: Renewal priority

Structural condition index	Implication	Failure impact rating (R_{imp})	Renewal priority
5	Failed or failure imminent	1 to 5	Immediate
4	Very poor condition High structural risk	5 1 to 4	Immediate High
3	Poor condition Moderate structural risk	4 to 5 1 to 3	Medium Low
2	Fair condition Minimal structural risk	1 to 5	Low
1 or 0	Good or excellent condition	1 to 5	Not required

6.6 NUMERICAL EXAMPLE

An underground pipeline network under a heavy roadway subjected heavy load operating conditions, passed under commercial and residential areas is taken as a numerical example to validate the proposed risk-cost optimisation management strategy in this Chapter. The underground pipeline network consists of approximately 789 kilometres of sanitary flexible underground metal pipelines, constructed in 1940. The network consists of six segments of pipeline, termed as A to F (Table 6.5). The whole network constructed above the ground water table. As mentioned earlier, LCC includes all appropriate costs including initial construction costs, maintenance, repair and renewal costs, social costs and decommissioning costs as well as carbon dioxide emissions mitigation cost is used as an objective function. The analysis period under consideration should be long enough to cover the service life of the infrastructure system. All alternatives for maintenance and renewal should be considered. The essence of LCC is that one alternative may have a higher initial cost, but its costs over the asset's life cycle may be lower than other alternatives.

Table 6.5: Pipe materials and location properties

Pipe section	Material	Location	Embed soil	Length (km)	Mean diameter (mm)	Thickness (mm)	Soil height (m)	Traffic load (kPa)
A	Steel	Commercial	Clay	155	500	8	2.0	100
B	Ductile iron	Commercial	Clay	96	600	8	2.0	100
C	Steel	Residential	Sand	112	600	9	2.1	100
D	Steel	Residential	Sand	223	480	7.5	2.5	90
E	Ductile iron	Residential	Sandy Gravel	88	350	7	2.2	100
F	Ductile iron	Commercial	Sandy Gravel	115	500	8	1.8	100

Table 6.6: Statistical properties of the materials and soils

Symbol description	Mean value	Coefficient of Variation %	Distribution
Buoyancy factor, R_w	1.00	-	-
Trench width, B_d	2.00 m	-	-
Soil reaction modulus, E'	4.04 MPa	-	-
Shape factor for steel pipe	4.0	-	-
Shape factor for ductile iron pipe	4.4	-	-
Capacity modification factor for pipe, ϕ_p	1.00	-	-
Capacity modification factor for soil, φ_s	0.90	-	-
Tensile strength of pipe for Steel	450 MPa	-	-
Tensile strength for Ductile Iron	330 MPa	-	-
Poisson Ratio for steel pipe	0.3	-	-
Poisson ratio for ductile iron pipe	0.27	-	-
Elastic modulus of steel pipe	210 GPa	1.0	Normal
Elastic modulus of DI pipe	170 GPa	1.0	Normal
Soil modulus, E_s	2×10^3 kPa	5	Normal
Unit weight of soil, γ	18.0kN/m^3	2.5	Normal
Traffic load (Live load), P_s	Refer to Table 6.5	10.0	Normal
Deflection coefficient, K_b	0.11	1.0	Lognormal
Multiplying constant, k	2.0	10.0	Normal
Exponential constant, n	0.3	5.0	Normal
Thickness of pipe, t	Refer to Table 6.5	1.0	Normal

The capital cost, maintenance cost and failure consequence cost are predicted or calibrated based on real case study on Municipal Infrastructure Investment Planning (MIIP) in Canada, (Rahman and Vanier, 2004), Melbourne water report (2012) and Davis et al (2008) report. The capital cost, maintenance cost and failure consequence cost (future values) are mentioned in Table 6.7 on the yearly basis. As discount rate is not currently available in the cost breakdown, a typical discount rate (UK) 5% is considered in this example. Two different typical flexible underground metal pipes, namely, steel and ductile iron (DI) have been used in the whole network.

Table 6.7: Cost break down for pipe network (Future value)

Pipe section	Operation cost	Maintenance cost	Failure cost
A	£88050	£19100	£88.4m
B	£47800	£7960	£78.1m
C	£71300	£7920	£87.3m
D	£84030	£11200	£132m
E	£29040	£7920	£69.2m
F	£53200	£7108	£86.5m

The statistical properties of materials are shown in Table 6.6. It is presumed that the whole underground pipeline network located in a high seismic vulnerable zone area. Table 6.7 summarises the cost data (Future value) for the whole network sections (A – F). The pipes in the network are consisted of medium size steel and ductile iron pipes. The network is subjected to corrosion and its corrosion rate is modelled using Eq. (3.1). The underground pipeline material, location and soil parameters are listed in Table 6.5. There are 9 random variables (elastic modulus of pipe, soil modulus, soil density, live load, deflection coefficient, corrosion coefficients, pipe wall thickness and height of the backfill) where the mean and coefficient of variation are listed in Table 6.6. All of them are considered as a uniformly distributed, except the deflection coefficient which is log-normal distributed. After the pipe's life cycle, the pipe is disposed, recycled, or abandoned.

6.7 RESULTS AND DISCUSSION

The structural reliability of the underground pipeline network is first estimated and then the risk-cost optimisation is performed to predict the optimal maintenance or renewal time which takes into account the reliability analysis and life cycle cost. The probability of pipeline system failure (reliability) is predicted by MCS for every failure mode and then an upper and lower bound is predicted as a series system. Then the optimal time to repair or replace is estimated with respect to LCC using GA which is performed in MATLAB software. The proposed maintenance strategy enables decision maker to choose a feasible renewal method based on the calculated optimal renewal time. The results and discussion are presented as follows:

6.7.1 Pipe reliability

The probabilities of failure due to corrosion induced deflection, buckling, wall thrust and bending with respect to time are estimated using MCS method based on the parameters and basic variables given in Tables 6.5 and 6.6. The occurrence of either failure mode of the pipe will constitute its failure. Therefore the probability of failure of the underground pipeline network is determined as a series system using Eq. (3.32a) and the results are shown in Figures 6.2 – 6.7. When the thickness of the pipe is reduced due to corrosion, the moment of inertia and the cross-sectional area of pipe wall are decreased with a resulting reduction in pipe strength as Eqs. (3.5) and (3.6), respectively. As all the random variables are considered as uniformly distributed, except the deflection coefficient which is log-normal distributed. Thus Rackwitz-Fiessler algorithm has been applied to transform its distribution from log-normal to normal in this study.

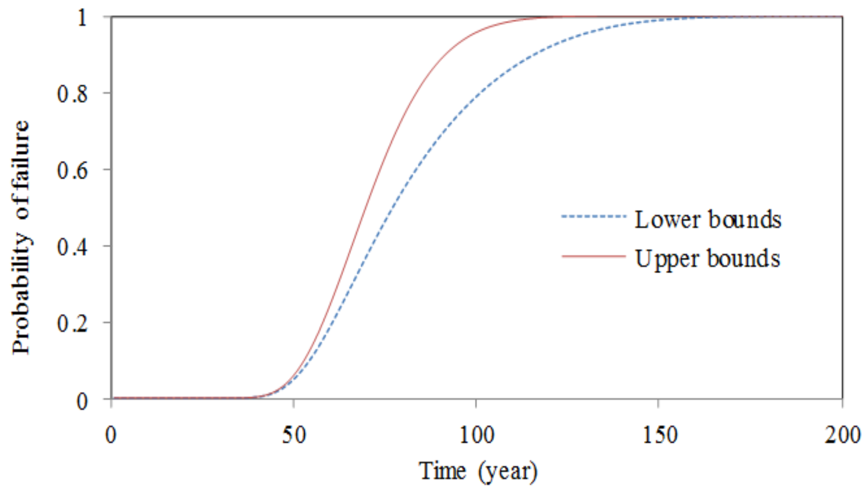


Figure 6.2: Probability of failure for pipeline section A using MCS

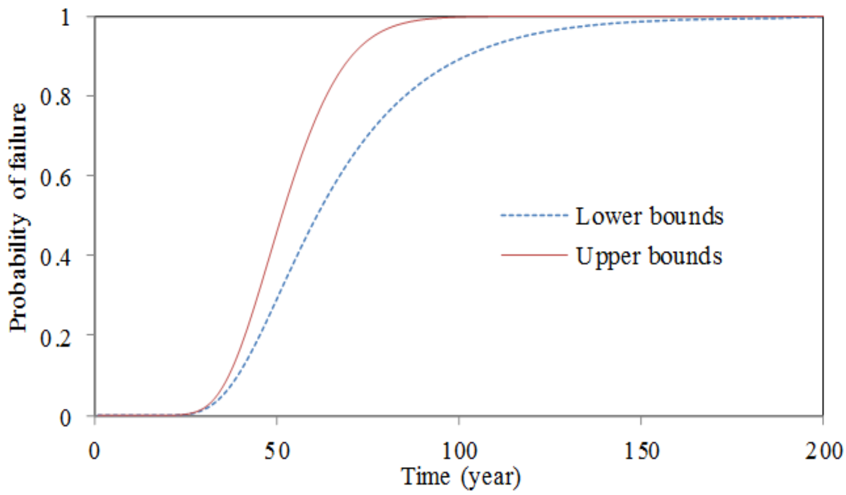


Figure 6.3: Probability of failure for pipeline section B using MCS

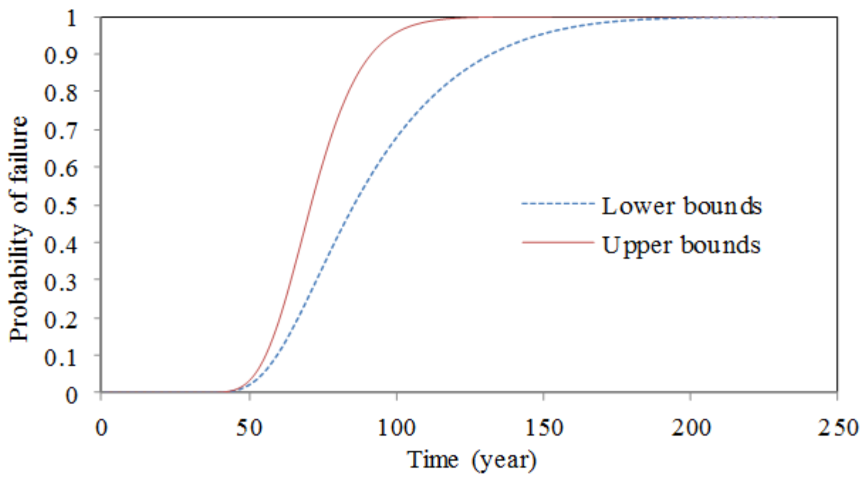


Figure 6.4: Probability of failure for pipeline section C using MCS

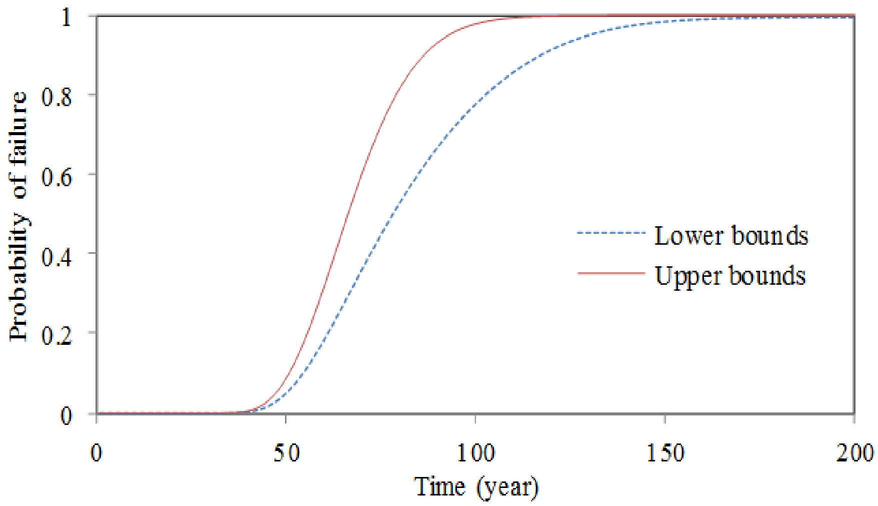


Figure 6.5: Probability of failure for pipeline section D using MCS

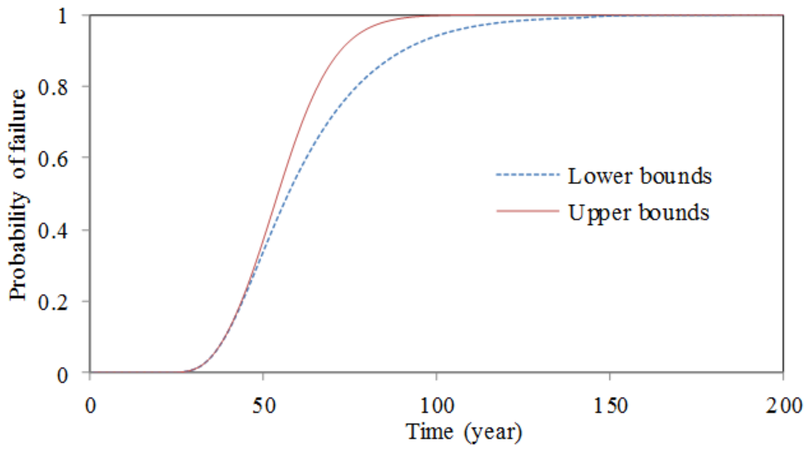


Figure 6.6: Probability of failure for pipeline section E using MCS

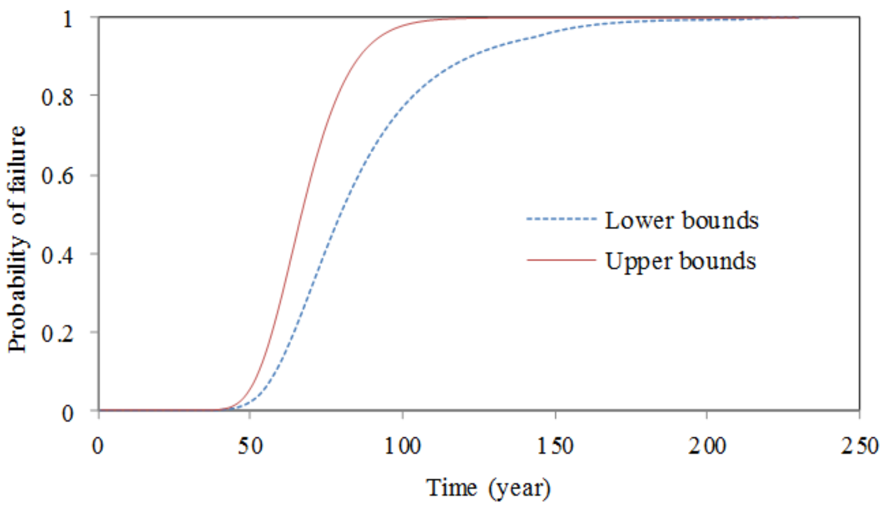


Figure 6.7: Probability of failure for pipeline section F using MCS

The study shows that on average the probability of pipe failure at the beginning is close to zero and it remains unchanged until about 45 years of service life, then it gradually changes as time increases and after 50 years, the probability of failure rises drastically. The upper bounds of the failure probability obtained from Figures 6.2 – 6.7 have been used for the subsequent risk-cost optimisation as a worst case scenario.

6.7.3 Optimal cost and time

As shown in Eq. (6.3), the failure risk cost is calculated by multiplying failure cost with the probability of system failure. Once the probability of system failure has been calculated, the optimal time to repair or replace and the associated life cycle cost are obtained from the risk-cost optimisation using GA. In this example, the population size and the maximum number of generations were set to 100 and 150 respectively. The algorithm used a single point cross over with probability of 0.50. The mutation probability was set to 0.50 and the bit mutation probability was set to 0.01. GA used a tournament selection scheme, with tournament size of 4. Figures 6.8 – 6.13 show the convergence of total LCC obtained from risk-cost optimisation for different pipe sections, A – F. The optimal LCC cost is associated with the first maintenance.

Next, the proposed maintenance strategy is extended to determine an applicable and feasible renewal method using Tables 6.1 and 6.2. The recorded database shows that the underground pipelines are built on clay, sand and sandy gravel type soil. In addition, all types of pipelines are above the groundwater level. Based on this information and according to Table 6.2, the possibility of soil loss for sanitary underground pipeline sections A and B is low, whereas for sections C to F, the possibility of surrounding soil loss is high. The condition index (CI) for is estimated using Eq. (6.6) as shown in Table 6.7 by substituting the identified optimal time to renew from the risk-cost optimisation process. Applicable renewal categories are then selected from Table 6.1 based on the underground pipeline CI and the possible scenario of soil loss. The sections A, B and C pipelines are required to renew using non-structural or semi-structural lining method based on the estimated CI and low possibility of soil loss. On the other hand, due to high possibility of soil loss and CI >2, the sections D and E pipelines are needed to renew using semi-structural or structural liners. Finally, due to high possibility of soil loss and CI>3, the section F should be renewed with structural liners or replacement.

Alternatively, replacement is also recommended for other sections if the repair cost becomes greater than the cost of replacing the pipes.

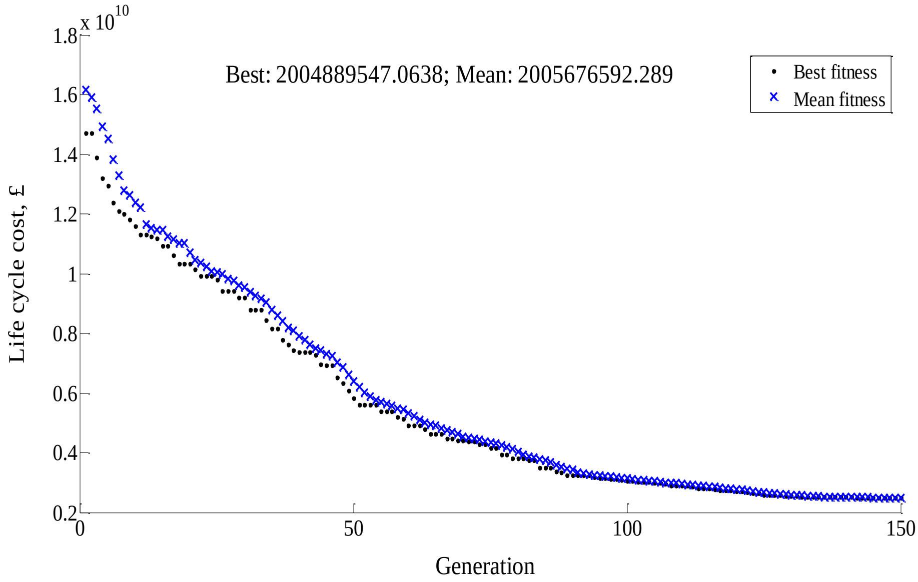


Figure 6.8: Life cycle cost for pipeline section A using GA

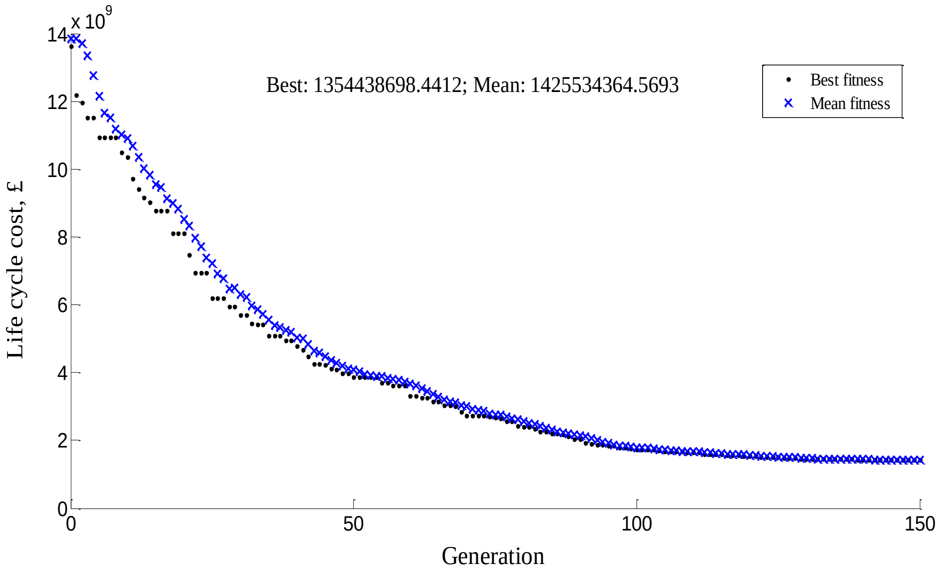


Figure 6.9: Life cycle cost for pipeline section B using GA

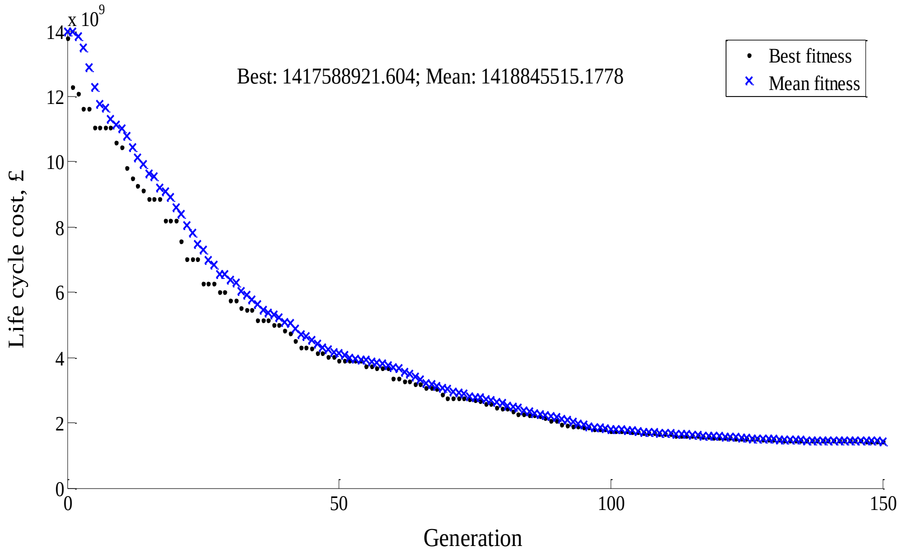


Figure 6.10: Life cycle cost for pipeline section C using GA

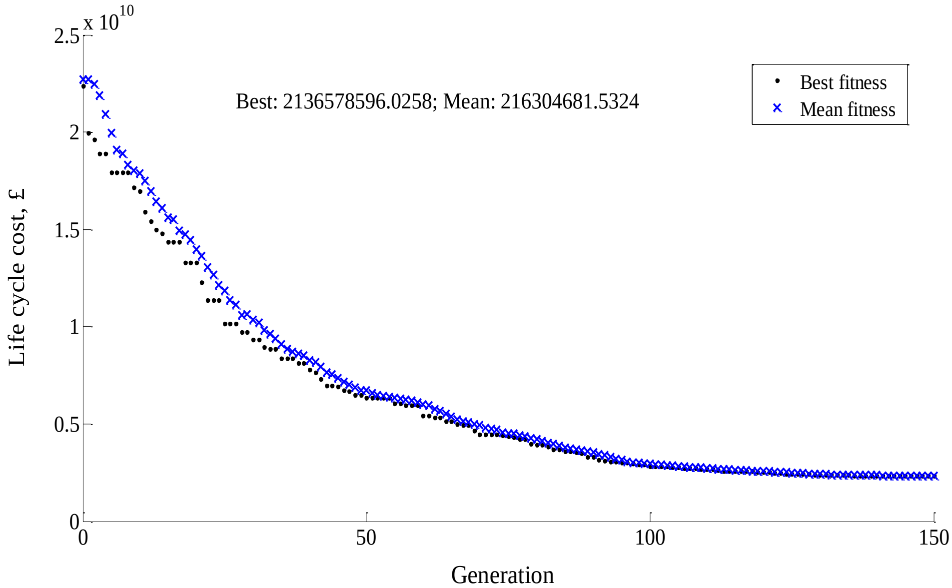


Figure 6.11: Life cycle cost for pipeline section D using GA

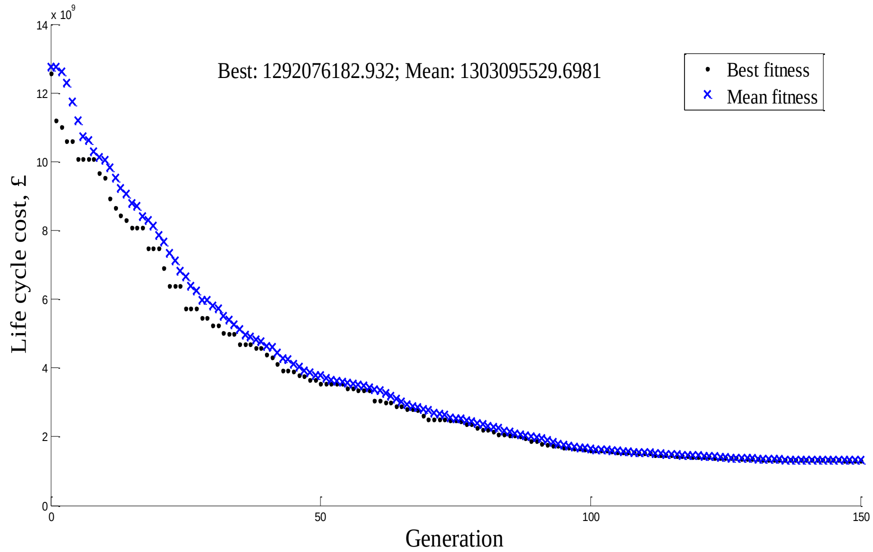


Figure 6.12: Life cycle cost for pipeline section E using GA

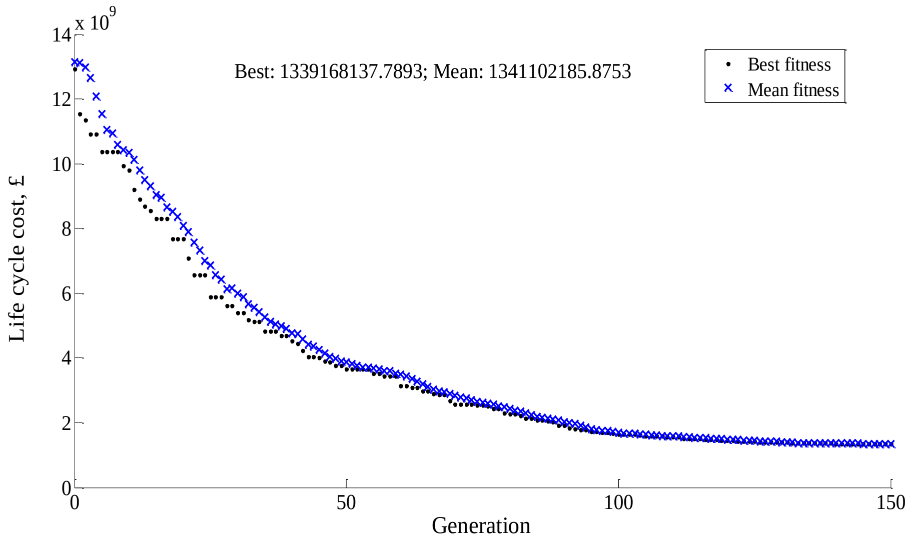


Figure 6.13: Life cycle cost for pipeline section F using GA

6.7.4 Renewal priority selection

The renewal approach is illustrated for the exampled underground pipeline which consists of steel pipes and ductile iron pipes. Based on the underground pipeline's inventory information and alignment, an impact assessment has been carried out considering all six major impact factors as mentioned in Section 6.6.2. For example, an impact assessment for Section A can be shown as below Table 6.8.

Table 6.8: Impact assessment for pipe section A

Factor	Degree of impact	Rationale
Location	High (3)	Commercial area
Embedment soil	Medium (1.5)	Clay
Size	Low (1.0)	Diameter < 900 mm
Burial depth	Low (1.0)	Ranges from <3 m
Function (sanitary)	Medium (1.5)	Sanitary pipeline
Seismic zone	High (3)	High seismic area

Table 6.4 summarises the renewal priority based on the structural condition index and failure impact ratings (Zhao et al, 2001). The renewal priority index (PI) is predicted based on pipe failure impact rating and structural CI as shown in Table 6.4. Applying the weighted formula Eq. (6.7), the degree of impact 1.88 is predicted for pipeline section A. Therefore, the corresponding failure impact rating is 3 (Table 6.3), which means that the impact on underground pipeline section A is moderate in terms of likelihood of failure and/or the severity of failure consequence. With respect to this impact rating with the structural condition index, the renewal priority can be selected in decision making process. According to Table 6.4, the pipe section A has low structural risk and therefore, low renewal priority need to be given as shown in Table 6.9. Once renewal is accompanied the pipe's overall serviceability is increased (failure probability is reduced) due to repair or replace the pipe.

Table 6.9: Results of pipelines risk-cost optimisation using GA

Pipe section	Optimum Life cycle cost (£b)	Renewal time (year)	Structural Condition index (CI)	Renewal priority	Renewal methodology
A	2.0	62	2.2	Low, minimal structural risk	Non-structural or semi-structural
B	1.35	63	2.3	Low, minimal structural risk	Non-structural or semi-structural
C	1.41	66	2.25	Low, minimal structural risk	Non-structural or semi-structural
D	2.13	62	2.2	Medium, poor condition	Semi-structural, structural or replacement
E	1.29	72	2.5	Medium, poor condition	Semi-structural, structural or replacement
F	1.33	88	3.5	Immediate, high structural risk	Structural or replacement

6.7.5 Parametric study

A parametric study has been carried out to analyse the effects of different parameters on reliability and life cycle cost of the underground pipeline network. For example, if soil properties, such as soil modulus or soil density changes, this will affect probability of failure and hence reliability and life cycle cost of the pipeline network. As shown in Figure 6.14, the life cycle cost increases drastically when soil density is increased from 16 kPa to 20 kPa. The parametric study also demonstrates that with increasing soil height above pipeline decreases service life and increases life cycle cost of the pipeline network as illustrated in Figure 6.15 for soil height from 3.0 m to 3.75 m. Figure 6.16 shows that when discount rate varies from 5% to 7%, the whole life cycle cost also varies significantly. Similarly, other factors such as pipe dimension including pipe thickness and diameter, live load, etc. influence pipe failure probability and consequently affect its life cycle cost. Due to sudden increase the failure probability after 40 to 45 years (Figures 2 – 7) the life cycle cost is low until 40 years and then drastically increases (Figures 6.14 – 6.16).

From analysis of the different parameters of the pipeline materials, adjacent soil types, live load and discount rate influence the pipe reliability and cost in different ways. For example, if the soil type changes (soil modulus, soil height and soil density etc.) from location to location, the life cycle cost also varies with change of probability of failure due to change of soil types.

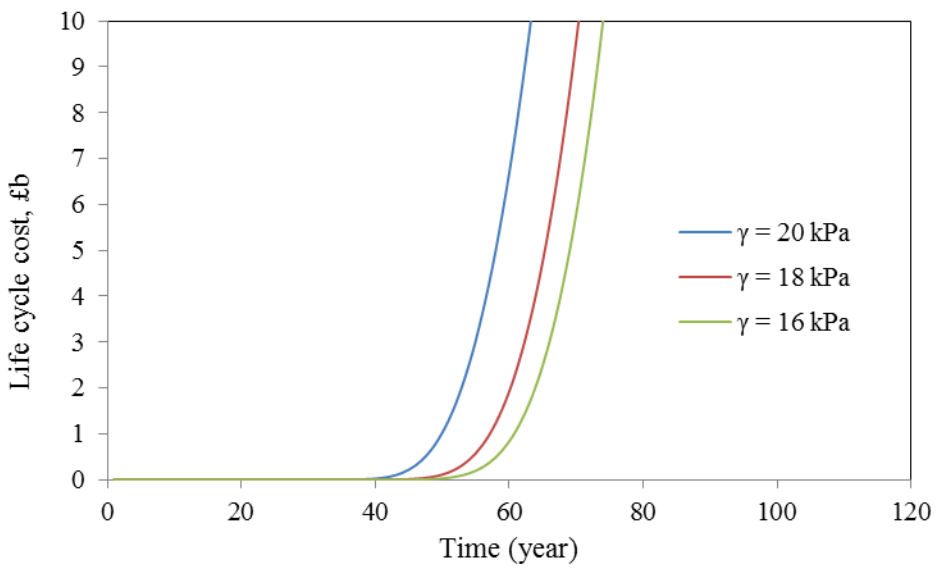


Figure 6.14: Life cycle cost of whole pipeline network with different soil densities

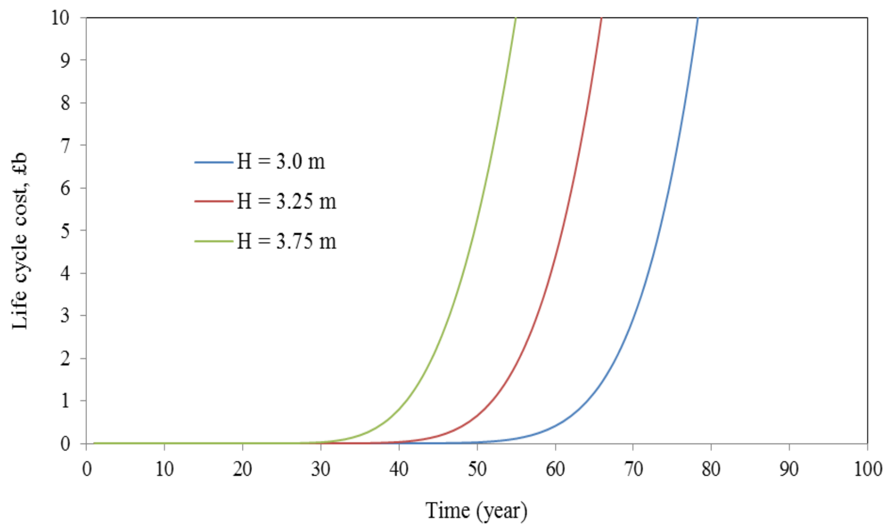


Figure 6.15: Life cycle cost of whole pipeline network with different soil heights

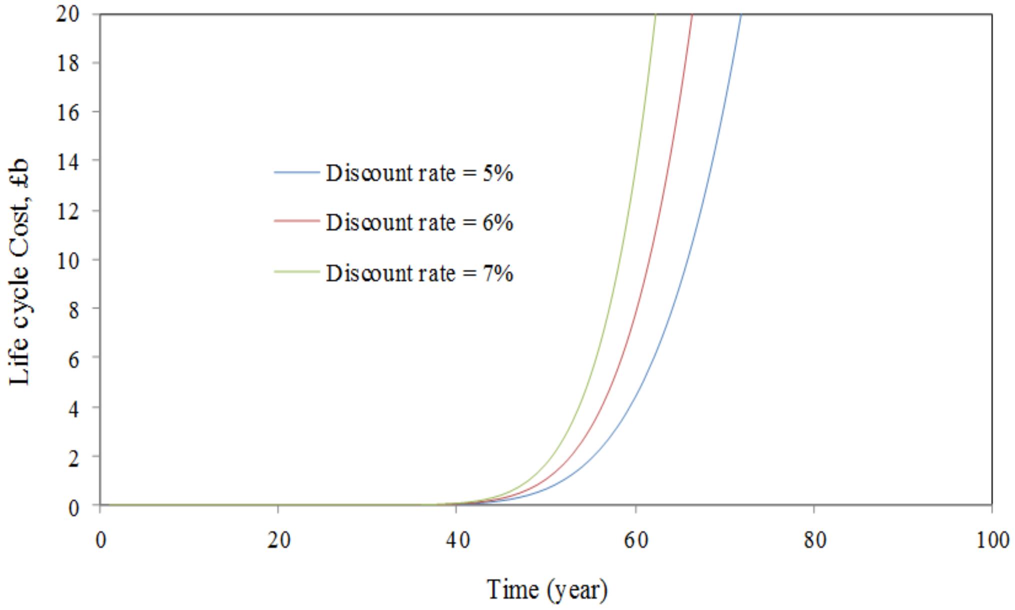


Figure 6.16: Life cycle cost of whole pipeline network with different discount rates

6.8 SUMMARY

This Chapter presents a novel integrated approach for systematising manages of flexible underground metal pipeline network. It follows that a rigorous decision process should find a balance between the risk of failure and the cost to mitigate it. The proposed management strategy also enables decision maker to select appropriate renewal methods based on the identified optimal time to renew, pipe condition index and the possibility of surrounding soil loss. A numerical example is presented to validate the proposed risk-cost management strategy with a view to prevent the unexpected failure of underground flexible metal pipes by prioritising the maintenance options based on the failure severity and structural reliability. The whole process has taken about 1 hour and 35 minutes in 1.6-GHz Pentium IV personal computer. In this process, the corrosion model Eq. 3.1 or 3.2 has been used as a simulation tool for obtaining pipe thickness reduction with respect to time to predict the reliability. If historical data and current pipe thickness are available, then the real data can be used instead of Eq. (3.1) or (3.2) in the proposed approach to estimate pipe reliability and determine management strategy. The proposed technique can help in making the appropriate decisions concerning the intervention to ensure the reliable and serviceable operation of the underground pipes. It is recommended that more field studies should be conducted in the future to acquire the necessary data to increase reliability on the assumptions made in this research. This will, in turn, result in better asset and capital utilisation.

CHAPTER SEVEN

RISK-COST OPTIMISATION USING SUBSET SIMULATION

7.1 INTRODUCTION

For the underground pipeline, the increased safety requirements and the goal of introducing effective optimisation is very challenging and it is difficult to have an algorithm that performs uniformly efficient for all problems. In this Chapter, Subset Simulation (SS) (Au and Beck, 2001; Au and Beck, 2003; Au et al, 2007; Li, 2011), which is originally a reliability analysis method, is developed to solve underground pipeline risk-cost optimisation problems by introducing artificial probabilistic assumptions on design variables. The basic idea is to deal the optimisation problems in the context of reliability analysis. The objective function itself may have many local optima but its cumulative distribution function (CDF) has only one maximum value at its tail as a continuous function. It turns out the searching process of an optimisation problem equivalent to exploring the process of the tail distribution in a reliability problem.

The reliability of a system is the probability to perform its required functions under stated conditions for a specified period of time. In engineering reliability analysis, it is calculated based on specified probabilistic modelling of the underlying uncertainties or random variables which is called stochastic algorithm (Li, 2011; Schueller and Pradlwarter, 2007). As failure is an exception rather than the rule in properly designed systems, therefore, an engineering reliability analysis involves a rare event simulation. Finding the global optimum, on the other hand, involves simulating the extreme events which also can be considered as rare occasions in the design variable space. If stochastic algorithms are adopted, the objective function is evaluated at the optimum random points in the design variable space. Based on this idea, an extreme event i.e., optimisation problem is a special case of a rare event in reliability problem (Khan et al, 2013; Li, 2011).

It is commonly believed that there is no single universal method which is capable of solving all kinds of global optimisation problems efficiently because each method has its own definition and limitations. A common feature of most stochastic optimisation algorithms is that they are developed based on the observations of random phenomenon in nature. Hence, the random sampling and/or random manipulation play an important role in the implements of these algorithms. These random features provide the possibility of jumping out of local optimums. Various sophisticated numerical techniques based on gradient information have been well documented (Ravindran et al, 2006), but most of them are vulnerable to converge into a local optimum due to nonlinear, multimodal or even discontinuous objective functions. Stochastic optimisation algorithms are commonly used for solving global and local optimisation problems. Many are based on probabilistic assumptions on the design variables and the objective function. Among stochastic optimisation algorithms, Simulated Annealing (SA) and Genetic Algorithm (GA) have been most successful (Spall, 2003). But these are computationally expensive traditional algorithm. In addition, there is no absolute assurance that these methods will find a global optimum.

In the previous Chapter GA has been used in underground pipeline risk-cost optimisation process. To overcome the difficulties of GA as mentioned above, a stochastic optimisation algorithm, SS has been developed in this Chapter which found more robust and easy to implement for solving the nonlinear, multimodal optimisation problems. SS is a relatively new method and has not yet been applied in pipe maintenance optimisation. This Chapter is devoted to extend the application of SS idea where an artificial reliability problem is constructed by randomising the design variables. Along the spirit of Subset Simulation, this artificial reliability problem is decomposed into a series of conditional probability problems. The modified Metropolis-Hastings algorithm (Au and Beck, 2001; Au et al, 2007) is implemented to generate efficiently the conditional solutions in each simulation level. An ascending sequence of the objective function values is chosen adaptively so that the estimated conditional probabilities are equal to the specified value. With increasing the sequence, the value of objective function is approaching to the global optimum.

The contents of this Chapter are structured as follows. The basic of SS method is presented in Section 7.2, where the analogy between an optimisation problem and a reliability problem is interpreted. Then in Section 7.3, the procedure of Subset Simulation for optimisation and the modified Metropolis-Hastings algorithm are described. Several computational issues to improve the efficiency and robustness of SS for optimisation are discussed in Section 7.4. A numerical example is presented in Section 7.5 to validate the method. Results and discussion are presented in Section 7.6, where the effectiveness of SS for optimisation process is demonstrated and compared with the results obtained from GA. Finally, summary is given in the last Section 7.7.

7.2 BASIC OF SS OPTIMISATION

The analogy between an optimisation problem and a reliability problem allows an optimisation problem to solve using SS method as shown in Figure 7.1. Many optimisation algorithms have its own probability density function (PDF) and cumulative distribution function (CDF). Let h_{opt} be the global maximum of *h*, where $x = x_{opt}$. By the definition of the CDF, a CDF curve is monotonic, non-decreasing and right-continuous and its value at $h = h_{opt}$ is unity. A reliability problem including classical and stochastic ones can be employed to perform as an optimisation algorithm (process). However, solving optimisation problems by reliability methods is still in infancy condition compared to other available methods, such as GA, FSM, ACOA, SFLA etc., due to lack of research and applications in practical problem (Li and Au, 2010).

The basic difference between a reliability and optimisation problem analysis is that the aim of a reliability analysis is to evaluate the probability of an event, while the aim of an optimisation problem is to locate a point or region where the objective function is minimised or maximised, i.e. taking extreme values. One can therefore treat the optimisation problem as to locating a rare event, because an extreme event is also a special case of a rare event. Based on these observations, an optimisation problem can be converted to a reliability problem, which makes it possible to using a reliability method to solve an optimisation problem. To view the optimisation problem in the framework of reliability analysis, the design variables are artificially considered to be random (Li and Au, 2010). This induces the objective function h to P_F (Figure 7.1).

Consider a global optimisation problem given by

Max $h(x)$, such that $x \in \Omega$

where $h : \Omega \subset R^n \to R$ is a real valued function, *x* is the design variable vector and Ω is a closed and bounded set. The global maximum (x_{opt}, h_{opt}) as in Eq. (7.1) is the point such that

$$h_{opt} = h(x_{opt}) \geq h(x) \tag{7.1}$$

In Eq. (7.1), only one variable x is involved, and h is a function of x. The optimisation problem is defined as finding the maximal value of h, i.e., $\max h(x)$.

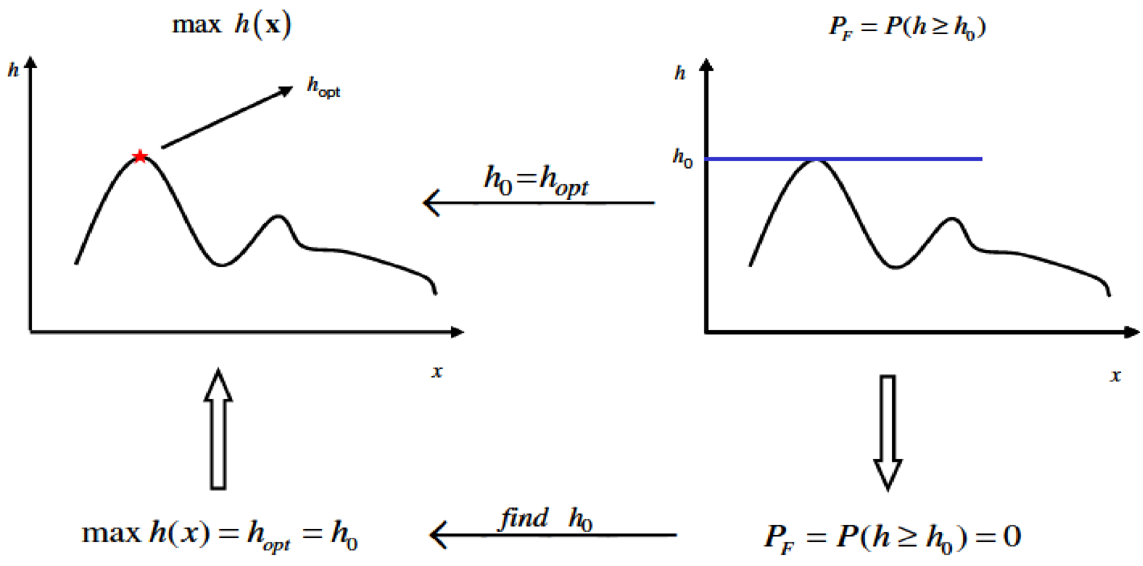


Figure 7.1: Conversion between an optimisation problem and a reliability problem

If the design variable x to be random, a reliability problem can be defined to estimate the probability of h exceeding a given threshold h_0, therefore the failure probability can be estimated as Eq. (7.2)

$$P_f = P(h(x) \geq h_{opt}) \tag{7.2}$$

The reliability problem is often concerned a rare event simulation problem since a very small probability of failure is involved in practice. Geometrically, the region of $h > h_0$ in a reliability problem is broader than the one of the maximum points in an optimisation problem. In other words, the region needed to be found in an optimisation problem is a reduced region in a reliability problem. The attention here is on the point or region where the objective function attains the largest value which can be a challenging problem when the objective function has many local optimums or when the dimension of the design variable space is large (Li, 2011). Recall that, the artificial reliability problem is not to compute the failure probability but to search for the corresponding point h_{opt} of zero failure probability given by Eq. (7.2). After randomising the design variable, the objective function maps the multi-dimensional design variable vector into a random variable *h*. This mapping also transforms all points that take the same value onto one point on the non-decreasing CDF curve of the randomised objective function *h*. Hence, the trend trapping in local optimums can be easily avoided (Li and Au, 2010).

Based on aforementioned conventions, it is clear that an artificial reliability problem can be dealt with an optimisation problem in the framework of reliability analysis. Along the same spirit of Subset Simulation, it can generate samples (solutions) that progress toward the maximum in a more efficient way, simultaneously as the rare event region is gradually being populated.

7.3 METHODOLOGY

SS for optimisation problems exploits the entire design variable space to search for the global maximum of the objective function rather than to estimate a zero probability for an artificial reliability problem. The procedure of SS optimisation algorithm is presented as follows.

First, select the distributional parameters for design variables. In the original optimisation problem each design variable as a random variable with an artificial probability density functions (PDF) $f(x)$. If there are n numbers of design variables denoted as $x = \{x_1, x_2, ..., x_n\}^T$, then the corresponding PDFs of these design variables are denoted as $f_1(x_1), f_2(x_2), ..., f_n(x_n)$. Then the joint PDFs of all design parameters can be expressed as Eq. (7.3) (Au and Beck, 2003; Ching et al, 2005)

$$f(x) = \prod_{i=1}^{n} f_i(x_i). \tag{7.3}$$

Generate N independent and identically distributed samples $\{x_1, x_2, ..., x_n\}$ by direct Monte Carlo simulation according to the artificial distributions. Each sample $x_i (i = 1,2, ..., n)$ has n components, i.e., $x_i = \{x_i^{(1)}, x_2^{(2)}, ..., x_i^{(n)}\}$, where $x_i^{(j)} \{j = 1,2, ..., n\}$ are generated from $f_j(x_j)(j = 1,2, ..., n)$. Calculate the constraint fitness function values (if any) and the objective function values of the samples and then sort them according to the double-criterion ranking algorithm. Refer a x_N as the best solution and x_1 as the worst. Select the distributional parameters for design variables. The modified Metropolis-Hastings algorithm (MMH) is employed for generating samples conditional on the intermediate event. In the each simulation level, a Markov chain can be generated with the same conditioning. Since the initial samples obey the conditional distribution, all these Markov chains are automatically in stationary state and samples in these Markov chains distribute according to the conditional distribution. If the number of samples in each level is a constant number, then the length of each Markov Chain will be $1/p_{k-1}$ (k = 2, . . .,m) where p_{k-1} is the level probability in the last simulation level and m is the total simulation levels. Evaluate and sort the objective function values of new generated samples. Then determine the $N(1-p_k)$ th percentile $h_{k,N(1-p_k)}$ from the ascending sequence of $\{h_{k,l} : l = 1,....., N\}$ so that the probability of the conditional event is satisfied, as shown in Eq. 7.4. (Li, 2011)

$$P(F_{\mathrm{k}} \mid F_{\mathrm{k\text{-}1}}) = P(h(x) \geq h_{k,N(1-p_k)} \mid F_{k-1}) \approx p_k\} \tag{7.4}$$

Again, these samples whose objective function values larger than $h_{k,N(1-p_k)}$ are chosen to provide ‘seeds’ for the sampling operation in the next simulation level. The procedure is repeated until a stop criterion is met or the computational budget of the objective function evaluations is exhausted. Note that the total number of samples here is equal to $N + \sum_{k=2}^{m}(1-p_k)N$. One important aspect required to address in details is how to generate the conditional samples in a simulation level. The Metropolis-Hastings algorithm (MH) is used to achieve this purpose. However, it has been reported by Au and Beck, (2001) that the MH algorithm does not work well if the dimension of the design variable is high, because a zero acceptance ratio for the next candidate state results to extremely frequent repeated samples in a Markov Chain. The modified Metropolis-Hastings algorithm (MMH) should be used for this case by generating the candidate state component by component so that the acceptance ration of individual component remains non-vanishing as the dimension increases (Au and Beck, 2001; Au and Beck, 2003). Another difference between the MH algorithm and the MMH algorithm is the dimension of the proposal PDF, which is employed to generate a candidate state for a Markov Chain. The MMH algorithm uses a group of one-dimensional proposal PDF instead of an n-dimensional proposal PDF.

Let $f_i^*(\xi_i \mid x_i), i = 1,2,....,n$ to be a series of PDFs which depend on x_i. In order to generate the next Markov Chain sample $x_{k+1} = \{x_{k+1}^{(1)}, x_{k+2}^{(2)},...., x_{k+1}^{(n)}\}^T$ from the current sample $x_k = \{x_k^{(1)}, x_k^{(2)},...., x_k^{(n)}\}^T$ conditional on an event F_j, the MMH algorithm is presented as follows (Au and Beck, 2001):

a) Generate a candidate state $\xi_{k+1} = \{\xi_{k+1}^{(1)}, \xi_{k+2}^{(2)},....., \xi_{k+1}^{(n)}\}^T$ from the proposal PDFs. $f_i^*(\xi_i \mid x_i), i = 1,2,....,n$

For each component $i = 1,2,....,n$

(1) Generate a pre-candidate component $\xi_{k+1}^{(1)}$ from $f_i^*(\xi_i \mid x_i)$

(2) Compute the acceptance ratio as Eq. (7.5):

$$r_{k+1}^i = \frac{f_i(\xi_{k+1}^{(i)}) f_i^*(x_k^i \mid \xi_{k+1}^{(i)})}{f_i(x_k^{(i)}) f_i^*(\xi_{k+1}^{(i)} \mid x_k^i)} \tag{7.5}$$

(3) Set the ith component of ξ_{k+1} according to Eq. (7.6)

$$\xi_{k+1} = \begin{cases} \xi_{k+1} \ \textit{with probability} \min(1, r_{k+1}(i)) \\ x_k^{(i)} \ \textit{with probability} \min(1, r_{k+1}^{(i)}) \end{cases} \tag{7.6}$$

b) When $\xi_{k+1} \neq x_k$ perform an evaluation of the objective function $h(\xi_{k+1})$. If $\xi_{k+1} \in F_j$, accept it as the next state, otherwise reject it and take the current state as the next one, i.e., set $x_{k+1} = x_k$. Au and Beck (2007) have proved that the next sample will be distributed as if the current one is, and hence is the stationary distribution of the Markov Chain. The choice of proposal PDF affects the efficiency of the algorithm. According to Li (2011), the uniform PDF centred at the current sample with width equal to two times of the standard deviation of last simulation level which is a good candidate for the proposal PDF. Furthermore, the width for each artificial random variable will be in a manner of dynamical shrink with increasing the simulation level. This strategy is beneficial for convergence when the sequence of objective function is approaching a global optimum.

Algorithm of proposed Subset Simulation optimisation process can be described as follows:

For i = 1 to n
  Set an artificial PDF for each design variable
End
For i = 1 to N
  Randomly generate x_i
  Compute the objective function value $h(x_i)$
End
Sort $x_i\,(i = 1,2,..., N)$ according to $h(x_i)(i = 1,2,..., N)$
Get the top Np_1 samples from the ascending sequence
Denote these as $s_i\,(i = 1,2,..., Np_1)$
Get $h_{1,N(1-p_1)}$
$K = 2$
Do
  $l = [1/ p_{K-1}]$
  For $i = 1$ to Np_{K-1}
  For j = 1 to l
    Get a new sample $x_{l(i-1)+j}$ and the corresponding objective value $h(x_{l(i-1)+j}$ from s_i using MMH algorithm
   End
End
Sort $x_i\,(i = 1,2,..., N)$ according to $h(x_i)(i = 1,2,..., N)$
Get the last Np_K samples from the descending sequence which belong to F_K
Denote them as $s_i\,(i = 1,2,..., Np_K)$
Get $h_{K,N(1-p_K)}$
$K = K + 1$
While (stop criterion not fulfilled)

7.4 COMPUTATIONAL ISSUES IN SS OPTIMISATION

There are some computation issues which need to be considered to execute the SS optimisation methods are presented as follows:

7.4.1 Artificial PDFs for input variables

In SS, the choice of the distribution for the input random variables directly affects optimisation process. A truncated Gaussian distribution may be used to handle simple bound on individual design variable as shown in Eq. (7.7) (Li and Au, 2010)

$$f(x;\mu,\sigma,x_u,x_l)=\frac{\phi(\frac{x-\mu}{\sigma})}{\varphi(\frac{x_u-\mu}{\sigma})-\varphi(\frac{x_l-\mu}{\sigma})} \tag{7.7}$$

where $\phi(\cdot)$ is the probability density function of the standard Gaussian distribution, $\varphi(\cdot)$ is the cumulative distribution function of the standard Gaussian distribution and the definition domain, $\Omega=\{x:x_l\le x\le x_u\}$. The mean μ should be chosen close to the global optimum. If no prior information on the problem is available, one may locate it at the centre of the definition domain. The standard deviation of the artificial distribution controls the range to be explored and it has an influence on the efficiency. If it is too small, most of the samples will cluster in a small region and then the sequence of objective function will increase slowly. If it is too large, the samples will scatter over a large region and it would require a longer process to converge to the global optimum. In this regard, one strategy is often used, called three sigma limits in reliability engineering, setting the distance from sampling centre to the upper or lower bound equals to three times of standard deviations (Li, 2011)

$$\sigma_i=\frac{L_i}{6} \tag{7.8}$$

where L_i is the interval length of definition domain of the *i*-th input variable x_i, and σ_i is the corresponding artificially standard deviation.

7.4.2 Stopover conditions

In SS optimisation process, three types of stop criteria can be used to terminate the searching process.

Firstly, the searching process can be stopped when the failure probability is associated with the artificial reliability problem is less than some specified value level, normally it is denoted as ε_1, as the global optimum is approaching as P_f (Li and Au, 2010)

$$P_f=\prod_{k=1} p_k\le\varepsilon_1 \tag{7.9}$$

where ε_1 is a specified value. However, according to Li (2011), this kind of stop criterion is not work well for many cases.

Secondly, the searching process can be stopped based on the convergence in the objective function values sequence (Li, 2011), i.e.,

$$| h_{N(1-p_{k-1})} - h_{N(1-p_k)} | \leq \varepsilon_2 \tag{7.10}$$

where ε_2 is a specified tolerance value. This criterion is used in many computational techniques in many science and engineering problems.

The third criterion is based on the sample statistical property in each simulation level. The standard deviation of samples in each simulation level is used to check the convergence of the searching process. This stop criterion can be expressed as following Eq. (7.11) (Li and Au, 2010)

$$\frac{\hat{\sigma}_{k-1} - \hat{\sigma}_k}{x_u - x_l} \leq \varepsilon_3 \tag{7.11}$$

where $\hat{\sigma}_k$ is the estimator of standard deviation of samples in k-th simulation level. In order to eliminate the effects of different scaling of design variables, the interval length of definition domain can be used as a reference in this stop criterion.

The idea of this stop criterion stems from the fact that when the searching procedure is approaching the global optimum, the more repeated samples would be found in the sequence and then the estimator of standard deviation of samples will tend to be zero. When the stop criterion is satisfied, the largest value in the objective function sequence is taken as the maximal value and the corresponding sample as the solution. According to different researchers, such as Li and Au (2010) and Li (2011), ε should be within the range of 10^{-5} to 10^{-7}.

7.4.3 Level probability

The SS for optimisation is a procedure of continuous regeneration, trial and selection method. Each new simulation level is an improvement on the previous one that went before, which is realised by the level probability p_k as shown in Eq. (7.4). The level probability p_k plays an important role in the original SS for reliability analysis, which controls the efficiency of calculation and the choice of level probability as a trade-off between the number of samples required in each simulation level and the number of simulation levels required to reach the target failure region. Au and Beck (2007) suggested that p_k takes a constant value of 0.1 to 0.2 in a real reliability problem. In SS for optimisation, the level probability is a control parameter which regulates the convergence of the optimisation process. If very small is used, the algorithm would have a low probability of reaching a global optimum. Therefore, the level probabilities must be large enough to permit the locally developed Markov Chain (MC) samples to move out of a local optimum in favour of finding a global optimum, especially in the early simulation level. However, a large value would increase the number of simulation levels. The level probability is used to select a sub-population which provides the sampling 'seeds' for the next simulation level.

The selection process needs to consider the constraint fitness function and objective function simultaneously. The samples are first sorted according to the constraint fitness function values. Those samples that satisfy the constraints will appear at the top of the list with the same value. Then these samples are sorted again according to the objective function values. The first ranking is based on the constraint fitness function is designed to search the feasible domain, while the second ranking is based on objective function searches for the optimal solution. In this manner, the searching processes for the feasible region and the optimal solution proceed altogether.

7.5 NUMERICAL EXAMPLE

An underground pipeline network under a heavy roadway subjected heavy load operating conditions, passed under commercial and residential areas are taken as a numerical example to validate the proposed risk-cost optimisation management strategy in SS method in this Chapter. The underground pipeline network consists of approximately 789 km of sanitary flexible buried metal pipelines, constructed in 1940 as mentioned in the previous Chapter. The whole network consists of six segments of pipeline, namely, A to F (Table 6.5). The whole network constructed above the ground water table. LCC is used as objective function which includes all appropriate costs including initial construction costs, maintenance, repair and renewal costs, social costs, decommissioning costs as well as carbon dioxide emissions mitigation cost in this study. The analysis period under consideration should be long enough to cover the service life of the infrastructure system. All alternatives for maintenance and renewal should be considered. The essence of LCC is that one alternative may have a higher initial cost, but its costs over the asset's life cycle may be lower than other alternatives. The capital cost, maintenance cost and failure consequence cost are predicted or calibrated based on real case study on Municipal Infrastructure Investment Planning (MIIP) in Canada, (Rahman and Vanier, 2004), Melbourne water report (2012) and Davis et al (2008) report. The capital cost, maintenance cost and failure consequence cost (future values) are mentioned in Table 6.7 on the yearly basis. A typical discount rate (UK) 5% is considered in this Chapter.

The statistical properties of materials are shown in Table 6.6. It is presumed that the whole underground pipeline network located in a high seismic vulnerable zone area. Table 6.7 summarises the yearly basis cost data (Future value) for the whole network, sections A – F. The network is subjected to corrosion and its corrosion rate is modelled using Eq. (3.1). The underground pipeline materials, location and soil parameters are listed in Table 6.5. There are 9 random variables (elastic modulus of pipe, soil modulus, soil density, live load, deflection coefficient, corrosion coefficients, pipe wall thickness and height of the backfill) where the mean and coefficient of variation are listed in Table 6.6. After the pipe's life cycle, the pipe is disposed, recycled, or abandoned.

7.6 RESULTS AND DISCUSSION

SS optimisation process has been developed to solve the risk-cost optimisation problem to validate the proposed method. The life cycle cost in Eq. (6.4) is used in SS method where CO_2 cost is also included in risk-cost optimisation process. To make a fair and reliable result considerable computational effort and time have been spent and checked the best number of samples required for achieving reasonably good solution. The results are presented as follows:

7.6.1 Pipeline reliability

First, the probabilities of buried pipe failure due to corrosion induced excessive deflection, buckling, wall thrust and bending with respect to time are estimated based on the parameters and basic variables given in Tables 6.5 and 6.6 as mentioned in Chapter Six. The failure probabilities are predicted using SS method and results are shown in Figures 7.2 – 7.7. All the random variables are considered as uniformly distributed, except deflection coefficient which is log-normally distributed. The occurrence of either failure mode of the pipe will constitute its failure. Therefore, the probability of failure of the underground pipeline network is determined as a series system using Eq. (3.32a) and the results are shown in Figures 7.2 – 7.7. When the thickness of the pipe is reduced due to corrosion, the moment of inertia and the cross-sectional area of pipe wall are decreased with a resulting reduction in pipe strength as Eqs. (3.5) and (3.6), respectively.

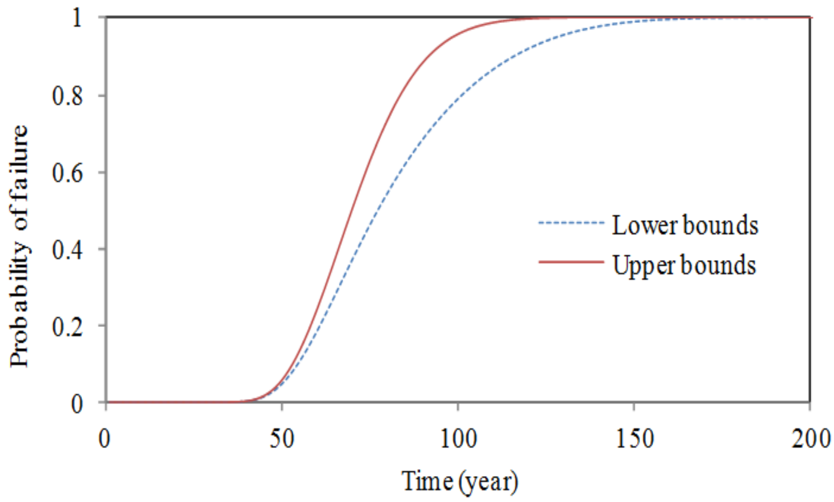


Figure 7.2: Probability of failure for pipeline section A using SS

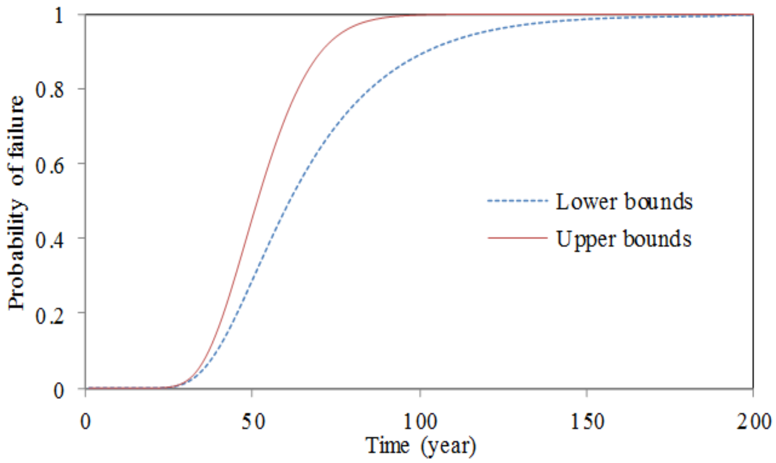


Figure 7.3: Probability of failure for pipeline section B using SS

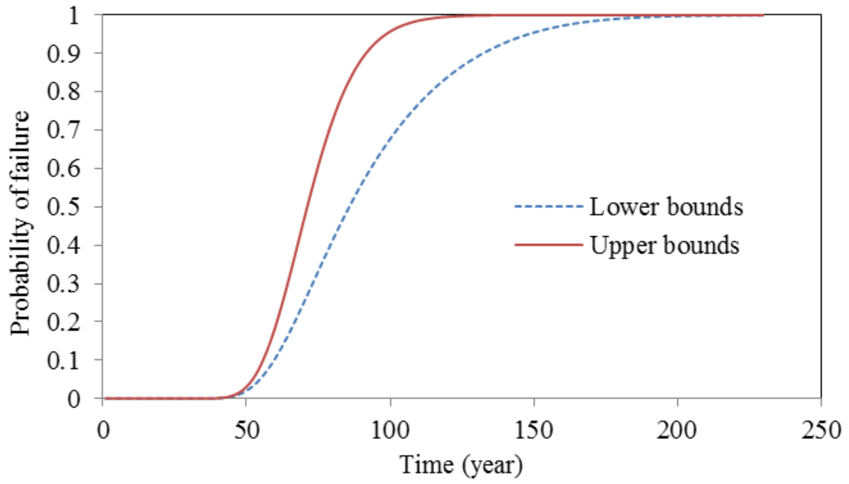


Figure 7.4: Probability of failure for pipeline section C using SS

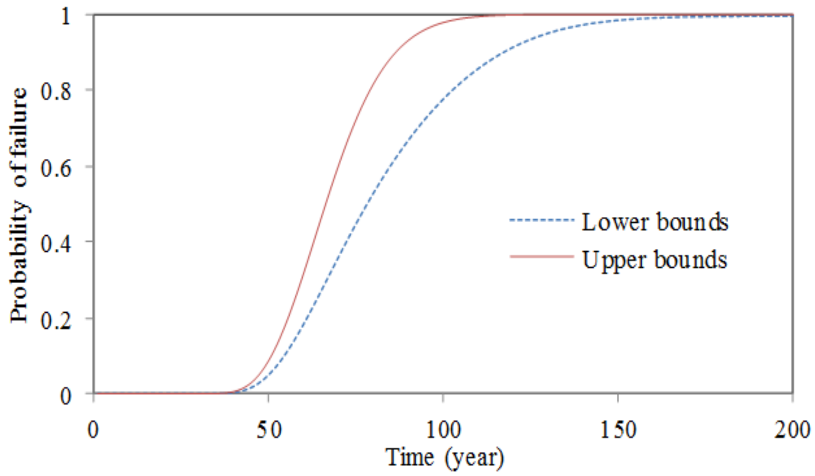


Figure 7.5: Probability of failure for pipeline section D using SS

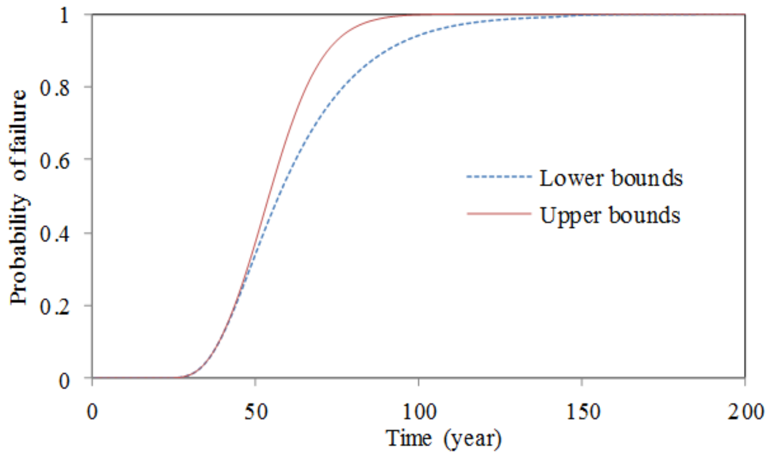


Figure 7.6: Probability of failure for pipeline section E using SS

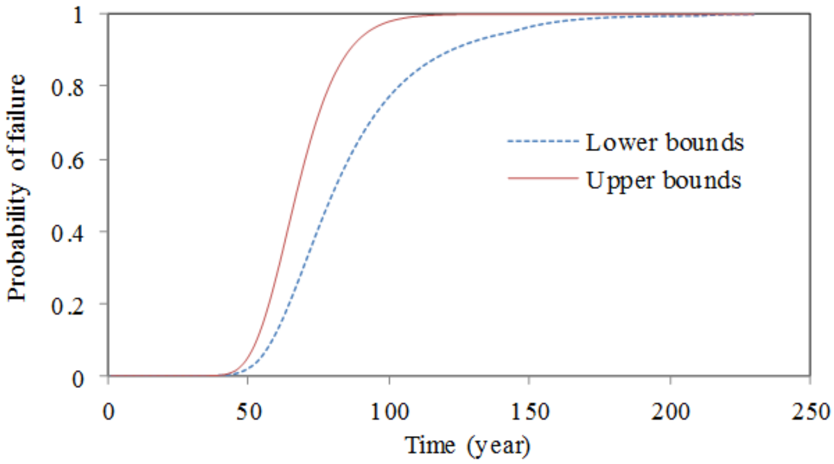


Figure 7.7: Probability of failure for pipeline section F using SS

The study shows that on average the probability of pipe failure at the beginning is close to zero and it remains unchanged until about 45 years of service life, then it gradually changes as time increases and after 50 years, the probability of failure rises drastically. Upper failure probability (P_f) as shown in Figures 7.2 – 7.7 has been used for the subsequent risk-cost optimisation for sections A to F as a worst case scenario.

7.6.2 Optimum renewal cost, time and priority

As shown in Eq. (6.3), the failure risk cost is calculated by multiplying failure cost with the probability of system failure. Once the probability of system failure has been calculated, the optimal time to repair or replace and the associated life cycle risk and cost (Eq. 6.4) are obtained from the risk-cost optimisation using Subset Simulation. Table 7.1 summarises the statistical performance of SS optimisation process, where 500 numbers of samples, level probability 0.1 and stopover value 10^{-5} are used in this study. The Table 7.1 shows the convergence of total LCC obtained from risk-cost optimisation where the optimal LCC cost is associated with the first maintenance.

Next, the proposed maintenance strategy is extended to determine an applicable and feasible renewal method using Tables 6.1 and 6.2. The recorded database shows that the underground pipelines are built on clay, sand and sandy gravel type soil. In addition, all types of pipelines are above the groundwater level. Based on this information and according to Table 6.2, the possibility of soil loss for sanitary underground pipeline sections A and B is low, whereas for sections C to F, the possibility of surrounding soil loss is high. The condition index (CI) for the underground pipeline network is estimated as shown in Table 7.1 using Eq. (6.7) by substituting the identified optimal time to renew from the risk-cost optimisation. Applicable renewal categories are then selected from Table 6.1 based on the underground pipeline CI and the possible scenario of soil loss. The sections A, B and C pipelines are required to renew using non-structural or semi-structural lining method based on the estimated CI and low possibility of soil loss. On the other hand, due to high possibility of soil loss and CI >2, the sections D and E pipelines are needed to renew using semi-structural or structural liners. Finally, section F should be renewed with structural liners or replacement (CI>3, high possibility of soil loss). Alternatively, replacement is recommended for other sections if the repair cost becomes greater than the cost of replacing the pipes.

Table 7.1: Results of pipeline risk-cost optimisation using SS

Pipe section	Optimum Life cycle cost (£b)	Renewal time (year)	Structural Condition index (CI)	Renewal priority	Renewal methodology
A	2.1	60	1.9	Low, minimal structural risk	Non-structural or semi structural
B	1. 29	61	2.1	Low, minimal structural risk	Non-structural or semi-structural
C	1.32	67	2.3	Low, minimal structural risk	Non-structural or semi-structural
D	1.9	59	2.0	Medium, poor condition	Semi-structural, structural or replacement
E	1.28	71	2.5	Medium, poor condition	Semi-structural, structural or replacement
F	1.31	86	3.2	Immediate, high structural risk	Structural or replacement

Based on the underground pipeline's inventory information and alignment, the renewal assessment has been carried out considering all six major impact factors and results of the renewal priority based on the structural condition index and failure impact index using Table 6.4. According to Table 6.4, the pipes which are in fair or minimal structural risk condition needs low renewal priority and on the other hand, pipe with highly structural risk condition requires immediate rehabilitation or replacement for safety of the network. The results are shown in Table 7.1. Finally, the comparisons are made with the GA results to check the accuracy of the SS optimisation process as shown in Table 7.2.

Table 7.2: Comparison between SS and GA results

	SS method			GA method		
Pipe section	Optimum Life cycle cost (£b)	Renewal time (year)	Structural Condition index (CI)	Optimum Life cycle cost (£b)	Renewal time (year)	Structural Condition index (CI)
A	2.1	60	1.9	2.0	62	2.2
B	1. 29	61	2.1	1.35	63	2.3
C	1.32	67	2.3	1.41	66	2.25
D	1.9	59	2.0	2.13	62	2.2
E	1.28	71	2.5	1.29	72	2.5
F	1.31	86	3.2	1.33	88	3.5

Table 7.2 shows a good agreement between these two optimisation processes. The obtained optimal costs and renewal time from SS and GA methods are very close. The renewal time and methodologies are same for both optimisation processes. The advantage of SS optimisation process is that it takes about 30 minutes to execute the current problem, whereas GA optimisation process takes more than 1 hour and 30 minutes. Note that the computational speed is measured in terms of Central Processing Unit (CPU) time on a 1.6-GHz Pentium IV personal computer in this Chapter.

7.7 SUMMARY

New optimisation technique SS has been developed for reliability based risk-cost optimisation process for buried pipeline network to demonstrate the robustness and efficiency of the proposed algorithm in this Chapter. Current Chapter focuses on testing its performance on buried pipelines risk-cost optimisation process and improving its efficiency by combining with local search strategies. SS illustrates that large value of N tends to increase the number of objective function evaluation which is time consuming process. On the other hand, the small value of N may cause the generated samples not to cover the searching space well and thus lead to a fail in finding a good optimum solution. Therefore, in practice, this number should not be too large or too small. A numerical example is presented to validate the technique. Then comparison is made with the results of GA to check the accuracy the SS optimisation process. The study shows a good agreement between these two methods. But SS takes only one third computational time of GA. The proposed algorithm is found to be competitive in exploiting the feasible regions and providing optimal designs in solving complex problems. The proposed risk-cost optimisation approach can help the management in making correct decisions concerning the intervention year and renewal methodology. The method produces a rational good result with much less computational effort.

CHAPTER EIGHT

CONCLUSIONS AND RECOMMENDATIONS

8.1 CONCLUSIONS

A comprehensive discussion and analysis have been conducted on flexible buried metal pipeline reliability prediction and risk-cost optimisation process in this research. The main conclusions and recommendations for improved reliability prediction and optimisation of buried pipes are summarised in this Chapter. It is concluded that the proposed approach will provide an enhanced reliability prediction and risk-cost optimisation for flexible underground metal pipelines. In general, this approach can be applied for other types of structures. The key outcome of this research is to predict more accurate and realistic reliability and risk-cost optimisation of buried pipelines.

First, this research presents a time-dependent reliability analysis of flexible buried pipelines due to corrosion induced deflection, buckling, wall thrust and bending stress. In reliability analysis, probability of failure with respect to time is predicted for every failure mode using HL-RF algorithm and MCS. The results suggested that excessive bending is the most critical failure mode whereas buckling is the least susceptible during the whole service life of the pipe. Then correlations among the failure modes are predicted in this study which indicates that these failure modes are strongly correlated and correlation is about 1. Correlations between random variables, such as soil density and soil modulus or loading and pipe stiffness with known correlation coefficients (0 – 0.9) in different failure modes also have been assessed with varying time. The results indicates that the probability of failure due to corrosion induced wall thrust is lower when soil modulus and soil density are positively correlated whereas it is higher when loading and pipe stiffness are negatively correlated due to corrosion induced bending stress. In addition, parametric study and sensitivity analysis have been performed to analyse the effect of the design variables on the reliability of the flexible underground metal pipeline system. The parametric analysis demonstrates that behaviour of buried pipes is considerably influenced by uncertainties due to external loads, corrosion parameters, pipe materials and surrounding soil properties, etc. The sensitivity analysis suggested that among all random variables in reliability prediction, the relative contribution of the corrosion parameters, multiplying constant, k and exponential constant, n are highly remarkable.

To enhance the reliability prediction, SS has been developed in pipeline failure probability analysis which is new in this area. A numerical example has been conducted to illustrate the robustness and effectiveness of SS method. The application of SS method is verified with respect to the standard MCS. One of the major complications to estimating small failure probabilities is to simulate rare events. SS resolves this by breaking the problem into the estimation of a sequence of larger conditional probabilities. It is found that the reliability analysis calculated by SS is in good agreement with that from MCS, while the efficiency of the SS method, which is indicated by the sample size and computational time, is higher than that of MCS.

ROC curve has been introduced in application for reliability analysis due to above mentioned failure modes. The *ROC* curve provided a model performance assessment for pipe failure state function of reliability prediction. The analysis shows that *ROC* curve is a useful technique to predict the optimum threshold value and accuracy of the results. The study reveals that with increasing inaccurate pipe data, say 10% to 20%, the area of the *ROC* curves (both classical and *NPI*) are decreased for every failure mode. The area under the curve provides an objective parameter of the accuracy of an analysis, combinations of sensitivity and specificity values. Choosing the optimal operating point on the ROC curve which involves both maintenance and financial issues, can be ideally implemented in a formal risk-cost management process of buried pipeline network.

Next, this research presents a novel integrated approach for systematising manages of flexible underground metal pipeline network using GA. LCC has been used as an objective function to optimise risk and cost. A numerical example is presented to validate the proposed risk-cost management strategy with a view to prevent the unexpected failure of underground flexible metal pipes by prioritising the maintenance options based on the failure severity and structural reliability. A parametric study has also been carried out to analyse the effects of different parameters, such as soil density, soil height and discount rate on reliability and life cycle cost of the pipelines. The study shows that if soil properties, such as soil modulus or soil density changes, this will affect probability of failure and hence reliability and life cycle cost of the pipeline network. The parametric study demonstrates that with increasing soil height above pipeline decreases service life and increases life cycle cost of the pipeline network. Similarly, with increasing discount rate increase the life cycle cost and decreases the service life.

New optimisation technique, SS has been developed for reliability based risk-cost optimisation process for buried pipeline network to improve the optimisation process. This method is new in risk-cost optimisation application. The proposed algorithm is found to be competitive in exploiting the feasible regions and providing optimal designs in solving complex problems. A numerical example is presented to validate the technique. Then comparison is made with the results of GA to check the accuracy the SS optimisation process. The results show a good agreement between these two methods. The advantage of SS optimisation process is that it takes less than one third of GA computational time to execute the current risk-cost optimisation problem.

In summary, the proposed approach is a simplified approach which can be used as a rational tool for concerned decision makers with regard to strengthening and rehabilitation of existing and new pipelines. Precise prediction of reliability (probability of failure) and reliability based management of buried pipeline system can help engineers and managers to obtain a cost-effective strategy in the controlling the pipeline system. The reliability based risk-cost optimisation method is designed to maximise the performance of pipeline distribution networks with minimal risk and optimum cost. The proposed maintenance strategy will enable the decision makers to select appropriate renewal methods based on the identified optimal time to renew, i.e., repair or replace the pipes.

8.2 RESEARCH LIMITATIONS

There are some limitations in the current research work. The limitations of the reliability estimation and developed risk-cost optimisation process for underground pipelines in this research can be summarised as follows:

1. This research shows that among all random variables in reliability prediction, the relative contribution of the corrosion parameters, multiplying constant, k and exponential constant, n are highly remarkable. But these are highly uncertain and are typically determined from regression analysis on observed and experimental data obtained for

specific soil and environmental conditions. Therefore, more concern should be taken in order to determine the values for corrosion parameters.

2. Only numerical simulations are used in reliability prediction. Therefore, validation is required by lab and field test.

3. Due to lack of sufficient real pipe data, the *ROC* curve has been applied for generated data, assuming different percentages of inaccuracy. Real case data are required to analyse the method.

4. Predicting future costs is not straight forward as interest rate is time dependent. In risk-cost optimisation process, assuming that the discount rate will be constant over the life cycle of the pipeline structures. But it is highly unlikely that material, labour and energy costs will change at exactly the same rate. Therefore, major cost elements (capital, maintenance, operation, etc.) can vary accordingly.

5. Pipe structural priority index (PI) is obtained according to the time of the collected data. It should be updated when data is changed as pipe materials and other critical factors, i.e., accessibility, depth, etc., may change after rehabilitation works.

8.3 RECOMMENDATIONS FOR FURTHER RESEARCH

It is hoped that the proposed methods in this research would improve the ability of concerned industry in predicting and preventing catastrophic failures of the underground pipelines. In the reliability estimation, among the applied three methods MCS and HL-RF methods are more challenging than SS method for small probability of failure prediction. In the risk-cost optimisation process, Genetic Algorithm method is more challenging compared to the SS optimisation method as SS method showed a good capability to execute the optimisation processes of buried pipes in less time with good accuracy. The listed issues which can be considered for future work to enhance and extend the developments made in this research:

1. In this research, the progression of corrosion depth on pipes wall was assumed linear with respect to time. The corrosion rate remains unlikely to be linear with changing

the environmental conditions. The reliability prediction over service life will be much more accurate if the non-linearity of corrosion process can be developed. To obtain the realistic relationship between the corrosion depth and time in a buried metal pipe, an extensive lab experiment is suggested.

2. For further works in the field of failure assessment of buried pipes, it is suggested to model the pipeline and existing loads using finite element software, such as ABAQUS or ANSYS to verify pipe behavior and deterioration process, e.g., corrosion induced deflection, buckling, bending, etc.

3. Receiver Operating Characteristic (*ROC*) curve has been introduced in application for reliability analysis in this thesis. Real case data should be analysed on *ROC* curve for advanced application for underground pipeline reliability accuracy prediction.

4. Develop an automated tool to implement the developed risk-cost optimisation procedure and algorithms in this research and employ it to real case studies.

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