Reliability-based Analysis and Maintenance of Buried Pipes Considering the Effect of Uncertain Variables

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DECLARATION

I certify that the work contained in this thesis, or any part of it, has not been accepted in substance for any previous degree awarded to me, 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 the contents are not the outcome of any form of research misconduct.

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Abstract

The failure of the buried pipeline are rare events, and when it occurs, it poses a significant threat to the environment, human lives, and nearby assets. The performance of the buried pipeline is analysed based on the pipe failure modes such as pipe ovality, buckling pressure, and total axial and circumferential stresses. Also, the input parameters for pipe and soil properties are affected by imprecision and vagueness, particularly in the process of estimating the values. In the literature, many researchers have sought for effective methods to compute the reliability of buried pipe by considering the effect of uncertain variables. However, the existing methods such as Monte Carlo simulation are limited because of their computational capability. Often, they can only account for the aleatory type of uncertainty. Furthermore, with the increasing need in the use of buried pipelines, developing a robust and effective framework becomes necessary to overcome or mitigate against the possibility of failure.

In this research, the concept of Line Sampling (LS), Important Sampling (IS) and a combination of LS and IS have been adapted for time-dependent reliability analysis of buried pipe. Similarly, a fuzzy-subset simulation framework is developed for the performance analysis of buried pipe considering aleatory (random) and epistemic (fuzzy) uncertainty. The structural response of the buried pipe was assessed and quantified based on the structural failure modes. The methods open a new pathway for a structured approach with a good computational efficiency based on complete probability and non-probability description of input parameters. The performance of buried pipe is also assessed based on fuzzy robustness measure, which is a dimensionless measure used to account for the impact of the uncertain variables. The approach gains its efficiency by scrutinising the structural robustness at every membership level with respect to various degrees of uncertainty. The principle of fuzzy set and a Hybrid GA-GAM optimisation algorithm is integrated to form a framework employed to determine a robust and acceptable design for buried pipe. The purpose of the approach is to optimise the design variable while considering the adverse effect of the uncertain fuzzy variables. The outcome based on the methods mentioned above demonstrates the importance of accounting the effects of uncertain variables.

The reliability method based on fuzzy approach has been extended to estimate the optimal time for the maintenance of the buried pipeline. The strategy aimed at assessing the cost-efficiency required for the determination of the optimal time for maintenance using multi-objective optimisation based on the fuzzy reliability, risk, and total maintenance cost. The framework suggested in this study underlines the significance of the analysis of buried pipe and provides valuable guidance for improving safety in the reliability-based design, which is demonstrated using a numerical example. The key outcome of this research shows a new insight into the analysis of buried pipe by considering the effect of aleatory and epistemic type of uncertainty.

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ACRONYMS

AWWA	American Water Works Association
CDF	Cumulative Distribution Function
COV	Coefficient of Variation
CPSA	Concrete Pipeline Systems Association
CPU	Central Processing Unit
CUI	Command User Interface
CWWA	Canadian Water and Wastewater Association
DSW	Dong, Shah, and Wong
FORM	First Order Reliability Method
GA	Genetic Algorithm
GAM	Goal Attainment Method
IS	Important Sampling
LHS	Latin Hypercube Sampling
LS	Line Sampling
MC	Monte Carlo
MCMC	Markov Chain Monte Carlo
MCS	Monte Carlo Simulation
MFL	Magnetic Flux Leakage
MMA	Modified Metropolis Algorithm
MOOP	Multi-Objective Optimisation Problem
NRC	National Research Council
PDF	Probability Density Function
PGD	Permanent Ground Deformation
RDO	Robust Design Optimisation
SORM	Second Order Reliability Method
WRC	Water Research Centre

SYMBOLS

A	Effective length of pipe which the load is computed
A_s	Cross- sectional area of pipe wall per unit length
B_d	The trench width
B'	The empirical coefficient of elastic support
C	Depth of soil cover above the buried pipe
C_d	Calculation coefficient for earth load
C_F	Future cost
C_L	Live load distribution coefficient
C_T	Corrosion pit depth
C_t	Surface load coefficient
C_{TO}	Total cost
D	Pipe diameter
D_1	Deflection lag factor
d	Distance from the pipe to the point of application of surface load.
d_f	Frost depth
E	The elastic modulus of pipe
E_s	Soil modulus
E'	Modulus of soil reaction
F_y	The minimum tensile strength of pipe
f_{frost}	Frost load multiple
$g(x)$	Performance function
H	The Bousinesq function to determine the influence of stress
H_w	The height of ground water above the pipe and
h_f	The total frost heave
idd	Independent and identically distributed
I	The moment of inertia
I_c	Impact factor
k	Multiplying constant
K_s	The backfill sidewall shear stiffness

K_{tip}	The stiffness of elastic half-space of unfrozen soil below freezing front
K	Bedding constant
K'	Numerical value which depends on poison ratio
K_m	Bending moment coefficient
K_d	Deflection coefficient
L_W	Live load distribution width
P	Pressure on pipe due to soil load plus live load
p_s	Frost load at any point
P_F	Probability of failure
PGV	The maximum horizontal ground velocity
P_p	Pressure transmitted to the pipe as a result of the concentrated load
P_v	Pressure on pipe due to soil load
P_s	Live load
P_W	Hydrostatic pressure
P_{sp}	Geostatic load
RSR	Reserve strength of a structure
s	The location below the surface where frost load is calculated
S_h	The hoop stiffness factor
t	Pipe thickness
T	Time of exposure
T_{op}	Optimised time required for the replacement
T_d	The designed life
M_s	Secant constrained soil modulus
n	Exponential constant
N_{TS}	Number of time steps
N	Number of samples
N_s	Sequence of points that lie within the failure domain
N_T	Total number of samples
R	The radius of pipe
R_{w}	The water buoyancy factor which can be expressed
v_s	Poison ratio

v_p	Poison ratio of the pipe material
V_{AF}	Vertical arching factor
V_0	The initial corrosion rate
W_A	Soil arch load
β	The attenuation factor
φ_p	Capacity modification factor for pipe
φ_s	Soil capacity modification factor
δ	Coefficient of variation
δ_u	Unitary coefficient of variation
ε_g	Ground strain
σ_b	Through-wall bending stress
σ_F	Circumferential stress due to internal fluid pressure
σ_S	Stress due to external soil loading
σ_L	Stress due to frost action
σ_V	Stress due to traffic load
σ_T	Stress due to temperature difference
$\sigma_F^{/}$	Axial stress due to internal fluid pressure
σ_θ	Total circumferential stress
σ_X	Total axial stress
ρ	Internal fluid pressure
γ	Unit weight of the backfill soil
α_p	Expansion coefficient of pipe
$\underline{\alpha}$	Important unit vector
Δy	Vertical deflection of the buried pipe
ΔT	Temperature difference between the fluid and the surrounding group
$\Delta y/D$	Pipe ovality
$\mu(x)$	Membership function

CHAPTER ONE

1 INTRODUCTION

1.1 Background

Buried pipe networks are vital engineering infrastructure and are mostly used to transport crude oil, potable water, sewage sludge, brine and natural gas. The transported fluid and the pipe, in many instances, are placed or passed under a railway or roadway. Also, pipelines are buried within the top layer of soil deposits and therefore are affected by the type of surface loading (cyclic or non-cyclic loading), the geology of the surrounding soil, corrosion, frost action, thermal effect and environmental hazard such as an earthquake (Abdoun et al., 2009; Moser & Folkman, 2001; Ogawa & Koike, 2001; Sadiq et al., 2004). As a result, buried pipelines are designed to resist the adverse effect of the conditions mentioned above and including the effect of internal pressure.

Furthermore, the geological formation of the soil, frost action and thermal effect are affected by seasonal climatic changes, which result in variabilities of the design parameters (Moser & Folkman, 2001; Phoon & Kulhawy, 1999a; Whidden, 2009). For instance, the annual seasonal variation for the soil moisture content or increase/decrease in the underground water table can cause significant differences in the soil suction, and in some cases result in substantial movement of the ground, which affects the soil parameters. Based on this, the variabilities of the input parameters for a buried pipe can increase the possibility of pipe failure over time. Figure 1.1 shows some examples of design parameters including different loading and environmental conditions that affect the performance of buried pipe over time (St. Clair & Sinha, 2014). The impact of these design parameters in relation to a particular type of pipe material can lead to the failure of the buried pipe.

The buried pipeline, like other engineering structures, deteriorates over time (Ahammed, 1998). The deterioration of a metallic pipe usually occurs due to the damaging effect of the surrounding environment and the mechanism that leads to their failure are often complex and difficult to completely understand (Kleiner & Rajani, 2001a). For buried metallic pipe, one of the most predominant deterioration mechanism of the exterior walls of the pipe is active corrosion effect (Mahmoodian & Li, 2017; Ossai et al., 2015; Sadiq et al., 2004). This effect is a significant potential threat to the safety of the structure, and it usually worsens over time. Kleiner & Rajani (2001b) suggested that the operators of buried pipeline throughout the world are challenged with the costly and risky task of operating and maintaining aged pipelines because of corrosion and the associated damaging effects.

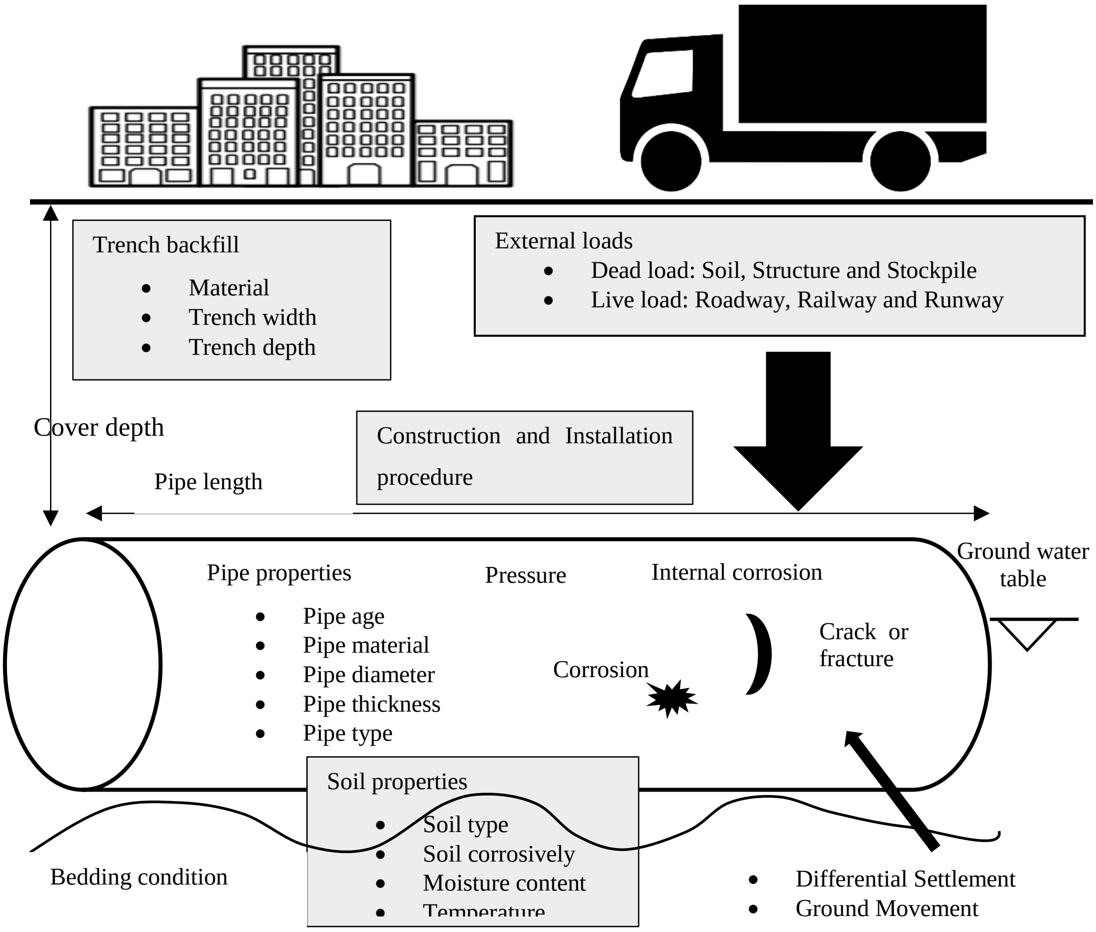


Figure 1.1: Factors that affect the performance of the buried pipe

The loss of pipe wall thickness due to corrosion is one of the major causes of failure for the buried pipeline (Ji et al., 2017). The corrosion activity can manifest in various forms such as uniform or localised and also internally and externally. As suggested in Rajeev et al. (2014), the loss of thickness as a result of corrosion can be idealised into two patterns: uniform corrosion and pitting corrosion as illustrated in Figure 1.2. The effect of corrosion will reduce the resistance of the pipe capacity, which will also decrease the factor of safety of the buried pipe (Gomes & Beck, 2014; Sadiq et al., 2004). The reduction of the pipe thickness due to the adverse effect of corrosion can induce the failure of the buried pipe when structural failure modes such as pipe ovality, through-wall bending stress, ring buckling, axial and circumferential stresses are examined. Also, the growing uncertainty associated with other design parameters contributes to the failure problem, which leads to a reduction in the performance and safety level of the buried pipeline. Therefore, for a buried pipeline in areas that are susceptible to active corrosion effect and in consideration of other uncertain parameters, a robust and reliable design is required to ensure an optimum working efficiency, safe operation, and insignificant downtimes during the designed life.

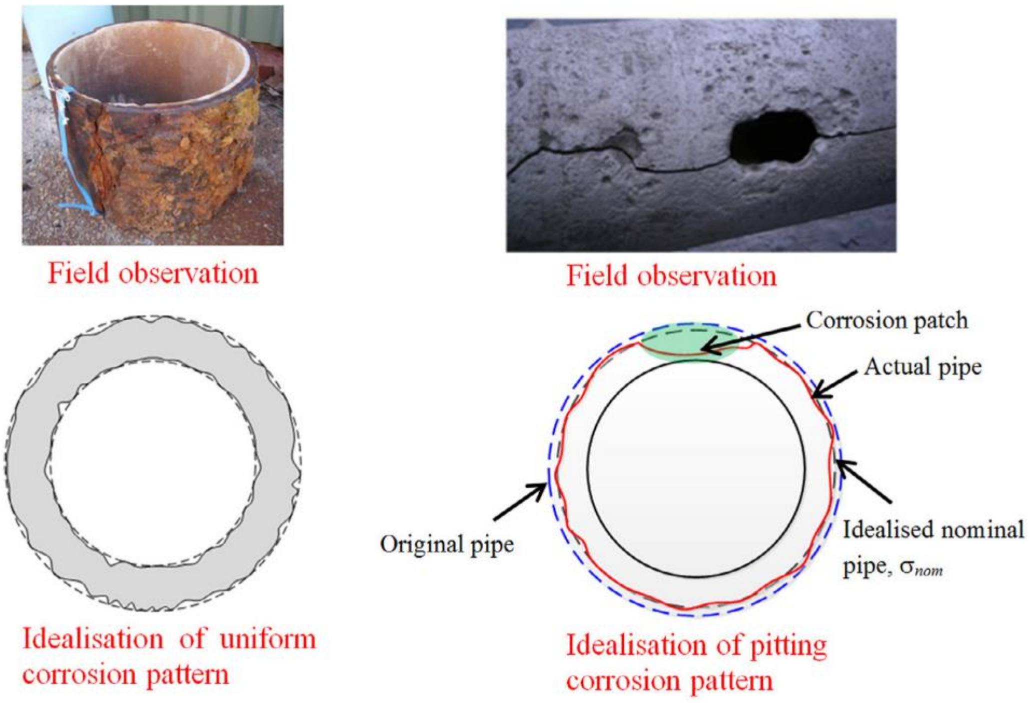


Figure 1.2: Typical corrosion patterns observed in water mains failure (Ji et al., 2017)

In recent time, various methods of predicting the reliability of a structure, e.g., First Order Reliability Method (FORM), Second Order Reliability Method (SORM), Important Sampling (IS), Latin Hypercube Sampling (LHS), Subset Simulation (SS), and Line Sampling (LS) have been applied in a range of engineering problems such as building and aerospace. The methods mentioned above are all available in the literature and can be found in (Au & Beck, 2001; Koutsourelakis et al., 2004; Melchers, 1999; Olsson et al., 2003; Schuëller et al., 2004; Zhang & Du, 2010; Zio, 2013). These methods are powerful tools used to analyse and assess the safety level of structure or systems at the design stage or during operation. For a buried pipeline, the reliability analysis helps to evaluate and assess the performance of the structure over a specific period in order to produce an optimum design. Also, the safety assessment of buried pipe structures is becoming more and more critical because the failure of a buried pipe system may cause a catastrophic environmental effect, especially when used for the supply of crude oil (Gomes & Beck, 2014). Halfawy et al. (2008) stated that municipalities are under increased pressure to adopt proactive and improved strategies that would lessen the risks, cost and maintain a satisfactory level of performance and service. However, since the failure of a pipe system may cause disastrous consequences, it is crucial to be able to assess the reliability and robustness of the pipe system effectively.

Uncertainty associated with design parameters is an unavoidable process that affects the performance of pipe systems over time. Despite the amount of effort and time put into the understanding of the causes of pipe failure, through the collecting and processing of data, the propagation and interpretation of uncertainty will remain an essential aspect of pipe reliability analysis (Kleiner & Rajani, 2001b; Rajeev et al., 2014). This is because randomness and fuzziness are often associated with the design parameters of the buried pipe. However, by studying the reliability and maintenance of a buried pipe system, the engineer can have a better understanding of the pipe performance at different time and when to carry out maintenance. By considering various failure modes, environmental effects such as corrosion and carrying out a parametric study, it is possible to identify and draw conclusions about which failure mode is the most critical and parameters that are the most sensitive over time. By considering uncertainty associated with the design parameters of buried pipe in the computation, intuitions into the effects of the variation of parameters on the assessment outcomes can be quantified and also useful to the designer and decision-makers.

1.2 Problem Statement

The study of the reliability of buried pipeline, particularly with the effect of active corrosion is an area that has attracted so much attention in the literature and which is vital to many engineers and infrastructure managers (Ahammed & Melchers, 1994, 1997; Babu & Srivastava, 2010; Caleyo et al., 2009; Sadiq et al., 2004; Tee et al., 2014). Over the years, corrosion effect has affected the safe operation of most engineering structures (Barone & Frangopol, 2014a; Sadiq et al., 2004). The development of corrosion is a continuous and time-dependent process and is non-uniform, e.g., pitting corrosion (Sadiq et al., 2004; Tee et al., 2013). Undoubtedly, the effect of pipe failure due to corrosion is significant, and as such, the buried pipe is provided with extra wall thickness, or external coatings to protect it from the adverse effect of corrosion. Ahammed and Melchers (1997) pointed out that this practice is not always entirely effective, particularly where pipe sections are joined.

For a buried pipeline, corrosion will gradually reduce the resistance of the mechanical and the structural properties, which can increase the possibility of failure over time (Gomes & Beck, 2014). This can be challenging for design engineers and infrastructure managers. Due to the nature of the deterioration process of the buried pipeline as a result of corrosion, the assessment and maintenance would require a robust and reliable approach to keep the possibility of failure and the risk under control. Therefore, the development of a reliable and efficient technique for the evaluation of the performance of buried pipe becomes a vital aspect of this study.

Pipelines are designed to meet a particular standard and to perform safely throughout their entire design life. During the design life, the buried pipe must be able to deal with the structural deterioration that diminishes the reliability of the pipe and the ability to withstand different types of loads and loading conditions. However, the analysis, assessment, and maintenance of pipeline structures involve uncertainties in the design parameters. These uncertainties can be due to the randomness of the physical phenomenon (aleatory uncertainty) and the incomplete knowledge of the physics of some of this phenomenon (epistemic uncertainty) (Apostolakis, 1990). Sadiq et al. (2004) suggested that the factors that add to the failure of a buried pipeline are associated with a high degree of uncertainty, especially corrosion rates because of large spatial and temporal variabilities. Similarly, Gomes & Beck (2014) and Kleiner & Rajani (2001b) stated that the deterioration process and the design of buried pipe structures is usually associated with a significant level of uncertainties due to limited information in the process of estimating the structural parameters. Therefore, it is necessary to perform the reliability analysis of buried pipe by considering the uncertainties associated with the design parameters.

In the design of buried pipeline, disregarding the effects of uncertainty is deplorable and can lead to disastrous consequences. Also, the risk associated with pipe failure involves high consequences and decisions are made on the basis of quantitative data that is limited and often expensive to collect. In spite of the availability of detailed physical failure models, designers need to make explicit judgements based on available information concerning the design of buried pipe structure. Hence, they must be able to have a high level of confidence in any proposed or adapted methodology to analyse the safety of the pipe system and avoid making the wrong decision that can be introduced at the modelling stage. As a result, a broad modelling approach of uncertainty associated with a buried pipe, which takes account of the randomness and fuzziness of the design parameters, offers new insight by helping to effectively evaluate the performance of the pipe structure.

The failure of buried pipe structures are associated with consequences, and as a result, risk-based assessment becomes necessary, and also, an essential tool for the evaluation and optimisation of maintenance. The risk is generally defined as the product of the probability of failure and the expected consequences in monetary terms due to the failure (Ang & Tang, 1984; Tee et al., 2014). The foreseeable effects are usually quantified in monetary terms, while the likelihood of failure is calculated using reliability techniques, and by means of a rigorous mathematical framework. Typically, this requires the specification of defined probability distribution models for the input parameters. The analyses of engineering structures including buried pipe are investigated based on simulation techniques and to obtain a numerical solution, especially where the analytical approach is considered not efficient. Simulation methods allow explicit consideration of uncertainty on the investigated problem, which provides a more robust tool for evaluating the failure probability and allows right decision to be made.

In a nutshell, five challenges need to be addressed in this study to properly analyse the reliability and robustness of buried pipe while considering the effect of uncertain variables. These include:

- For the propagation of uncertainty associated with the input variable due to randomness, the use of MCS can be computationally expensive. Therefore, the need to develop or adapt or improve an existing method that is time-dependent and computationally more efficient to evaluate the reliability of a buried pipe is essential.
- In the design of buried pipe, it is possible for the aleatory and epistemic type of uncertainties to coexist. Therefore, developing an approach to model the performance of the buried pipe by considering randomness and fuzziness associated with the input parameters become vital for a robust analysis.
- Buried pipeline have suffered damage due to the effect of corrosion and imprecision associated with the design parameters. Therefore, how can the behaviour of the buried pipe be assessed to sustain damage that can be caused by extreme loads or changes in environmental conditions without disproportionate failure?
- For the design of buried pipe, is it possible to optimise the performance of the structure by considering the adverse effect of the uncertainty associated with the input parameters through optimisation?
- When evaluating the time to carry out maintenance of a buried pipe based on the probabilistic approach, it is possible that the pipe segments will not necessarily fail at the optimal time. Therefore, the use of a non-probabilistic approach can produce an optimal time interval required to carry out maintenance of the buried pipe.

1.3 Aim and Objectives

The presented work herein contributes towards the solution of the above challenges, and this research aims to develop a framework for analysing the reliability and robustness of buried pipe structure in order to promote safety in reliability-based design and robust assessment. The framework will be developed using reliability methods, which is based on probabilistic and non-probabilistic approaches while considering the structural response. The responses from the failure modes considering uncertain variables will be extended to compute the corresponding reliability and the robustness of the buried pipe with respect to specific failure modes. However, the aim of this research will be achieved by pursuing the following specific objectives:

- To develop an approach to analysing time-dependent reliability of a buried pipeline considering the input parameters as random variables and to examine further the effect of varying some of the parameters.
- To develop and analyse the robustness behaviour of the buried pipeline based on the failure modes and taking into account the uncertainty associated with the design parameters.
- To develop an approach to optimise and analyse the performance of buried pipe based on the pipe failure mode and the expected value of a fuzzy output.
- To develop an approach to analyse the reliability of buried pipeline that simultaneously considers fuzzy and random variables.
- To evaluate the optimal time for the maintenance of buried pipe based on multi-objective optimisation using fuzzy reliability, risk and cost.

1.4 Research Contributions

This study has developed a robust conceptual framework for analysing and estimating the reliability and robustness behaviour of buried pipe, which plays an essential role in the management of pipe systems. The framework would assist in taking a decision at the design stage and at the point where maintenance interventions may be required to prevent unexpected failure of the buried pipe subjected to different loading conditions. The contributions of this research are briefly described as follows:

- The structural failure modes of buried pipe such as through-wall bending stress and total axial stress as explained in Chapter 3, Section 3.3 and 3.4 have been modified for a time-dependent problem. The rationale is because corrosion, which is one of the main prevalent challenges that affect the performance of buried pipe occurs over time. Therefore, the structural reliability of buried pipe has been analysed while considering the randomness associated with the design parameters and the modified failure mode formulas using LS and IS. Also, a combination of LS and IS methods have been adapted to estimate the reliability of a buried pipe while considering the above-mentioned pipe failure modes. For the combined approach, there is an improvement in the computational efficiency when compared to LS, IS, and MCS methods.

- The impact of fuzziness associated with the design parameters on the performance of buried pipeline is analysed based on the concept of a fuzzy-based robustness measure. The approach is based on the principles of robustness measure, fuzzy set theory, interval analysis and Shannon's entropy, which permits the inclusion of fuzzy variables in the characterisation of the uncertainty associated with the buried pipe structure. The outcome shows that the use of $\alpha - level$ discretisation in the assessment of a fuzzy-based robustness measure could produce credible results with a better understanding of the impact of uncertainties associated with the design of buried pipe.
- The uncertainty associated with the input parameters of a buried pipe is analysed through a multi-objective optimisation and the concept of the fuzzy set for an efficient design of buried pipeline. The approach is designed to optimise the expected value of a fuzzy output when the membership function is computed. The principles of fuzzy set and a multi-objective optimisation algorithm are utilised to account for the uncertainty associated with the uncertain parameters. Also, a Hybrid GA-GAM is used to perform the multi-objective optimisation. The outcome of the approach provides a set of optimal solution for the analysis of buried pipe.
- An optimisation based fuzzy-subset simulation approach is proposed for estimating the reliability of buried pipe by considering deterministic, random and fuzzy variables. The proposed method relies on the performance function of the structure, which involves deterministic values, random and fuzzy variables for the modelling of the buried pipe. The proposed method inherits the benefits of Monte Carlo approach in propagating the uncertainties associated with structural parameters but also demonstrates more robustness against the latter.
- The concept of multi-objective optimisation has been extended to evaluate the optimal time for maintenance of buried pipe by considering fuzzy annual reliability, risk and total maintenance cost. The purpose of this optimisation approach is (a) to maximise and evaluate the minimum annual structural reliability

of buried pipe over a 125 years life cycle, and (b) to minimise the total cost required to carry out maintenance within the design life. Also, the risk associated with the possibility of failure is analysed. It is important to note that the annual failure probability and reliability do not have or contain information concerning the consequences or severity associated with the pipe failure. Based on this, the risk associated with the pipe failure is also employed to determine the optimal maintenance time.

The above-stated contributions can be used to efficiently evaluate and analyse the performance of buried pipeline and also, serve as a managerial tool for design engineers in assessing and maintaining the performance of buried pipe. Using the proposed framework, the reliability and robustness behaviour of buried pipeline considering uncertainties that exist in the input parameters can be analysed. Also, the influence of design parameters can be analysed through sensitivity and parametric studies.

1.5 Structure of Thesis

The structure of the thesis is as follows:

CHAPTER 1 - Introduction: This Chapter explains background of the research area including problem statement, research aims and objectives, research contributions and structure of thesis.

CHAPTER 2 - Literature review: The concept of uncertainty, physical and environmental challenges and uncertainties associated with the design parameters of the buried pipe are explained. Also, the causes and consequences of buried pipe are reviewed including existing methods used in estimating the reliability, risk and maintenance of buried pipe and areas where there are gaps in knowledge.

CHAPTER 3 - Reliability analysis of buried pipe based on LS and IS methods: In this Chapter, LS, IS and a combination of LS and IS has been adapted to estimate the time-dependent reliability of buried pipe. The failure modes considered include total axial/circumferential stress and through-wall bending stress.

CHAPTER 4 – Fuzzy-based robustness assessment of buried pipe: The robust behaviour of buried pipeline under the influence of uncertain variables including reduction of pipe thickness has been analysed considering corrosion-induced failure modes such as pipe deflection, buckling pressure, wall thrust and bending strain. A numerical example has been used to elucidate the concept of fuzzy-based robustness measure of the buried pipe by considering the uncertainty associated with the design parameters.

CHAPTER 5 - Multi-objective optimisation of buried pipe based on the expected fuzzy output: In this Chapter, a fuzzy-based multi-objective design optimisation approach is proposed for the optimal analysis of buried pipe based on the expected value of a fuzzy output when the membership function is computed. A Hybrid GA-GAM is used to perform the optimisation.

CHAPTER 6 - Reliability analysis of buried pipe based on fuzzy and subset simulation: This Chapter presents a numerical strategy for estimating the reliability assessment of buried pipe considering random variables and fuzzy variables. The approach is based fuzzy set, and subset simulation and the optimisation is performed using GA. The proposed method relies on the performance function of the structure, which involves PDFs and fuzzy variables for the modelling of the pipe structure.

CHAPTER 7 - Maintenance of deteriorating buried pipe using optimisation involving fuzzy reliability, risk and cost: In this Chapter, a maintenance technique is proposed to determine the optimal time interval for the maintenance of the buried pipeline. The strategy is aimed at assessing the cost-efficiency required for the determination of the optimal time for maintenance using multi-objective optimisation based on the annual fuzzy reliability, risk, and total maintenance cost.

CHAPTER 8 - Conclusions and recommendations for future work: This Chapter presents a summary of the work and recommendations for potential future work.

Chapter Two

2 Literature Review

2.1 Introduction

The safety of the structural condition of the buried pipe is crucial to ensure continuity and the quality of service provided throughout the design life. The cost required for the replacement, repair, and expansion of existing buried pipe is usually high. However, targeted research programmes in Canada, Australia, United States and Europe acknowledge the need for methodologies to assess the level of deterioration and the possibility of failure (Scheidegger et al., 2015). This is because the complete failure of buried pipe would have a significant effect on the continuity of service and the environment. The understanding of the structural condition, physical and environmental condition, causes and consequences of failure and how it develops over time is essential to the development of an adequate reliability and maintenance strategies.

In this Chapter, a brief description of the concept of uncertainty and the characterisation of uncertainty is presented. The physical and environmental challenges of buried pipe are discussed including the uncertainties associated with the input parameters of the buried pipeline. Also, the causes and consequences of the failure of the buried pipe are explained. The existing approaches for the reliability, risk, and maintenance of buried pipeline are discussed including areas where there are gaps in knowledge.

2.2 The Concept of Uncertainty

The design of engineering structures (e.g., underground pipeline, retaining walls, and foundation design) is often associated with uncertainties, particularly in estimating the values of the design parameters (Beer et al., 2013; Möller et al., 2003). The presence of uncertainties affects the performance of engineering structures throughout the design life. Zio (2009) suggested that the presences of uncertainties are analysed to gain precise information on the performance of the system and failure behaviour, and for the purpose of protecting the system from the uncertain failure scenarios. The uncertainties involved in the parameter estimation of most engineering structures are classified as aleatory and epistemic uncertainties (Hanss & Turrin, 2010; Apostolakis, 1990). Although this classification of uncertainties is not in absolute terms, it makes provision for a proper distinction to be drawn (Apostolakis, 1990). The classified uncertainties are further described as a property of a structural parameter associated with randomness/variations (aleatory) and also, as a property linked to the poor understanding of the phenomenon or lack of knowledge (epistemic) (Hanss & Turrin, 2010).

Aleatory uncertainty is characterised by randomness or natural variability in the properties of a design parameter, such as the variation in the determination of the elastic modulus of pipe material or the soil modulus. The aleatory uncertainty is random and can be related to the outcome of an experiment. Hanss & Turrin (2010) suggested that an efficient representation of aleatory uncertainties can be realised by the use of random numbers and their PDFs derived from experimental data. Aleatory uncertainty can be considered to be intrinsic or inherent uncertainty, which cannot be eliminated from the associated parameter.

Epistemic uncertainty arises as a result of lack of knowledge or even complete absence of knowledge concerning the process used in estimating the values of design parameter (Hanss & Turrin, 2010). This type of uncertainty results from, for example, the vagueness of parameter definition, subjectivity in numerical implementation, or simplification and idealisation in the procedure of system modelling (Hanss & Turrin, 2010). Also, epistemic uncertainty can arise due to imperfect method of estimating a design parameter, such as the use of faulty instrument due to human error. As a result of the certain character of epistemic uncertainty, which is entirely different from the aleatory uncertainty, probability theory may not be suitable to characterise epistemic uncertainties efficiently. Therefore, an alternative approach of quantifying epistemic uncertainties is by the use of fuzzy numbers (Hanss & Turrin, 2010; Zadeh, 1965). The impact of all uncertainties on engineering structures can be performed systematically using the concepts and techniques that are embodied in the theory of probability (Hanss & Turrin, 2010). However, it is imperative that the presence of these uncertainties are adequately accounted for in the design of an engineering structure.

2.2.1 Characterisation of Uncertainties

In most cases, the design of an engineering structure is based on deterministic models, however, Khemis et al. (2016) and Li et al. (2016) suggested that the limitations of the deterministic approach paved the way for other models in many scientific works. Uncertainties are associated with engineering structures, therefore, considering their effect in the analysis becomes crucial for an efficient performance assessment of the structure. The determination of the actual value of a structural parameter that is random in nature from a possible range of values can be quantified using a probability distribution function (Ang & Tang, 2007; Baecher & Christian, 2005). Sriramula & Chryssanthopoulos (2009) suggested that the probability distributions form an important part of uncertainty modeling and the selection of a particular distribution may significantly affect the characteristic values considered in structural design. The distribution function is used to assign the probability of occurrence for each possible value. However, a discrete probability distribution is employed if the set of possible values for a random variable is countable; otherwise, a continuous probability distribution is used (Ang & Tang, 2007).

Table 2.1: Common probability distribution models

Distribution models			
Aleatory		**Epistemic**	
Continuous	Discrete	Continuous	Discrete
Normal	Poison	Interval	Real set
Uniform	Binomial	Fuzzy set	Integer set
Weibull Distribution	Negative Binomial		
Lognormal	Geometric		
Exponential			
Student t-Distribution			

In most engineering problems, the continuous probability distribution is often used more compared to the discrete probability distribution, for example, the design parameters associated with a mechanical and geometric property of materials (Ang & Tang, 2007). The continuous probability distribution is described using PDF or Cumulative Distribution Function (CDF). In the literature, there are several suggestions used to characterise the probabilistic models of the uncertainties associated with the input parameters (Beer et al., 2013a). Table 2.1 shows some of the common ones. Also, normal and lognormal distributions are among the most commonly used models, which depends on the behaviour of the parameter (Beer et al., 2013a; Limpert et al., 2001; Wang et al., 2016). However, the normal distribution is very popular and often used because of the central limit theorem (Beer et al., 2013a) and simplicity (Limpert et al., 2001). Limpert et al. (2001) suggested that the concise description of a normal sample is handy, well-known, and sufficient to represent the underlying distribution.

The PDFs of the design parameter are usually created from random data, which may not be available to a considerable extent and quality because of insufficient data and limitation in the experimental processes (Beer et al., 2013b; Hanss & Turrin, 2010; Li & Lu, 2014). The scarcity or lack of information concerning the uncertain parameters could also arise. However, it may be ideal to lessen the assumptions used for some of the well-defined probabilistic models because of imprecision in the parameters of the model (Beer et al., 2013a).

Considering a situation where there is an epistemic uncertainty, two different methods can be used to model the variabilities of the structural parameters based on subjective probability (Khemis et al., 2016). These include the Bayesian method and the set-theoretical model. The Bayesian approach relies on the theory of probability and denotes an excellent way to handle epistemic uncertainty (Beck & Katafygiotis, 1998). The set-theoretical approach includes fuzzy sets, interval analysis, etc. and is used to model the epistemic uncertainty based on set values. In recent times, the use of set-theoretical method has attracted strong consideration especially in the reliability assessment of an engineering system. The purpose of the fuzzy set permits the simultaneous analysis of different bound sets, and this is very useful in situations where the set bounds are not known explicitly to examine the sensitivity of input parameters on the possibility of failure (Beer et al., 2013a; Beer et al., 2013b; Li & Lu, 2014). In this study, a fuzzy set is utilised to analyse the performance of a buried pipe. For more information about fuzzy set, see Chapter 4 and 6.

2.3 Physical and Environmental Challenges of Buried Pipe

Buried pipes have sustained substantial physical and environmental damages during the service life (Kleiner & Rajani, 2001a; O'Rourke & Liu, 2012; Whidden, 2009). As a result of this, there is growing concern about the structural performance and the physical mechanism that leads to pipe failure. Kleiner & Rajani (2001a) suggested that the physical mechanisms that lead to pipe breakage are often very complex and not completely understood. However, the physical and environmental damages of buried pipe involves key areas such as: (a) the properties of pipe (e.g. material type and pipe wall thickness) and pipe-soil interaction; (b) load and loading condition (e.g. operational pressure, external load such as earth load, traffic load, frost load and seismic effect) and (c) deterioration of the pipe wall due to active corrosion effect (Kleiner & Rajani, 2001a).

The behaviour and failure modes of sections of buried pipe are somewhat well-known, and information about them is available in standard textbooks and design codes, e.g., (Alliance, 2001; Moser & Folkman, 2001; O'Rourke & Liu, 2012). Also, the traditional design of buried pipeline has been based on physical behaviour where allowances are made to provide pipe with the capacity to resist or withstand expected loads such as live or earth loads and with a sufficient safety margin (Moser & Folkman, 2001). However, these loads are associated with uncertainties, which affects the performance negatively over time. Based on this, it is crucial to overcoming the effect of the uncertainty and imprecision that exist in the design parameters. Hence, prediction of the optimal performance of buried pipe considering the deterioration of materials requires a good understanding of several components and causes of failure as briefly reviewed in the following subsections.

2.3.1 Seismic Action

Buried pipes have sustained substantial damage in the past, following earthquake occurrence (O'Rourke & Liu, 1999). The damage has been ascribed to the impact of transient action and permanent ground deformations (Liang & Sun, 2000; O'Rourke & Liu, 2012). These effects are further reviewed in the subsequent Section, and they are responsible for the majority of the seismic havoc caused in water distribution pipe network and oil and gas underground pipelines.

2.3.1.1 Transient Action

The transient action as a result of the earthquake effect is called a "wave propagation hazard," and is characterised by peak ground acceleration and velocity (Karamanos et al., 2014). Ground shaking causes the action due to the travelling body and seismic surface waves (Karamanos et al., 2014; Kouretzis et al., 2006). The transient action is associated with peak ground acceleration and velocity. The examination of wave impact on the buried pipeline is complicated, thus requires a wave propagation analysis in a three-dimensional soil-pipe system (Karamanos et al., 2014). Newmark (1967) developed a simplified method that can estimate the strain and curvature of the buried pipe that is caused by the travelling wave of constant shape regarding peak ground motion. Based on the developed approach, the axial strain that would develop due to longitudinal and bend deformation triggered by the action of the wave propagating parallel to the pipe can be estimated. Therefore, the maximum ground strain towards part of wave propagation is expressed in Eq. (2.1).

$$\varepsilon_g = \frac{PGV}{C} \tag{2.1}$$

Where PGV is the maximum horizontal ground velocity in the direction of wave propagation; C represents the apparent propagation velocity of the seismic wave.

Yeh (1974) extended the analytical solution of Newmark (1967) in other to account for obliquely incidence shear and Rayleigh waves. An angle of wave propagation that is relative to the longitudinal structural axis is introduced as a random problem variable. The hoop and shear strain developed due to the induced stress were addressed with the consideration of the time lag that is relative to the axial strains. The uncertainty associated with the analytical solution is reflected in most of the current design guideline for structures such as (Alliance, 2001; European Commitee for Standardisation, 2004). The design guideline for buried pipeline Alliance (2001) called on seismological evidence and univocally recommend the use of an ''apparent seismic wave velocity of the bedrock''. The value suggested for the estimation of the axial strains, regardless of local soil conditions is equal to 2000 m/s (Kouretzis et al., 2006).

2.3.1.2 Permanent Ground Deformation (PGD)

A significant amount of damage to buried steel pipelines are caused as a result of permanent ground induced actions due to earthquakes, such as landslides, movement of fault and liquefaction-induced lateral spreading (Dash & Jain, 2007; Datta, 1999, 2010; Vazouras et al., 2012). The ground induced actions are applied on the buried pipeline in a quasi-static manner and are not essentially linked with severe seismic shaking, but the buried pipe could be extremely damaged and evident threats to the environment (Karamanos et al., 2014). The analysis of PGD depends on the types of action induced. However, there are different methods presented by researchers for the response of buried pipeline under seismic event. See the following reference (Alliance, 2001; Dash & Jain, 2007; Karamanos et al., 2014; Kouretzis et al., 2006) for more information.

2.3.2 Frost Effect

The design code (American Water Works Association, 1977) suggested a procedure to determine earth and traffic load on the buried pipeline but did not include a process to calculate frost pressure, which affects the performance of the buried pipe. The high number of water mains breakages in winter has been attributed to the increased earth load exerted on the walls of the buried pipe (Kleiner & Rajani, 2001b). Rajani & Zhan (1996) presented a model to estimate frost load on buried pipes in trenches and under roadways. As described in Kleiner & Rajani (2001b) the frost load in a typical trench can be obtained using the expression in Eq. (2.2).

$$p_s = \sum_{i=0}^{N_T} \frac{\beta h_f^i}{\left[(1/K_{tip}) + \left(B_d/K_s d_f^i\right)\right]} H\left(s - d_f^i, B_d\right) \tag{2.2}$$

Where p_s is the frost load at any point s, d_f is the frost depth, i is the time step number, N_T is the number of time steps, h_f is the total frost heave, B_d is the trench width, K_{tip} is the stiffness of elastic half-space of unfrozen soil below freezing front, β is the attenuation factor, K_s is the backfill sidewall shear stiffness, H is the Bousinesq function to determine the influence of stress and s is the location below the surface where frost load is calculated.

In the model, the frost load is a function of the trench width, frost depth penetration, and other soil properties. In a trench, the frost load develops primarily as a result of different frost susceptibility of the backfill and sidewall of the trench and the interaction at the trench backfill sidewall interface (Kleiner & Rajani, 2001b). The introduction of a model for frost load has helped to improve the understanding of the mechanism that leads to the development of frost load and enabling a mitigation measure. Some of the input parameters are not readily available, which makes it difficult to use the model. The current validation data as described in Kleiner & Rajani (2001b) indicates that frost loads could develop up to twice the geostatic or gravity earth loads. Rajani & Makar (2000) suggested an alternative and simplistic approach to estimating frost load. Based on the proposed method, the frost load could be determined as a multiple of the earth pressure. For the mathematical formulation, see Chapter 3. The typical value of the frost load multiple is usually between 1 and 2. A value of 1 is used on a condition where there is no frost load, while the value of 2 is used when there is a maximum frost load acting on a buried pipeline (Rajani & Makar, 2000). The effect of frost action can lead to further reduction in the reliability of the buried pipe.

2.3.3 Thermal Effect

The thickness design approach of buried pipe as suggested by American Water Works Association (1977) does not consider the impact of the difference in temperature of the water mains and surrounding soil explicitly. Rajani & Makar (2000) suggested that this difference can lead to a further reduction in the factor of safety as it induces axial stresses on the pipeline. Failure of the buried pipeline will occur in longitudinal mode if the induced stresses exceed the axial tensile strength of the pipe. Rajani et al. (1996) developed an analytical solution for estimating the thermal stress of any pipe material under pressure and subjected to thermal and other operational loads. Rajani & Makar (2000) suggested that the analytical equation can be specifically simplified for a metallic pipe, where the ratio between the soil elastic modulus and the elastic modulus of the pipe material is slight? Also, the external pressure as a result of the soil reaction may be taken as zero. For the mathematical formulation, see Chapter 3. However, the reliability of the buried pipe depends on pipe size, the geometry of the trench, soil types, pipe thickness, and environmental and geo-environmental conditions.

2.3.4 Corrosion Effect

Unlike the loading conditions and the impact of geo-hazards on the buried pipe, corrosion has proven to be one of the most predominant causes of pipe failures and contributed significantly to the downtime. Every year, pipeline companies spent huge amount of money on various forms of corrosion control measures in order to maintain the integrity of pipelines (Ossai et al., 2015). Regrettably, the difficulties associated with getting an optimum and robust design, estimation of reliability, and appropriate maintenance strategies highlight the billions of dollars lost due to corrosion-induced failure (Bhaskaran et al., 2005; Gomes & Beck, 2014). As suggested in Brown (2014), about 80% per cent of failed pipelines are monitored in one form or another and between 20% and 65% of the amount spent on corrosion problems could be saved if there was a better understanding of corrosion process, protection and control techniques. Corrosion of buried pipelines can be attributed to various causes and are related to the physical and chemical factors as a result of corrosive environmental conditions. Figure 2.1 (Ossai et al., 2015) shows some of the causes of corrosion.

Corrosion of pipe could occur either internally or externally or both ways (Ahammed & Melchers, 1997; Sadiq et al., 2004). In the literature, there are various models developed by researchers to model the effect of external corrosion. Some of these models are reported in Table 2.2. These models are developed from experimental data using regression analysis. The reduction of buried pipe wall thickness due to corrosion loss can be relatively uniform or localised (Ahammed & Melchers, 1994). Kleiner & Rajani (2001a) suggested that the deterioration mechanism on the exterior walls of the cast and ductile pipes is electrochemical corrosion and the damage occurs in the form of corrosion pits. Therefore, the physical environmental conditions that surround the buried pipe have a significant effect on the rate of deterioration. Some of the factors that accelerate the corrosion of metallic pipes include the characteristic of the soil such as chemical and biological contents, soil moisture content, electrical resistivity, aeration, etc (Kleiner & Rajani, 2001a). Also, the interior of a buried metallic pipe can be subjected to erosion and crevice corrosion that may lead to a reduction in the effective inside diameter of the pipe. The internal corrosion can also reduce the performance of the buried pipe over time.

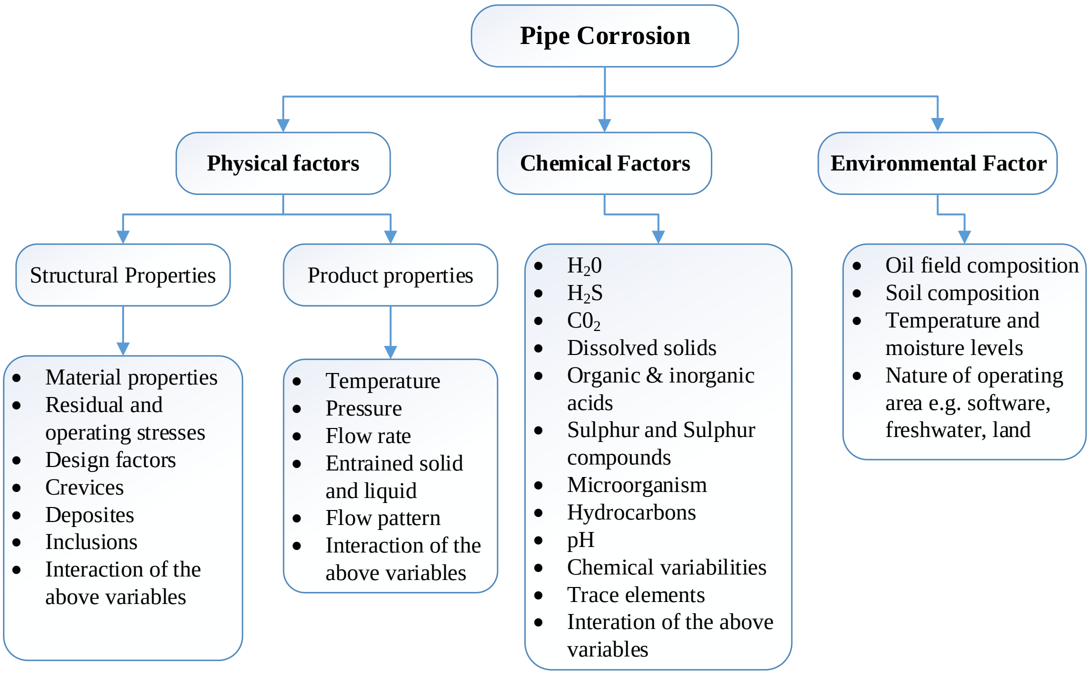


Figure 2.1: Causes of pipe corrosion

Table 2.2: Commonly used surface corrosion model

Model	Parameters description
$\boldsymbol{d = KT^n}$ $\boldsymbol{d_T = nKT^{(n-1)}}$ (Kucera and Mattson, 1987)	d = depth of corrosion pit (mm); K = constant (usually 2); n = constant (usually 0.3); T = exposure time (yr); d_T = corrosion rate (mm/yr)
$\boldsymbol{d = K_n Z^n}$ where $\boldsymbol{Z = \left[\frac{(10 - pH)T}{\rho_{soil}}\right]}$ (Rossum, 1969)	K_n = constant; ρ_{soil} = soil resistivity; pH = the acidic or alkaline nature of soil; n = related to soil redox potential;
$\boldsymbol{d = aT + b(1 - e^{-cT})}$ $\boldsymbol{d_T = a + bce^{-cT}\ (two - phase\ model)}$ (Rajani et al, 2000)	a = final pitting rate constant (typical value; 0.009 mm/yr); b = pitting depth scaling constant (typical value; 6.27 mm); c = corrosion rate inhibition factor (typical value; 0.14 yr^{-1})

2.4 Uncertainty Associated with the Design of Buried Pipe

Buried pipes are designed based on soil and pipe properties, and these properties are used to model the behaviour of the pipe (Moser & Folkman, 2001; Whidden, 2009). The analysis of the pipe response due to a particular failure mode is accurate to the point that the assumptions made in the mathematical representation of the soil and pipe properties are correct. Indeed, uncertainties affect the performance of a buried pipe and its modelling. On the one side, there are conditions where the determination of a particular soil or pipe properties, e.g. the estimation of the elastic modulus of pipe material, determination of soil modulus, are random. This type of uncertainty for a buried pipe system is classified as aleatory uncertainty as explained in Section 2.2. Another aspect of uncertainty comes from the incomplete knowledge concerning the properties of the design parameters and the conditions in which the phenomena occurs. This type of uncertainty is classified as epistemic uncertainty, which affects the performance of buried pipe in the hypotheses assumed and the values of the parameter of the model. Zio & Pedroni (2009) suggested that model uncertainty arises because mathematical models are simplified illustrations of real systems and, therefore, their outcomes can be affected by errors.

In the literature, considerable research has been performed to demonstrate the importance of considering uncertainties associated with the design parameters of an engineering structure. For example, Nadim (2015) presented an overview on how uncertainty associated with mechanical soil properties are dealt with in offshore site investigation and suggested ways for optimally utilising the reliability tools for this purpose. In the study, two problems were addressed. The first is the extraction of the maximum amount of information from site investigation and how to represent soil properties for the purpose of design while accounting for the uncertainties caused by natural variability of soil properties and interpretation of lab tests. Also, Lacasse & Nadim (1996) present a review of the uncertainties in characterising the properties of soil, and stresses the rationale for characterising the uncertainties for design purpose. Subsequently, the usefulness of estimating and, where possible reducing, the uncertainties is demonstrated using a case study. In the following subsection, sources of uncertainties are explained with particular reference to soil and pipe properties.

2.4.1 The Inherent Variability

The properties of soil changes over time due to the natural geologic and environmental processes that produced and continually modify the soil mass in situ (Phoon & Kulhawy, 1999a). Often, these processes will continue to occur and cause changes in the soil properties both vertically and horizontally. Soils are formed from weathering of rocks or weathered rock and minerals transported by water. Therefore, a soil deposit will consist of different layers of weathered rocks, which has been consolidated over a period and with different properties. As a result, the soil is seen as a complex engineering material with an inherent variability (Phoon & Kulhawy, 1999a). The inherent variabilities of soil properties, e.g., the elastic modulus of soil can be described using statistical parameters such as the mean, variance, and covariance.

As reported in Phoon & Kulhawy (1999a), if soil samples are collected over a period of one to two weeks, the properties of the soil can be regarded as time-invariant (Rethati, 1989). Also, if the time periods continue to increase, additional variability may be introduced into the data set due to the changes in the soil mass. The variation can be rather significant, in some cases. Unfortunately, the time interval over which the soil samples will be collected is often not reported. This makes it difficult to evaluate the significance of the temporal changes.

2.4.2 Measurement Error

For the design of buried pipe, most of the design parameters such as the height of backfill material and pipe thickness are measured using physical means. The process of measurement can introduce additional variability. The error generated as a result of measurement can be attributed to a variety of factors such as human error, equipment error, and limitations in the experimental process (Fornasini, 2008). Phoon & Kulhawy (1999a) stated that the effect of equipment error comes from inaccuracies in the measuring devices and variations in equipment geometries and systems employed for routine testing while the impact from the operator occurs from the limitations in the existing test standards and how the procedures are followed. However, an experiment that depends more on the operator and with a complicated procedure will have higher variability compared to the one with little dependency on the operator and simple procedure (Kulhawy & Trautmann, 1996; Phoon & Kulhawy, 1999a).

The measurement of uncertainty associated with a particular parameter using specific equipment can be quantified by taking a repeated measurement of the same parameter. The data generated from the experiment can be used to quantify the probability distribution model. Kulhawy & Trautmann (1996) suggested that the use of proper quality equipment and systematic control of procedure will likely have a small measurement error. In principle, the error due to measurement can be determined by analysing the variation of the data obtained through repeated measurement.

2.4.3 Transformation Uncertainty (Model Uncertainty)

Most often, the design parameters that are determined directly from field measurement may not be directly applicable to the design of the structure. Instead, there may be a need for the obtained values to be transformed into the appropriate design property using a mathematical model. In doing this, Phoon & Kulhawy (1999b) suggested that there may be some form of uncertainties that will be introduced because most transformation models are determined using empirical data fitting. Because of the simplifications and approximations, in theory, transformation uncertainty will still be present. Also, an effort to obtain high-quality data to quantify the uncertainty effect, may not significantly reduce transformation uncertainty because of the difference between theories and natural physical behaviour (Phoon & Kulhawy, 1999b). Therefore, transformation uncertainty occurs as an independent uncertainty in engineering structures. For example, when evaluating the corrosion empirical constant using values of corrosion pit depth from different environmental conditions, the transformation uncertainties will depend on the best fitting line for the regression analysis using different years of corrosion pit depth.

2.5 Analysis of Buried Pipe

The presence of uncertainties will affect the performance of buried pipe overtime if not accounted for at the preliminary stage of the design. As a result of this, it is crucial to overcoming the adverse effect of uncertainty in the design of buried pipe. Traditionally, the fundamental criterion used in the design of buried pipe is the resistance to internal pressure (Moser & Folkman, 2001). Once the criterion is evaluated, the obtained wall thickness is validated for suitability with regards to other measures such as external loads, and buckling pressure. This type of design is based on a deterministic approach, and the limitations have paved the way for other methods. Schuëller & Jensen (2008) suggested that the determination of structural performance based on the deterministic model is undoubtedly a simplification because physical measurement always shows variability and randomness. Furthermore, the analytical expressions used for the design of buried pipeline are formulated and solved based on physical and experimental models (Kleiner & Rajani, 2001a). The development of these models is associated with a significant amount of subjectivity that can lead to the introduction of an aleatory or epistemic form of uncertainty. Therefore, it is essential to consider the variabilities or randomness associated with the design parameters of the buried pipe.

The use of structural optimisation has gained an increasing significance in the design of structures and improving performance (Bucher & Frangopol, 2006; Okasha & Frangopol, 2009; Onoufriou & Frangopol, 2002). Under this trend, substantial progress has been made towards the design of engineering structures. Considering the importance and consequences associated with the failure of the pipe network, Sadiq et al. (2004) suggested that a risk-based maintenance management methodology can be more effective and independent. The reason is that it allows the optimisation of various types of structures within a network by considering both the probability of failure and the consequences of failure. Kleiner et al. (2004) considered the network renewal planning problem where the structural and the hydraulic capacity deterioration of the network are considered for the determination of the optimal rehabilitation schedule. In recent time, considerable attention has been given to the reliability of pipeline systems in conjunction with optimisation to achieve maximum benefits with the minimum cost (Moneim, 2011). Halfawy et al. (2008) suggested that an optimum management strategy must ensure efficient performance after rehabilitation and should provide reliable service with minimum interruptions. The causes and consequences of the failure of the buried pipe are reviewed in the following subsections.

2.5.1 Causes of Pipe Failure

The selection of the design parameters for buried pipe always varies and depends on the use (e.g., water supply and crude oil), service life and the nature of the surrounding environment (Whidden, 2009). Buried pipe have sustained substantial damages due to the impact of one or more of the aggressive environmental effects such as corrosion, frost action, and seismic effect (Karamanos et al., 2014; Ossai et al., 2015; Rajani & Zhan, 1996). As a result, there is growing concern about the maintenance of pipe integrity throughout the designed life. Chughtai & Zayed (2008) suggested that lack of comprehensive knowledge of the condition of buried pipelines increases chances of a catastrophic failure. However, it is not possible to completely understand all the conditions that affect the performance of buried pipe because of lack of knowledge or information with regards to the processes that are involved. Hence, the consideration of uncertainty of the design parameter becomes an essential part of the analysis of buried pipeline. The nature of pipe material, diameter, and age, including factors such as soil types and corrosion parameters have shown significant influence on pipe failure (Berardi et al., 2008; Fenner et al., 2000). Ahammed & Melchers (1997) suggested that for an underground pipe that is subjected to internal and external loading, the primary cause of failure is the loss of structural strength that is influenced by localised or overall reduction in pipe wall thickness. Table 2.3 shows some of the factors that affect the structural deterioration of buried pipelines as defined in Rostum (2000).

Leis & Parkins (1998) stated that the leading causes of damage or failure of the buried pipeline are stress corrosion cracking, wall thickness reduction, and the presence of stress concentrators. Corrosion affects buried pipe both internally and externally. In practice, there are a considerable amount of anticorrosion protection efforts, but the damage due to corrosion still occurs on a large scale and remains a matter of concern because of the amount needed for the rehabilitation (Ahammed & Melchers, 1997; Sadiq et al., 2004). Fares & Zayed (2010) suggested that the magnitude of failure modes is different among pipelines and varies with the life cycle. Farshad (2006) also pointed out that at a microscopic level, changes in pipe strength and stiffness are the two most important aspects that are involved in the long-term behaviour of the pipe. Similarly, as suggested in (Berardi et al., 2008; Fenner et al., 2000) pipe thickness, pipe elastic modulus, diameter, and age, with or without additional factors such as soil types have contributed to pipe failure. It is important to note that during installation of buried pipe, other damages such as mechanical deformations and thermal effect can affect the residual stress and increase the possibility of pipe failure.

Table 2.3: Factors that affect the structural deterioration of the buried pipe

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 network		
Internal protection	Salt for de-icing of roads		
External protection	Temperature		
Pressure class	External corrosion		
Wall thickness			
Laying depth			
Bedding condition			

Ahammed & Melchers (1994) pointed out that the reduction of wall thickness for metal pipes arises from pitting and crevice corrosion. The study further explains that the decrease in pipe thickness weakens the capacity of the pipe resistance and thus, reduces the safety of the structure. Also, Gabriel (2011) states that the mechanical strength of a buried pipe begins to reduce soon after installation. The reduction of pipe wall thickness due to corrosion could have an adverse impact on the failure modes of buried pipe.

2.5.2 Consequences of Pipe Failure

According to Piratla et al. (2012), a significant portion of the buried pipeline for water and wastewater in Europe is approaching the end of its service life, and thus, essential construction works will be required to perform proper rehabilitation or renewal of this vital infrastructure. The primary design requirement of buried pipeline considering the physical and environmental challenges and the associated uncertainties is the safety of the structure during the designed life. In recent time, there is an increase in the structural performance of a buried pipeline especially in areas that are prone to geo-environmental hazards (Karamanos et al., 2014). To accurately quantify the extent of damage on the buried pipe, underground-induced action requires appropriate performance criteria (Vazouras et al., 2012). However, the consequences of the failure of the buried pipe may include loss of life, injuries, and environmental contaminations. Although, some of these consequences cannot be evaluated in monetary terms.

The most common way of quantifying consequences associated with pipe failure is to evaluate the losses related to the failure regarding cost. The cost related to structural pipe failure can be a direct cost, e.g., cost of replacing the failed part or indirect cost, e.g., environmental contaminations cost. Barone & Frangopol (2014a) suggested that the direct consequences of structural failure are often associated with repair/replacement cost of the structural component while the indirect consequence is the estimation cost derived from failure, which may not strictly be related to rebuilding the structure. In this case, the indirect effects of pipe failure may contain, for example, injuries, fatalities or environmental contaminations as a result of the structural failure of the buried pipe. The failure of the underground pipeline can pose severe health and environmental issues to the public especially when it is used to transport crude oil.

According to Davies et al. (2001), OFWAT, the water services regulation authority in England and Wales, estimated the length of public sewer to be about 302 000 km and with a gross replacement cost of £104 billion. The report also suggested that water companies in England and Wales currently spend approximately £230 million per annum on sewer maintenance. About £150 million is spent on infrastructure renewals that is planned while the remaining £80 million is spent on operating expenditure, encompassing reactive and planned maintenance (Davies et al., 2001). Similarly, in Canada, Canadian Water and Wastewater Association (CWWA) estimated that CAN $11.5 billion will be required to upgrade the water main by 2013 (Kleiner et al., 2001). These statements indicate that a considerable huge amount of money is required to carry pipe maintenance per annum.

2.6 Reliability, Risk, and Maintenance of Buried Pipe

2.6.1 Estimating the Reliability of Buried Pipe

The reliability estimation of buried pipelines have received greater attention and traditionally defined by a scalar performance function in a d-dimensional space where $g(x) < 0$ denotes the failure domain and $g(x) > 0$ represents the safe domain. There are so many methods in the literature on how to estimate the reliability of a structural system based on limit state function and considering the randomness associated with the structural parameters. The methods used in the estimation of structural reliability have been grouped into an approximate method and a simulation-based method (Schuëller et al., 2004). The approximate method includes FORM and the Second Order Reliability Methods (SORM). The details of the approximate methods are available in the literature, for example, (Melchers, 1999; Schuëller et al., 2004). The second method is based on simulation approach, and examples include Monte Carlo Simulation (MCS), Important Sampling (IS), Subset Simulation (SS), Latin Hypercube Sampling (LHS), and Line Sampling (LS), etc. For more information, see (Au & Beck, 2001; Koutsourelakis et al., 2004; Pradlwarter et al., 2007; Zio, 2013). The challenges with the use of the FORM is that it ignores all the non-linearity and does not provide information on the accuracy, which means there is no confidence interval for the estimate that would be determined

(Schuëller et al., 2004). On the other hand, SORM does not ignore all the non-linearity. The use of MCS is not computationally efficient because it takes a long time to calculate small failure probability due to the required number of samples. However, the advanced MC methods such as IS, LS, and SS are sometimes called 'variance reduction techniques' and are considered more computationally efficient.

For the reliability of buried pipeline, Babu & Srivastava (2010) pointed out that the reliability factors that represent the combined influence of total variability and derivations of analytical formulations are often challenging to compute. The prediction of the reliability of the response of an engineering structure throughout its life cycle depends on probability modelling of the load and strength of the structural system as well as the use of appropriate structural reliability methods (Estes & Frangopol, 2001). Fetz & Tonon, (2008) suggested that the implementation of a probability assessment for a structural system faces challenges from (1) relationship between random variables, (2) too many random variables involved, (3) information about the rare scenarios, and (4) too many interactive response variables. In a simulation-based method for estimating the probability of failure, the input parameters are treated as continuous random variables (Sivakumar & Rao, 2005). The performance of the structural system due to different failure criteria is express in a probabilistic framework (Sivakumar & Rao, 2005). This probabilistic framework could either be a probability of failure or as a reliability index. In other to account for different sources of uncertainties involved in the estimation of input parameters of the buried pipeline and also, the selection of a proper value for the factor of safety, an adequate level of past experiences and sound engineering judgements is required (Sivakumar et al., 2006).

Consequently, the approximate and simulation methods are used to capture uncertainty due to randomness associated with the design parameters and are called the probabilistic methods. The probabilistic approach has attracted the most attention among researchers (Kroese & Chan, 2014; Pradlwarter et al., 2005; Schuëller & Jensen, 2008; Tee & Khan, 2014). For a buried pipe, Sivakumar et al. (2006) analysed underground steel pipe reliability due to deflection, buckling and wall thrust, which is based on pipe installation time. Sadiq et al. (2004) used MC simulations to estimate the failure probability of buried pipe for a probabilistic risk analysis while considering a corrosion associated failure.

Similarly, Tee et al. (2014) estimated a time-dependent failure probability of buried pipe considering the failure mode of deflection, buckling bending stress, and wall thrust using subset simulation.

However, Beer et al. (2013) suggested that the use of the probabilistic technique can be difficult because the data needed for the estimation of the mathematical statistics are always not available to a large extent. Therefore, the drawback with the use of the probabilistic method is the inability to obtain sufficient information to precisely define the PDF of the uncertain parameter in practice (Yin et al., 2018). Based on this, the probabilistic method can be used only when there is precise information about the input variables in order to define their PDFs. In the design of buried pipe, the statistical data to determine the PDFs of the input variables, e.g., loads and resistance may not be present. As a result, an alternative non-probabilistic method (e.g., interval modelling and fuzzy set) can provide the required framework for the reliability assessment of a buried pipeline. The buried pipe is designed to meet some specific requirement and for a safe operation throughout their entire design life. To achieve this, the design needs to be robust and to be able to deal with the uncertainties associated with the design parameters. However, it is possible for fuzzy variables with membership functions and random variables with PDFs to occur simultaneously.

2.6.2 Risk Assessment and Maintenance of Buried Pipe

Assessment of risk associated with a buried pipe can be analysed qualitatively or quantitatively. Qualitative risk assessment deals with simple descriptions of different types of hazards, the associated consequences and likelihood, and reporting all these aspects in a constructive and opportunely built risk matrices (Arunraj & Maiti, 2007; Barone & Frangopol, 2014b). The assessment of risk associated with pipe failure is crucial for prioritising the renewal of pipeline and also the inspection scheduling and monitoring of performance (Rahman & Vanier, 2004). Halfawy et al. (2008) suggested that a risk index that starts from 5 is regarded as the most critical, while 1 is considered as least critical. The least critical with an index 1 is equivalent to category C manuals, and an index 5 is equivalent to a risk category A, as reported in (Water Research Centre, 2001). Chughtai & Zayed (2008) analysed risk assessment by using a 'risk factor' that is measured on a 1–5 scale, ranging from 'acceptable' to 'critical,' which reflects the consequence of pipe failure instead of using a monetary value.

Rajani & Makar (2000) stated that the decision to repair or replace the current pipe is typically based on the level of performance indicators such as structural integrity, hydraulic efficiency, and system reliability. However, the planning process for the renewal of the buried pipeline remains subjective and heuristic, which is considered mainly as an art as it is science (Halfawy et al. 2008). Water Research Centre (WRC) in the UK, used a 'priority index' to obtain the emergency of pipe management. The 'priority index' is defined for each pipe to illustrate the level of urgency for intervention. The 'priority index' ranges from A – F, where index A, denotes an immediate intervention is required, and index F shows that no action is needed (Water Research Centre, 2001). Similarly, McDonald & Zhao (2001) suggested a rating system ranging from 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.

The quantitative risk assessment associated with the failure of the pipe is defined as the product of the failure probability for each pipe segment at time t and the associated consequences due to failure. Due to the deteriorating condition of the buried pipeline, the assessment and maintenance would require proper inspection and maintenance activities to keep the risk under control. Therefore, the evaluation and determination of the optimal time for maintenance of engineering structures become an essential research area in the field of engineering (Faber et al., 1996). Considering the safe operation of the buried pipe, Hong (1999) stated that the optimal maintenance programme should be defined based on a minimum acceptable level of failure probability. Similarly, regarding cost Laggoune et al. (2010) suggested that the optimal maintenance planning should be defined based on the minimum expected cost. The two viewpoints play a vital role in regards to when maintenance should be carried out. Also, Barone & Frangopol (2014a) suggested that the increase in the number of systems that reached critical conditions, due to deterioration of the structural resistance, has directed the attention of researchers to the development of a method that would provide cost-effective maintenance approach.

Several techniques are proposed to analyse the structural performance of a deteriorating buried pipe. These methods are aimed at the assessment of the structure using a robust and comprehensive framework and to ensure the reliability of the structure. Risk assessment of an engineering structure has been recognised in recent time as a crucial part of decision making (Barone & Frangopol, 2014b). As a result of this, several performance indicators have been proposed to evaluate a time-dependent structural performance of deteriorating buried pipeline structures (Ahammed & Melchers, 1997; Sadiq et al., 2004; Tee et al., 2014). Over the years, optimisation algorithms are used while considering maintenance times as design variables and allow the identification of possible opportunity for maintenance during the design life cycle.

2.7 Research Gaps and Limitations

In Sections 2.2 to 2.6, a detailed review and explanation of uncertainties, physical and environmental challenges, uncertainties in the design of buried pipe, causes and consequences of pipe failure and reliability, risk and maintenance of the buried pipeline. Based on the review, the following areas in the subsections are identified as the research gaps and have been addressed in the subsequent Chapters.

2.7.1 Reliability of Buried Pipe Considering Random and Fuzzy Variables

In the literature, the reliability prediction of the buried pipeline has been analysed based on the approximate method (e.g., FORM) and simulation methods (e.g., MCS and Subset simulation) as explained in Section 2.6.1. While most of the works are based on the installation time of pipe, few have addressed time-dependent reliability. In all, the computational efficiency and applicability of the structural reliability methods play a vital role in choosing a particular method. In such case, the use of advanced Monte Carlo Simulation such as Line Sampling (LS), Important Sampling (IS), Subset Simulation (SS) methods, etc. represents a useful option for analysing the reliability of buried pipe. As a result, this part of the report proposed time-dependent reliability by adapting a combination of LS and IS to estimate the failure probability of buried pipe while considering the randomness associated with the design parameters. The adapted approach increases the computational efficiency and is used to determine the reliability of a buried pipe considering the randomness of input parameters and the effect of the underground water table.

In most practical engineering design of buried pipeline, fuzzy variables with membership functions and random variables with PDFs could co-occur. In such a situation, pipe structures are designed to meet some specific requirement and for a safe operation throughout their entire design life. To achieve this, the design needs to be robust and to be able to deal with the uncertainties associated with the design parameters. The presence of this form of uncertainty makes the analysis more complicated and thus requires a more robust and efficient modelling approach. Based on this, an optimisation based fuzzy-subset simulation approach for the reliability analysis of buried pipeline is proposed. The method has been utilised to deal with the limitations of the probabilistic approach, especially where the data for proper evaluation of the PDF of the input parameters is considered not adequate. Also, there is no such work found in the literature for the reliability analysis of flexible buried pipe considering fuzzy and random variables.

2.7.2 Fuzzy-based Robustness Assessment of the Buried Pipeline

In practice, the sources of uncertainties for the design of buried pipe are quite diverse, e.g., variations in loading conditions of the structural system, properties of the engineering material, geometry, and the boundary conditions. So a fuzzy-based robust assessment of buried pipeline is proposed based on the fuzzy alpha-level set, interval analysis and evaluation of fuzziness using an analogy to Shannon's entropy. The aim is to analyse the capability of the buried pipe system to resist the variabilities associated with the design parameters and without obvious effects on the serviceability. The robustness is considered as a measure to assess the ability of buried pipe to sustain damage that may be caused by extreme loads or changes in environmental conditions without disproportionate failure. As a result, the structural robustness illustrates a high degree of objectivity between the variability of the design parameters and the equivalent variability in the response of the structure. Therefore, a buried pipe structure can be considered as robust if it can survive dangerous circumstances such as exceptional overloading, unpredicted events, and severe environmental conditions without any significant damage to safety and serviceability state of the structure. However, there is no such work found in the literature with respect to fuzzy-based robustness assessment of buried pipe.

2.7.3 Design Optimisation Considering Uncertain Variable

The presence of unavoidable uncertainties in the structural parameters contributed to the introduction of the concept of "robust design" in the optimisation of engineering structure to reduce the adverse effect of the uncertain variables (Beyer & Sendhoff, 2007). Marano & Quaranta (2008) suggested that the standard optimal solutions can be very sensitive to small parameters variations and because they deal only with the best structural performances, by minimising a deterministic objective function without taking into account the parameters of uncertainty. Based on this, fuzzy-based multi-objective design optimisation is proposed and applied to the design of buried pipe. There is no such work found in the literature, and the optimisation is performed using a Hybrid GA-GAM.

2.7.4 Reliability and Risk-based Maintenance of Buried Pipe

Structural deterioration of buried pipeline due to adverse corrosion effect is among the leading causes of increasing possibility of pipe failure. As a result, maintenance intervention becomes a fundamental task for good engineering management programme. Also, due to the effect of uncertainty in the design of a buried pipeline, there is a need to develop a maintenance approach based on the non-probabilistic method that can help to determine an optimal time interval for maintenance. For this reason, a maintenance technique is developed to determine the optimal time for the maintenance of buried pipeline using the fuzzy-based approach as a non-probabilistic method for computing pipe reliability and risk, based on α-level set. The strategy aimed at assessing the cost-efficiency required for the determination of the optimal time for maintenance using multi-objective optimisation based on the fuzzy annual reliability, risk, and total maintenance cost. Also, there is no such work found in the literature.

2.8 Chapter Summary

In this Chapter, the concept of uncertainty and the characterisation of uncertainties are explained. An overview of the physical and environmental challenges which affect the performance of buried pipeline are discussed. These include seismic action, frost effect, thermal effect, and corrosion effect. Also, the sources of uncertainties associated with the input parameters for the design of buried pipe are explained regarding the inherent variability, measurement error, and transformation uncertainty. Subsequently, the causes and consequences of the failure of the buried pipe are reviewed. The understanding of the challenges and the causes of failure is essential in formulating an approach that will be used to solve the problem. The adverse effects of these challenges and causes of failure cannot be undermined in any proper analysis of a buried pipe system. Also, a comprehensive review of the existing methods used in the design optimisation, reliability, and maintenance of buried pipeline is reported including areas where there are gaps in knowledge. The reviewed works cut across other engineering field and in some cases may not be directly linked to the subject area. However, their importance in engineering disciplined has been acknowledged. The identified gaps in knowledge have formed the reason for this research, and they have been addressed in the later Chapters of this Thesis. In Chapter 3, the reliability of a buried pipeline has been analysed considering an aleatory type of uncertainty using LS and IS, and a combination of LS and IS. The combined approach has been utilised to analyse the effect of the underground water table, corrosion empirical constants, and bending moment coefficient on the performance of buried pipeline.

CHAPTER THREE

3 RELIABILITY ANALYSIS OF BURIED PIPE BASED ON LINE AND IMPORTANT SAMPLING METHODS

3.1 Introduction

A significant level of uncertainties exists in the processes and methods of estimating the values of the input parameters for the design of buried pipe. The uncertainties can be due to the imprecision associated with the methods of estimating the values of the parameters (aleatory uncertainty) or lack of knowledge concerning the processes involved in estimating the values of the parameter (epistemic uncertainty). However, an aleatory type of uncertainty due to randomness associated with the input parameters is considered in this Chapter. Estimating a small failure probability using MCS can be significant because of the required number of samples. In such a situation, the use of advanced MCS methods such as LS, IS, and SS methods represent a useful option for evaluating the reliability of a buried pipeline.

In this Chapter, the reliability of buried pipe is performed by adapting LS, IS and a combination of LS and IS. For the LS and the combined methods, an “important direction” that points towards the failure domain of interest is determined. The considered methods are aimed to reduce the variance of the failure probability estimator while considering the randomness associated with the input parameters. Also, the methods are adapted for time-dependent reliability since corrosion, which is one of the main prevalent challenges that affect the performance of buried pipe occurs over time. The application to the buried pipe is investigated based on the failure modes of total axial stress and through-wall bending stress due to concentrated load. In addition, the work performed a parametric study by analysing the effect of having the underground water table located above and below the buried pipeline.

The rest of this Chapter is organised as follows. Section 3.2 presents the concept of structural reliability analysis of buried pipe, which includes methods that can be used to estimate the reliability of buried pipeline such as MCS, LS and IS. In this Section, the computational steps for the combination of LS and IS is also presented. Section 3.3 presents an application to the buried pipe and the considered failure modes (pipe ovality, through-wall bending stress, ring buckling, and wall thrust). Section 3.4 explained the total circumferential and axial stresses. Section 3.5 explained the pipe corrosion while Section 3.6 presents the limit state function for the failure mode. In Section 3.7, the numerical example is explained, and Section 3.8 shows the results and discussion including the parametric studies. Section 3.9 summarises the Chapter.

3.2 The Concept of Pipe Structural Reliability

The structural behaviour of a buried pipeline can be described using a response variable y. This response variable can represent the failure mode or displacement of the pipe structure from the original position. The values of the response variable will depend on the input variables $x = (x_1, \dots, x_n)$, which may represent the material properties of pipe and soil, and loading conditions. The relationship between the response variable and the input variables of pipe structure can be expressed as shown in Eq. (3.1)

$$y = g(x_1, \dots, x_n) \tag{3.1}$$

Where $g(x)$ denotes the pipe performance function. The performance of the pipe structure can be measured by comparing the pipe structural response against a particular critical value y^*. If the critical value y^* is greater than the pipe structural response y, then the structure is safe; but, if the critical value y^* is less than the pipe structural response y, then the structure is considered to have failed. Considering any of the pipe failure criterion, the failure domain of the pipe can be defined in the input space as expressed in Eq. (3.2)

$$F = \{x\colon\ g(x) > y^*\} \tag{3.2}$$

Based on Eq. (3.2), the failure domain of the pipe structure will comprise a set of values from the input variables that will lead to the failure of the structure considering the exceedance of the critical value or threshold. The design of most engineering structure including a buried pipeline is often based on a deterministic approach, that is the loads, and the structural parameters are assumed as deterministic values. However, Pradlwarter et al. (2005) suggested that the deterministic approach is a simplification of the actual problem because the inherent uncertainties associated with the parameters are not treated by rational means. This implies that there is a need to account for the uncertainties associated with the input parameters in analysing the performance of engineering structure. In this Chapter, the randomness associated with the input parameters are considered, and probabilistic methods (LS, IS, MCS and a combination of LS and IS) adapted to estimate the failure probability of a buried metal pipe. The methods are briefly described in the subsequent subsection.

3.2.1 Monte Carlo Simulation

The MC approach is a statistical sampling approach that has been used in different engineering fields and to analyse the performance of structures. From a mathematical viewpoint, MC can be used to estimate the expected value of a specific quantity of interest (Robert & Casella, 2004). In particular, the goal is to evaluate the expectation $E_{\pi}[h(x)]$ of a function $h: X \to \mathbb{R}$ with respect to the PDF $\pi(x)$,

$$E_{\pi}[h(x)] = \int_{x} h(x)\pi(x)dx. \tag{3.3}$$

The concept behind MC technique is a direct application of the law of large numbers (Zuev, 2015). This law suggests that if x^1, x^2, … x^N are independent and identically distributed from the PDF $\pi(x)$, then the empirical average i.e., $\frac{1}{N}\sum_{i=1}^{N} h\,(x^i)$ converges to the true value as N goes to $+\infty$ (Zuev, 2015). Consequently, if the number of sample is large enough, then, the expectation of the function can be estimated using the expression in Eq. (3.4).

$$E_{\pi}[h(x)] = \frac{1}{N}\sum_{i=1}^{N} h(x^i) \tag{3.4}$$

Therefore, in the standard normal space, the probability of failure can be expressed as shown in Eq. (3.5).

$$P_F = \int_F \pi_n(x)\mathrm{d}x_1, \dots, \mathrm{d}x_n \tag{3.5}$$

Where π_n is the joint Gaussian Probability Density Function (PDF) of x. Therefore, introducing the failure counter, where $I_F(x) = 0$ if $\mathrm{g}(x) > 0$ and $I_F(x) = 1$ if $\mathrm{g}(x) \le 0$. The failure probability associated with a structure is analysed as the expectation of the indication function and can be expressed as (Zio, 2013).

$$P_F = \int_F \pi_n(x)\mathrm{d}x_1, \dots, \mathrm{d}x_n = \int_F I_F(x)\pi_n(x)\mathrm{d}x_1, \dots, \mathrm{d}x_n = E_{\pi}[I_{\pi}(x)] \tag{3.6}$$

With respect to Eq. (3.6), the failure probability can be estimated using MCS as expressed in Eq. (3.7).

$$P_F \approx \hat{P}_F = \frac{1}{N}\sum_{i=1}^{N} I_F(x^i) \quad (3.7)$$

In analysing the reliability of a structure, the standard measure of the accuracy of the unbiased estimate of the probability of failure is the coefficient of variation (COV). COV is a measure of the relative variability and can be defined as the ratio of the standard deviation to the expected value of $\hat{P}_F$, (i.e. $\delta_{\hat{P}_F} = \sqrt{V[\hat{P}_F]}/E_\pi[\hat{P}_F]$) (Zuev, 2015). The smaller the COV, the more accurate the method used to compute the failure probability. Therefore, the COV for MCS can be estimated using

$$\delta_{MCS} = \sqrt{\frac{1-\hat{P}_F}{N\hat{P}_F}} \quad (3.8)$$

MCS is a very convenient method to estimate the failure probability of a structure, but the approach requires a significant sample size in order to simulate a small failure probability. In this study, MCS is used to provide the benchmark result and validate the outcome of the LS, IS and a combination of LS and IS.

3.2.2 Important Sampling (IS)

In the reliability analysis of a structural system, the estimation of a small failure probability using MCS, that is, an unacceptable performance is often challenging because of the required number of samples. Also, the computational process can be time-consuming due to the sample size. As suggested in the literature, Important Sampling, which is one of the most prevalent methods in the context of simulation can be used to assess the reliability of a structure (Schuëller et al., 2004). The underlying theory is to draw samples of the vector of random parameters from a distribution that is concentrated in the 'important region' of the random parameter, which is the failure domain (Echard et al., 2013). Based on the rules of IS and considering the weighting of the samples, IS requires the definition of a joint PDF for the new sampling. Considering that the design point x^* can be identified by FORM, therefore, an auxiliary PDF denoted as the importance density can be expressed as

$$h_x(x) = f_x(x)|_{\mu=x^*} \tag{3.9}$$

This means that the expression $h_x(x)$ is similar to the original joint PDF $f_x(x)$ if the mean values of the input variables is changed as the design point. Therefore, the failure probability can be expressed as (Der et al., 1987; Echard et al., 2013)

$$P_F = \int_{\mathbb{R}^n} I_F(x) \frac{f_n(x)}{h_n(x)} h_n(x) dx_1 \dots dx_n \tag{3.10}$$

Usually, the joint PDF is often taken in the standard space as an n-Gaussian one centred in the most probable failure point (Echard et al., 2013). Since $h(.)$ is a PDF, the integral can be interpreted as an expectation. Therefore, the integral can be estimated using

$$P_F \approx \hat{P}_F = \frac{1}{N_{IS}} \sum_{i=1}^{N_{IS}} I_F(\tilde{x}^i) \frac{f_n(\tilde{x}^i)}{h_n(\tilde{x}^i)} \tag{3.11}$$

The variance and the COV for the probability of failure can be estimated using the expression in Eq. (3.12) and Eq. (3.13).

$$\mathrm{V}[\hat{P}_F] = \frac{1}{N_{IS}} \left(\frac{1}{N_{IS}} \sum_{i=1}^{N_{IS}} \left(I_F(\tilde{x}^i) \left(\frac{f_n(\tilde{x}^i)}{h_n(\tilde{x}^i)} \right)^2 \right) - \hat{P}_F{}^2 \right) \tag{3.12}$$

$$\delta_{IS} = \frac{\sqrt{\mathrm{V}[\hat{P}_F]}}{\hat{P}_F} \tag{3.13}$$

3.2.3 Line Sampling

3.2.3.1 General Concept

LS approach was developed by Schuëller et al. (2004) to estimate the reliability of a structure with high dimension involving linear and non-linear problems. The method uses lines instead of points to probe the failure space of interest and reduces a high dimensional problem that is in standard normal space to a number of conditional one-dimensional problems (Koutsourelakis et al., 2004; Pradlwarter et al., 2007). The conditional failure probability of the structural systems is computed from the normal cumulative distribution $\Phi(.)$ (Schuëller et al., 2004). The efficiency of LS has been demonstrated in the literature (Koutsourelakis et al., 2004; Pradlwarter et al., 2007) to estimate the reliability of linear and non-linear systems associated with the random process.

For the analysis of a structure using LS, the vector $\underline{x} = x_1, x_2, \dots, x_j, \dots, x_n \in \mathbb{R}^n$ of an uncertain parameter defined in the original space can be transformed into the vector $\underline{\theta} \in \mathbb{R}^n$, where each element of the vector $\theta_j, j = 1, 2, 3, \dots, n$ is associated with the standard Gaussian distribution (Koutsourelakis et al. 2004; Schuëller et al. 2004; Zio, 2013). Therefore, the joint PDF $\theta_j, j = 1, 2, 3, \dots, n,$ of the random parameter can be expressed as shown in Eq. (3.14)

$$\varphi(\underline{\theta}) = \prod_{j=1}^{n} \phi_j(\theta_j) \tag{3.14}$$

Where $\phi_j(\theta_j) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x_j^2}{2}}, \quad j = 1, 2, 3, \dots, n$. The mapping of the initial physical vector $\underline{X} \in \mathbb{R}^n$ to the standard normal vector $\underline{\theta} \in \mathbb{R}^n$ is denoted as $S_{X\theta}(.)$ and the inverse is $S_{\theta X}(.)$. The transformations of the physical space into standard normal space is generally non-linear and can be obtained by applying Rosenblatt's or Nataf's transformations (Huang & Du, 2006; Zio & Pedroni, 2010). Using transformation, the limit state function $g_x(.)$ of the structural system define in the physical space can be transformed into $g_\theta(.)$ of the standard normal space.

3.2.3.2 Determination of the "Important Unit Vector"

The use of LS method requires the determination of an "important unit vector" $\underline{\alpha}$. In the literature, three different methods are available for the determination of the important unit vector. The methods are the design point direction, the gradient of performance function in the standard normal space and the normalised centre of mass. For more information, see (Koutsourelakis et al. 2004; Zio, 2013). Herein, the normalised centre of mass is used because it provides a good approximation of the important domain of the failure space. When using the normalised centre of mass approach, a point $\underline{\theta}^0$, which falls within the failure space F is chosen. This point can be determined using MCS approach and subsequently used as the initial point of a Markov chain since it lies entirely in the failure domain. Because of this, a Metropolis–Hastings algorithm can be employed to evaluate a sequence of N_s points $\{\underline{\theta}^u,\ u = 1, 2, 3, \dots, N_s\}$ that lie within the failure domain (Metropolis et al., 1953). The point taken from the failure domain is used as the initial point of a Markov chain and Metropolis– Hastings algorithm is employed to generate a sequence of N_s points that lied in the failure domain. The Markov chain simulation technique is used because it can accelerate the efficiency of exploring the failure region. Then, the unit vector $\underline{\theta}^{u}/\| \underline{\theta}^{u} \|, u = 1, 2, 3, \ldots, N_s$ are averaged to determine the important unit vector as $\underline{\alpha} = \frac{1}{N_s}\sum_{u=1}^{N_s} \underline{\theta}^{u}/\| \underline{\theta}^{u} \|$ as shown in Figure 3.1 (Koutsourelakis et al., 2004). This method provides a good approximation of the important unit vector by considering all the relevant samples within the failure region.

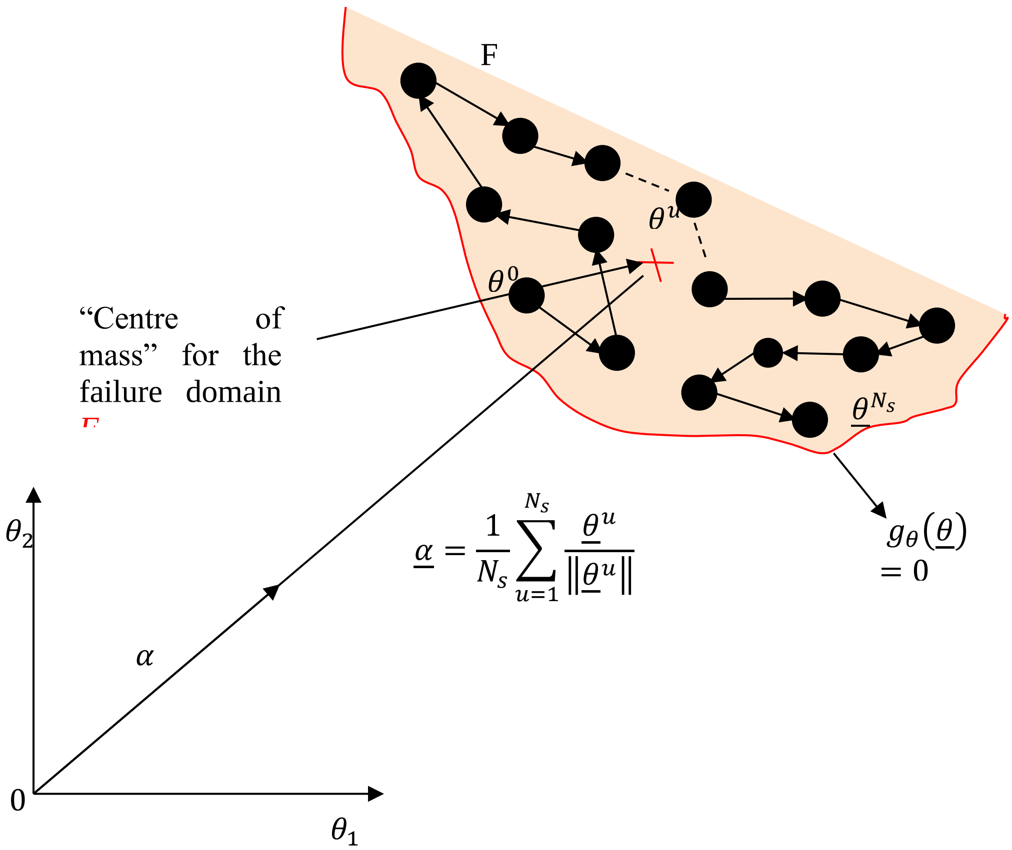


Figure 3.1: Important unit vector as the normalised "centre of mass"

3.2.3.3 Formulation of LS Method

Mathematically, the probability of the event F of a structural failure can be expressed as a multidimensional integral as shown in Eq. (3.15)

$$P_F = \mathrm{P}(\underline{\theta} \in F) = \int I_F(\theta) q_{\underline{\theta}}(\theta) d\underline{\theta} \qquad (3.15)$$

Where $\theta_j, j = 1, 2, 3, \dots, n$ denotes the vector of uncertain input variables in the standard normal space, $q_{\underline{\theta}}: \mathbb{R}^n \rightarrow [0,\ \infty)$ is the multidimensional PDF, $F \subset \mathbb{R}^n$ is the failure domain and $I_F : \mathbb{R}^n \rightarrow \{0,\ 1\}$ is the indicator function. With no loss of generality, the standard normal random variables in the direction of the important unit vector $\underline{\alpha}$ can be assured by a suitable rotation of the axes (Koutsourelakis et al., 2004). Therefore, the failure domain F can be expressed alternatively as shown in Eq. (3.16)

$$F = \{\underline{\theta} \in \mathbb{R}^n: \theta_1 \in F_1(\theta_2, \dots, \theta_n)\} \tag{3.16}$$

Where F_1 is a function define in $\mathbb{R}^{n-1}$ and which takes values on the set of all subsets of $\mathbb{R}$. Considering an example of a failure domain that corresponds to a performance function as expressed in Eq. (3.17),

$$g(\underline{\theta}) = g_1(\underline{\theta}_{-1}) - \theta_1 \leq 0 \tag{3.17}$$

Where $\underline{\theta}_{-1}$ denotes the $n-1$ dimensional vector $(\theta_2, \dots, \theta_n)$. In that case, $F_1(\theta_{-1})$ is the half open interval $[g_1(\theta_{-1}), \infty)$ (Koutsourelakis et al., 2004). Then, the function that are similar to F_1 can be defined with respect to any direction in the random parameter space and for all measurable F. Therefore, combining Eq. (3.15) and Eq. (3.16), the probability of failure can be expressed as (Koutsourelakis et al., 2004; Zio, 2013):

$$P_F = \int_n \dots \int I_F(\theta) \prod_{j=1}^{n} \emptyset_j(\theta_j) d\theta \tag{3.18}$$

$$= \int_{n-1} \dots \int (\int I_F(\theta_{-1})\, \emptyset_1(\theta_1) d\theta) \prod_{j=2}^{n} \emptyset_j(\theta_j) d\theta_{-1} \tag{3.19}$$

$$= \int_{n-1} \dots \int \Phi(F_1(\theta_{-1})) \prod_{j=2}^{n} \emptyset_j(\theta_j) d\theta_{-1} \tag{3.20}$$

$$= E_{\theta_{-1}}[\Phi(F_1(\theta_{-1}))] \tag{3.21}$$

Where $\Phi(A) = \int I_A(x)\varphi(x)dx$ is called the Gaussian measure of A. From the Eq. (3.21), an unbiased MC estimator of $P(F)$ can be computed as:

$$\hat{P}_F = \frac{1}{N_T} . \sum_{k=1}^{N_T} \Phi(F_1(\theta_{-1}^{k})) \tag{3.22}$$

Where $\theta_{-1}^{k},\ K = 1, 2, \ldots, N_T$ are independent and identically distributed samples in the standard normal space. The variance of the estimator can be determined by the variance of $\Phi(F_1(\theta_{-1}))$. It is significant to note that the variance of the estimator takes values in (0, 1) i.e. $0 \leq \Phi(F_1(\theta_{-1})) \leq 1$ and $\Phi^2(F_1(\theta_{-1})) \leq \Phi(F_1(\theta_{-1})), \forall\theta_{-1} \in \mathbb{R}^{n-1}$ (Koutsourelakis et al. 2004; Zio, 2013). This means:

$$Var[\Phi(F_1(\theta_{-1}))] = E_{\theta_{-1}}[\Phi^2(F_1(\theta_{-1}))] - E_{\theta_{-1}}^2[\Phi(F_1(\theta_{-1}))] \tag{3.23}$$

$$\leq E_{\theta_{-1}}[\Phi(F_1(\theta_{-1}))] - E_{\theta_{-1}}^2[\Phi(F_1(\theta_{-1}))] \tag{3.24}$$

$$= P_F(1 - P_F) = Var[I_F(\theta)] \tag{3.25}$$

From the derivation, the COV $\delta_{LS} = \sqrt{(Var[\hat{P}_F]\,)}/P_F$ of the estimator in equation (3.22) will be smaller when compare to standard MC (Δ_{MC}) approach (Koutsourelakis et al. 2004; Zio, 2013). This means that the convergence rate that will be achieved using the LS method will always be smaller than the MC method. The variance of the estimator $\hat{P}_F$ in LS will always depend on the variability of the random variables $\Phi(F_1(\theta_{-1}))$ instead of the probability content (Zio, 2013).

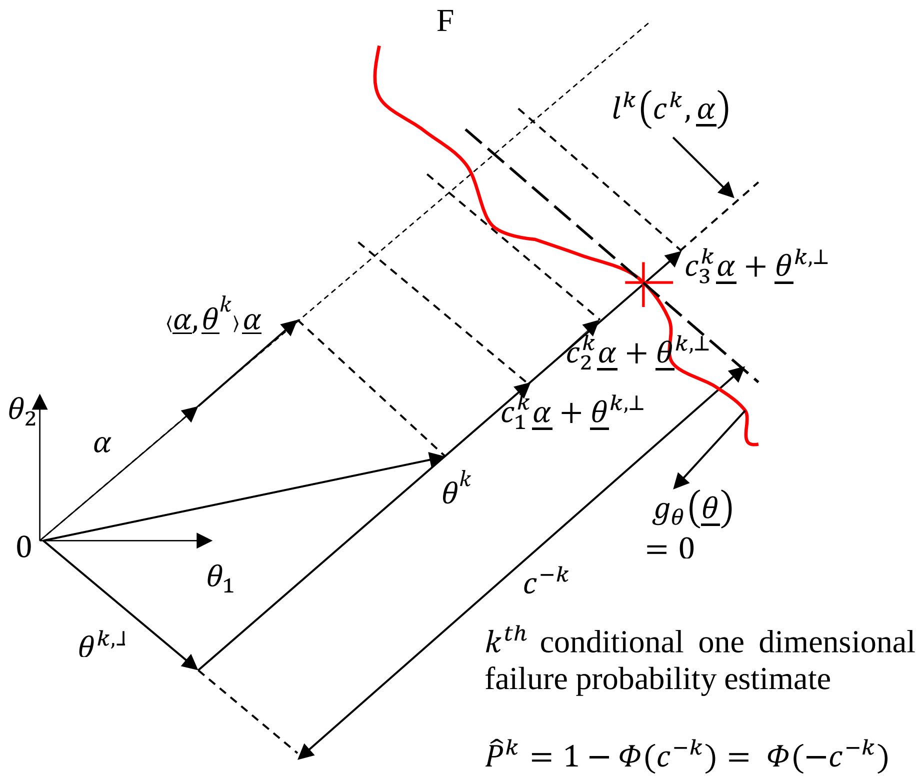


Figure 3.2: LS procedure

3.2.4 Methodology

The concept of LS, IS, MCS and a combination of LS and IS have been adapted in this Chapter to estimate the time-dependent reliability of buried pipe and considering the failure modes explained in Section 3.3 and 3.4. Figure 3.3 shows the flowchart of the adapted LS method used in the analysis. However, the rationale for combining the LS and IS techniques is to improve the efficiency of the approach for estimating the reliability of a structure while considering the randomness associated with the structural parameters. The computational procedure can be summarised as a two-stage process. The first stage deals with the determination of the "important unit vector $\underline{\alpha}$" and the second stage evaluates the probability of failure using the adapted method. The efficiency of the method will depend on the determination of the important unit vector. Therefore, the primary step is the searching of the optimal important unit vector and the drawing of the samples to estimate failure probability. The computational steps for the combined methods are summarised briefly below.

1. Generate samples from the PDFs of the input parameters.
2. Using a standard MCS, sample N_T vectors $\{x^k: K = 1,2,3, \dots, N_T\}$ with $x^k = \{x_1^k, x_2^k, x_3^k, \dots, x_j^k, \dots, x_n^k\}$ from the multidimensional joint PDF $q(.): \mathbb{R}^n \to [0, 1)$ of the input parameters.
3. The transformation of the input vectors. Transform the N_T sample vectors $\{x^k: K = 1,2,3, \dots, N_T\}$ defined in the physical space into N_T samples $\{\theta^k: K = 1,2,3, \dots, N_T\}$ defined in the standard normal space where each component of the random variables is associated with an independent central unit Gaussian standard distribution.
4. In the standard normal space, evaluate the "important unit vector" $\underline{\alpha} = (\alpha_1, \alpha_2, \dots, \alpha_j, \dots \alpha_n)$ that points towards the failure domain of interest, (see Section 3.2.3.2 and Figure 3.1).
5. Once the "important unit vector" has been determined, then estimate a conditional one-dimensional failure probabilities $\{\hat{P}_F^k: K = 1,2,3, \dots, N_T\}$ associated with N_T vectors corresponding to each one of the standard normal samples $\{\theta^k: K = 1,2,3, \dots, N_T\}$. For each samples, $\{\theta^k: K = 1,2,3, \dots, N_T\}$ that falls within the failure domain, the following steps can be performed, see Figure 3.2.
   a. For each sample vectors $\{\underline{\theta}^k: K = 1,2,3, \dots, N_T\}$, determine a vector $\{\underline{\tilde{\theta}}^k, K = 1,2,3, \dots, N_T\}$ as the sum of a deterministic multiple of the important unit vector $\underline{\alpha}$ and a vector $\underline{\theta}^{k,\perp}, K = 1,2,3, \dots, N_T$ that is perpendicular to the direction of the important unit vector $\underline{\alpha}$. This can be expressed as:

$$\underline{\tilde{\theta}}^k = c^k \underline{\alpha} + \underline{\theta}^{k,\perp} \tag{3.26}$$

   Where c^k is a real number with values between $-\infty \ and + \infty$.

   The relationship for the perpendicular direction is given as:

$$\underline{\theta}^{k,\perp} = \underline{\theta}^k - \langle \underline{\alpha}, \underline{\theta}^k \rangle \underline{\alpha} \tag{3.27}$$

   Where $\underline{\theta}^k: K = 1,2,3, \dots, N_T$ represents a random realisation of the input variables and $\langle \underline{\alpha}, \underline{\theta}^k \rangle$ represents the scaler product between the unit vector $\underline{\alpha}$ and the random variables $\underline{\theta}^k, K = 1,2,3, \dots, N_T$.

b. Calculate the value of c^{-k} as the intersection between the limit state function LSF $g_\theta(\underline{\tilde{\theta}}^k) = g_\theta(c^k\underline{\alpha} + \underline{\theta}^{k,\perp}) = 0$ and the line $l^k(c^k, \underline{\alpha})$ passing through $\underline{\theta}^k$ and parallel to the important unit vector $\underline{\alpha}$. The value of c^{-k} is determined by fitting a first or second order polynomial and find its root. For each standard normal random samples, two or three system performance evaluation is required.

c. Estimate the conditional one-dimensional probability associated with each random sample $\underline{\theta}^k, K = 1,2,3, \dots, N_T$. The associated conditional failure probability $\hat{P}_F^k, K = 1,2,3, \dots, N_T$ is given as:

$$\hat{P}_F^k = P[N(0,1) > c^{-k}] = 1 - P[N(0,1) > c^{-k}] \tag{3.28}$$

$$= 1 - \Phi(c^{-k}) = \Phi(-c^{-k}) \tag{3.29}$$

Where $\Phi(.)$ designates the standard normal cumulative density function.

d. Becuase the values of the variables c^{-k} follows a standard normal distribution, the sampling can be carry out in the important domain, rather than on the origin of the standard space. Therefore, the unbiased estimator of the failure probability from the important domain $\hat{P}_F^k, K = 1,2,3, \dots, N_T$ can be estimated using Eq. (3.30).

$$\hat{P}_f^k = (1 - \Phi(c^{-k}))\frac{\sum_{j=1}^{N_T} \hat{P}^j(c^k\alpha + \theta^{k,\perp})e^{-(c^k)^2/2}}{\sum_{j=1}^{N_T} e^{-(c^k)^2/2}} \tag{3.30}$$

6. From the result of the conditional one-dimensional failure probability $\hat{P}_F^k, K = 1,2,3, \dots, N_T$, calculate the failure probability and reliability of the structure using Eq. (3.31) and Eq. (3.32).

$$P_F \approx \hat{P}_F = \frac{1}{N_T}\sum_{k=1}^{N_T} \hat{P}^k(F) \tag{3.31}$$

$$P_R = 1 - P_F \tag{3.32}$$

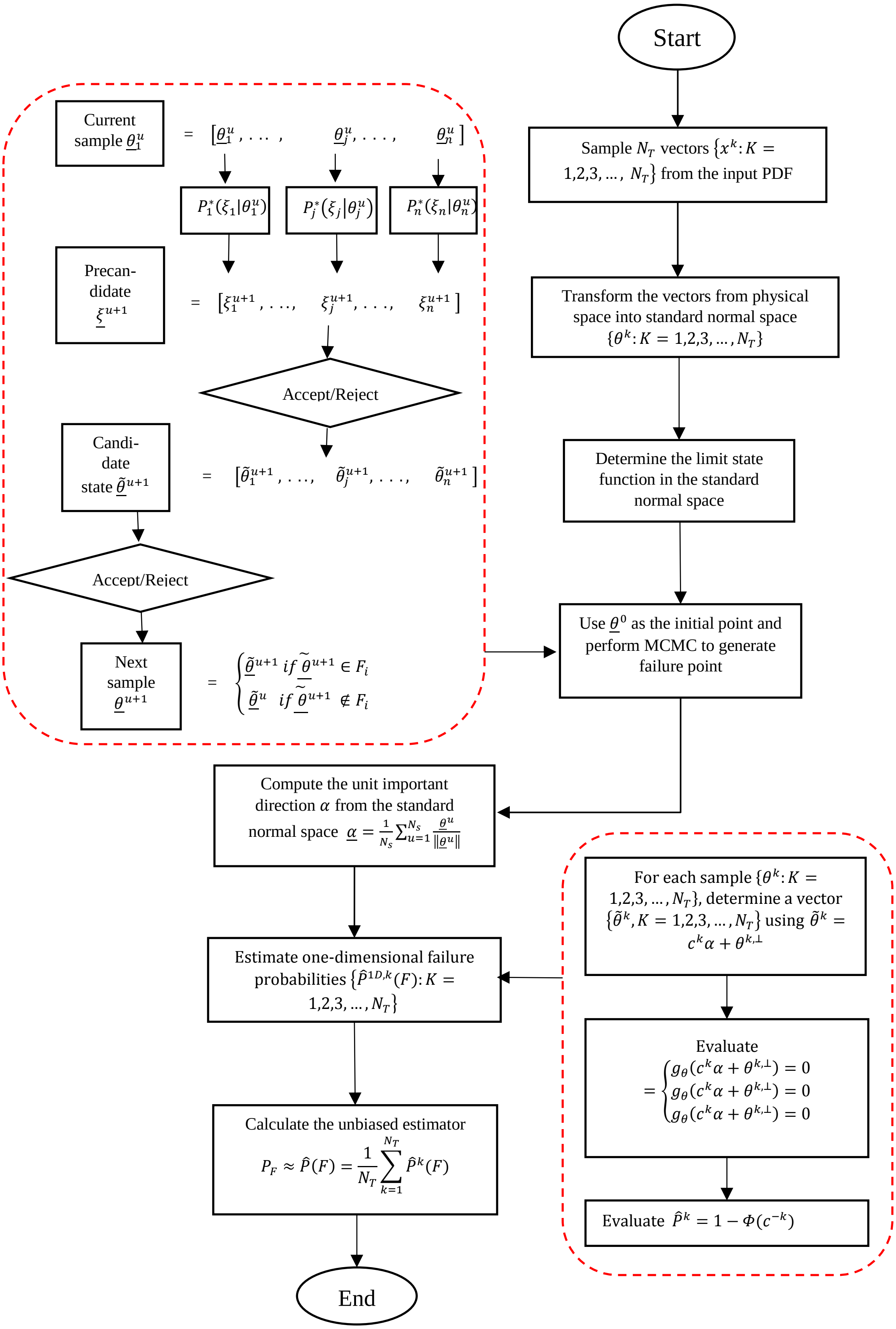


Figure 3.3: Flow diagram of the adapted LS method

3.3 Application to Buried Pipe

The design of buried metal pipe can be a fairly complicated process due to the loading conditions and the geo-environmental effects (Whidden, 2009). Stresses and strains can develop as a result of the impact of load and will affect the performance of pipe over time. For underground pipes under pressure, the impact of the load is usually classified into two broad categories: internal pressure and external loads (Moser & Folkman, 2001). The internal pressure is made up of the hydrostatic pressure and the surge pressure while the external loads are those caused by external soil pressure or live loads (Moser & Folkman, 2001). The loads due to differential settlement, longitudinal bending, and shear loadings are also considered to be external loads. Buried pipes are designed to sustain various loads that are expected to affect the performance during the intended life.

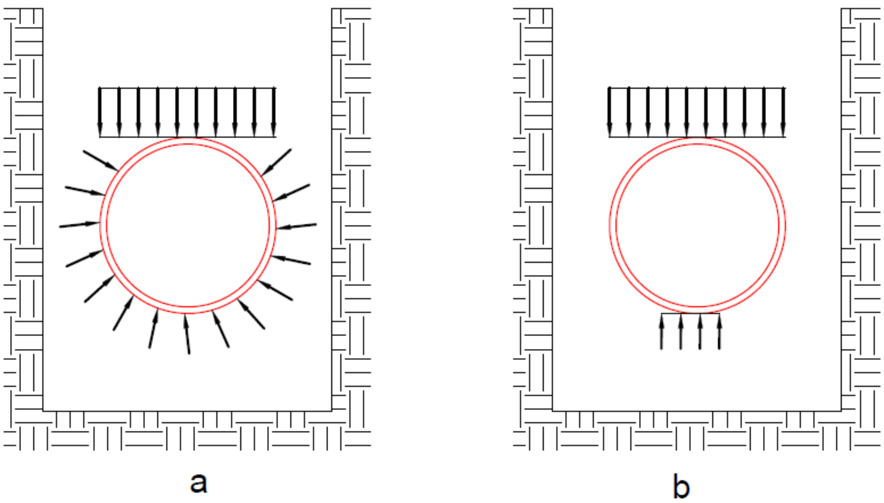


Figure 3.4: (a) Flexible pipe and (b) Rigid pipe

The classification of the buried pipe is based on their behaviour during installation and operation. Broadly, the buried pipe is classified as rigid or flexible pipe as shown in Figure 3.4 (Gabriel, 2011). The response of a rigid or flexible pipe to the external loads are different. Therefore, the failure modes will be different as well. In this study, a buried flexible metal pipe is considered. Cameron (2005) suggested that the amount of load a pipe can sustain will depend on the relative height of cover, nature of the backfill material, geometry of the trench and the relative stiffness of the pipe to the backfill. Similarly, Marston load theory, as cited by Moser & Folkman (2001), shows that the amount of load taken by a pipe will be affected by settlement or the relative movement of the backfill soil and the nature of the pipe material.

As a result of the impact of the internal and external loads, failure of buried pipe will occur when the applied stress (internal or external) exceeds the ultimate strength of the pipe material. In this case, the applied stress represents the response of the input variables y and the ultimate strength of the pipe material represents the critical value or threshold y^*. In the literature such as Alliance (2001) and BS EN 1295:1 (1997) different failure modes has been suggested for the design and assessment of buried pipeline. However, it is vital to have an approach that will be used to identify the most critical failure mode in order to avoid accidental economic loss and environmental pollution. The most critical failure mode will have a more significant contribution to the failure of the buried pipe structure. This study is concerned about a flexible buried pipe and the associated dominating failure modes as defined in the literature (Alliance, 2001; Babu & Srivastava, 2010; Sadiq et al., 2004). The failure modes include pipe ovality, through-wall bending stress, buckling pressure, wall thrust, and total circumferential and axial stress. These are succinctly explained in the following subsections.

3.3.1 Pipe Ovality

A buried pipe tends to resist the impact of live and earth load imposed on them, thereby causing the pipe to ovalise due to the resulting stress from the external pressures as shown in Figure 3.5. To analyse this effect, the Iowa deflection formula as defined in BS EN 1295:1 (1997) and BS 9295 (2010) can be modified to estimate the pipe ovality under the influence of earth and live loads. The modified Iowa deflection formula is expressed in Eq. 3.33. As stated in Gabriel (2011), the critical deflection for a flexible buried pipe can be estimated using 5% - 7% of the inside diameter.

$$\frac{\Delta y}{D} = \frac{D_1 K P}{\left(\frac{EI}{R^3} + 0.061E'\right)} \tag{3.33}$$

Where Δy = deflection of pipe in millimetre, K = bedding constant, P = the pressure on pipe due to soil load plus live load i.e. $(P_v + P_p)$, P_p = pressure transmitted to the pipe as a result of the concentrated load, P_v= pressure on pipe due to soil load, D_1 = deflection lag factor, R = the radius of pipe, E = the elastic modulus of pipe, I = the moment of inertia ($t^3/12$) and E' = the modulus of soil reaction and can be expressed as shown in Eq. (3.34). The modulus of soil reaction E' is a measure of the stiffness of the embedment material surrounding the pipe.

$$E' = \frac{K' E_S(1-V_S)}{(1+V_S)(1-2V_S)} \tag{3.34}$$

Where v_s is the poison ratio of the soil, K' is the numerical value which depends on poison ratio and E_s is the modulus of soil.

Buried pipes are also, predisposed to the action of concentrated or distributed live loads. The effect of concentrated live load on the buried pipe can be enormous, for example, locomotive loads, railway car, and truck wheel loads. In this situation, Alliance (2001) stated that Boussinesq's equation as expressed in Eq. (3.35), can be used to estimate the pressure of the concentrated surface load exerted on the buried pipe.

$$P_p = \frac{3P_S}{2\pi C^2\left[1+\left(\frac{d}{C}\right)^2\right]^{2.5}} \tag{3.35}$$

Where P_p = pressure transmitted to the pipe, P_s = concentrated load at the surface, above pipe, C = the depth of soil cover above the buried pipe, d = distance from the pipe to the point of application of surface load.

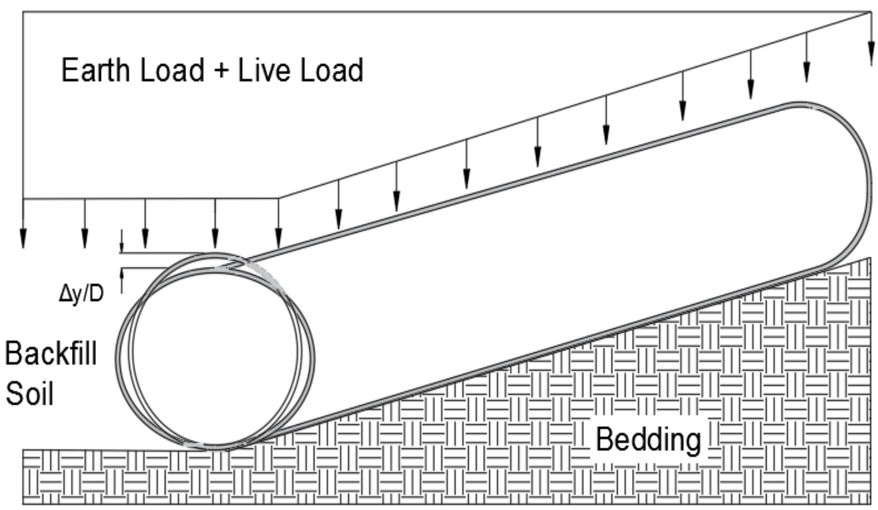


Figure 3.5: Ovality of buried pipe

3.3.2 Through-wall Bending Stress

A buried pipe subjected to live and earth load and a continuous increase in bending will fail due to increased ovalisation of the pipe cross-section and reduced slope in the stress-strain curve (Tee & Khan 2014). The bending stress of a buried pipeline depends on the dead and live loads acting on the pipe wall. For the safe performance of the buried pipe throughout the design life, the induced through-wall bending stress should not go beyond the tensile strength of the pipe material. Similarly, the induced longitudinal bending strain should not exceed the allowable bending strain. For most buried metal pipe, the allowable bending strain is between 0.15% - 2% and the allowable bending stress is the long-term tensile strength of the pipe material (Alliance, 2001; Mohr, 2003)

Considering the impact of surface and earth loads, the through-wall bending stress induced in the buried pipe, distributed as illustrated in Figure 3.6 can be calculated using the relationship in Eq. (3.36) (Alliance, 2001; BS EN 1295-1:1997).

$$\sigma_b = 4E\left(\frac{\Delta y}{D}\right)\left(\frac{t}{D}\right) \tag{3.36}$$

Where σ_b = through-wall bending stress, $\Delta y/D$ = pipe ovality.

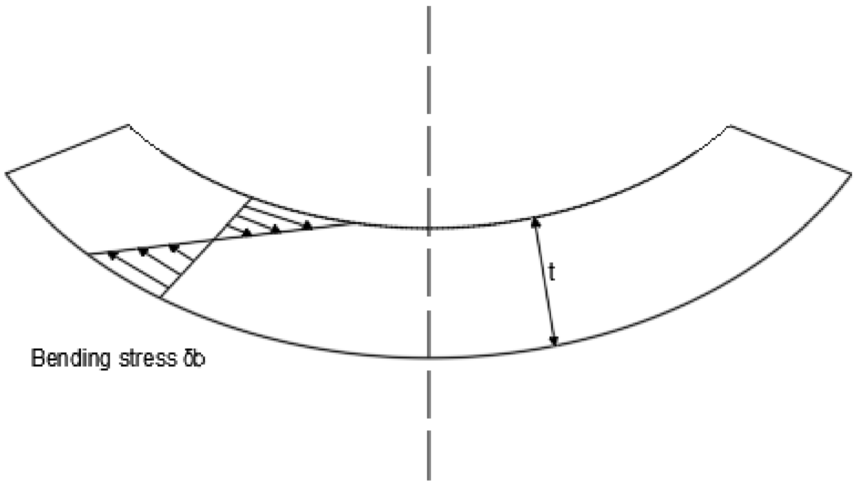


Figure 3.6: Through-wall bending stress

3.3.3 Ring Buckling

Ring buckling or buckling pressure of the buried pipe depends on the total vertical pressure (soil and surface load) that act on the pipe as illustrated in Figure 3.7 (Alliance, 2001). If the total vertical force is excessive, then the pipe can buckle in response to the applied load. However, with the increase in the vertical pressure, there will be a corresponding increase in the tangential compressive stress, and this will get to a state where the pipe will not be able to keep its initial circular shape and buckle as a result. Ring buckling of buried pipe can occur due to the insufficient stiffness of the pipe (AWWA, 1999). For the safe performance of buried pipe, the actual buckling pressure must be less than the critical buckling pressure. Based on the impact of the live and earth load, the actual and critical buckling pressure can be estimated using Eq. (3.37) and Eq. (3.38) (AWWA, 1999).

$$P_a = R_w \gamma_s + \gamma_w H_w + P_s \qquad (3.37)$$

$$P_{cr} = \sqrt{\left(32 R_w B' E_s \frac{EI}{D^3}\right)} \qquad (3.38)$$

Where R_w is the water buoyancy factor which can be expressed as $R_w = 1 - 0.33(H_w/H)$, E_s is the modulus of soil, H_w is the height of ground water above the pipe and B' is the empirical coefficient of elastic support which can be expressed as $B' = 1/(1 + 4\mathrm{e}^{-0.213H})$.

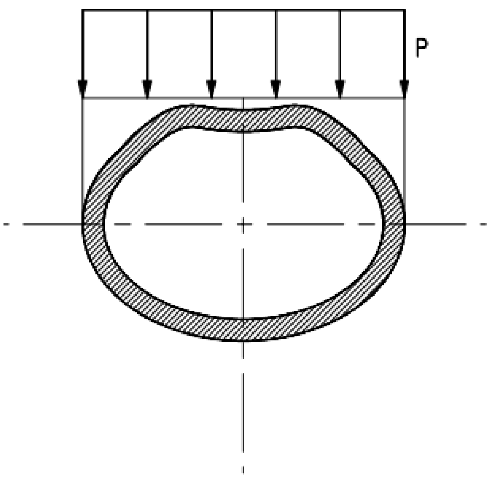


Figure 3.7: Ring buckling

3.3.4 Wall Thrust

Wall thrust or crushing of pipe wall is characterised with localised yielding and occurs when the induced wall stress reaches the yield stress of the pipe material. A buried pipeline can crush due to earth and surface loading acting on the pipe if burial depth is not enough (Gabriel 2011). Considering the effect of dead and live load, Gabriel (2011) suggested two conditions for analysing the wall thrust and they are as follows:

- Use short-term material properties if both dead and live loads need to be accounted for;
- Use long-term material properties if only dead load needs to be accounted for.

Based on the two conditions, the more conservative limit state function value would be considered for wall thrust analysis. Note that some flexible pipes have both short-term and long-term material properties (elasticity of modulus), where the short-term value is higher than long-term value, e.g., polyethylene pipe (Gabriel, 2011). In this case, the two conditions will be required to analyse the performance of the pipe based wall thrust. However, for metal pipes, e.g., ductile iron or steel pipe, only the first condition is considered for the assessment because the short-term and long-term properties of the pipe material are the same (Gabriel, 2011). The critical and the actual wall thrust can be evaluated using Eq. (3.39) and Eq. (3.40) respectively (Gabriel, 2011).

$$T_{cr} = F_y A_s \varphi_p \tag{3.39}$$

$$T_a = 1.3(1.5W_A + 1.67P_s C_L + P_W)(D_o/2) \tag{3.40}$$

Where F_y denotes the minimum tensile strength of pipe, A_s = the cross- sectional area of pipe wall per unit length and φ_p = the capacity modification factor for pipe. D_o = the pipe outside diameter, C_L = live load distribution coefficient (the lesser of L_W/D_o or 1.0), L_W = 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 using Eq. (3.41) and Eq. (3.42).

$$W_A = P_{sp} V_{AF} \tag{3.41}$$

$$P_W = \gamma_s H_w \tag{3.42}$$

Where P_{sp} = geostatic load ($P_{sp} = \gamma_s\big(H + 0.11x10^{-7}(D_o)\big)$, V_{AF} = vertical arching factor $V_{AF} = 0.76 - 0.71(\frac{S_h - 1.17}{S_h + 2.92})$, S_h = the hoop stiffness factor ($S_h = \varphi_s M_s\, R/EA_s$), φ_s = soil capacity modification factor, M_s = secant constrained soil modulus, R = the effective radius of pipe.

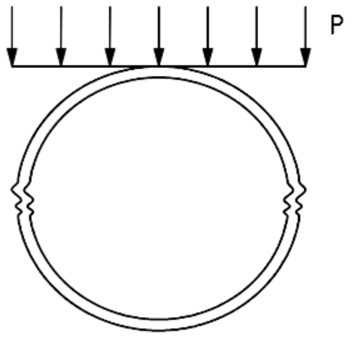


Figure 3.8: Wall thrust

3.4 Total Circumferential/Axial Stress

The pressurised underground pipeline can continuously be exposed to the action of both external and internal forces. The forces includes soil/earth load, traffic/vehicular load (such loads may be from the roadway or railway), the load due to frost action, internal fluid pressure, and stress due to thermal effect (Sadiq et al., 2004). The adverse impact of these forces needs consideration at the design stage. The stress produced by the internal pressure is considered due to uniform circumferential tension generated across the inner wall of the pipe. For pressurised buried pipelines, the primary stress is produced by internal pressure (Amirat et al., 2006). Also, the influence of other different forces as explained in Section 3.3.1 to 3.3.4 can be considered in the analysis of buried pipeline. Amirat et al. (2006) suggested that internal pressure of a buried pipe produces a uniform circumferential tension across the pipe wall, while external loads may produce bending stress in longitudinal and circumferential directions.

The external forces acting on a pressurised pipe can produce stresses in both circumferential and axial direction (Sadiq et al., 2004). However, Ahammed & Melchers (1994) suggested that if a pipe is loaded uniformly and supported along its length, then circumferential stresses could be more important than axial stresses. Internal fluid pressure produces the circumferential bending stresses in a pipe wall (due to external loads) in addition to the tensile hoop stress. Rajani et al. (2000) suggested a method for estimating the total external stresses including all circumferential and axial stresses acting on a buried pipeline. These stresses are shown in Table 3.1. As defined in Rajani et al. (2000), the circumferential stress σ_θ acting on the buried pipe can be expressed as shown in Eq. (3.43).

$$\sigma_\theta = \sigma_F + \sigma_S + \sigma_L + \sigma_V \tag{3.43}$$

Where σ_F = stress due to internal fluid pressure; σ_S = stress due to external soil loading; σ_L = stress due to frost pressure and σ_V = stress due to traffic/vehicular load.

Similarly, the axial stress σ_X acting on the pipe can be expressed as shown in Eq. (3.44).

$$\sigma_X = \sigma_T + \left(\sigma_F^{/} + \sigma_S + \sigma_L + \sigma_V\right)v_p \tag{3.44}$$

Where σ_T = stress as a result of a temperature difference; $\sigma_F^{/}$ = axial stress due to internal fluid pressure and v_p = Poisson's ratio of the pipe material.

Table 3.1: Summary of stresses/pressures acting on the buried pipe

Stresses acting on Buried Pipe	Model	Parameters description
Circumferential stress due to internal fluid pressure $\boldsymbol{\sigma_F}$	$\sigma_F = \rho D/2t$ Rajani et al. (2000)	ρ = internal fluid pressure (MPa); D = pipe diameter; t = pipe thickness
Stress due to external soil loading $\boldsymbol{\sigma_S}$	$\sigma_S = \dfrac{3K_m \gamma B_d^2 C_d E_p t D}{E_p t^3 + 3K_d \rho D^3}$ Ahammed and Melchers (1994)	K_m = bending moment coefficient; γ = unit weight of the backfill soil; B_d = width of ditch; C_d= calculation coefficient for earth load; E_p= modulus of elasticity of pipe material (MPa); K_d = deflection coefficient
Stress due to frost action $\boldsymbol{\sigma_L}$	$\sigma_L = f_{frost}\sigma_s$ Rajani et al. (2000)	f_{frost} = frost load multiple; σ_S = stress due to external soil loading
Stress due to traffic load $\boldsymbol{\sigma_V}$	$\sigma_V = \dfrac{3K_m I_c C_t F E_p t D}{A\left(E_p t^3 + 3K_d \rho D^3\right)}$ Ahammed and Melchers (1994)	I_c= impact factor; C_t = surface load coefficient; F = wheel load on surface (N); A = effective length of pipe which the load is computed;
Stress due to temperature difference $\boldsymbol{\sigma_T}$	$\sigma_T = -E_p \alpha_p \Delta T - v\sigma_h$ Rajani et al. (2000)	α_p = expansion coefficient of pipe; ΔT = temperature difference between the fluid and the surrounding group; v = poison ratio;
Axial stress due to internal fluid pressure $\boldsymbol{\sigma_F^{/}}$	$\sigma_F^{/} = \dfrac{v_p}{2}\rho\left(\dfrac{D}{t} - 1\right)$ Rajani et al. (2000)	v_p = poison ratio of the pipe material

3.5 Pipe Corrosion

The gradual loss of pipe thickness as a result of corrosion can be relatively uniform or localised (Ahammed & Melchers, 1997; Sadiq et al., 2004). The rate of corrosion in uncoated CI pipes is generally high in early age (Sadiq et al., 2004). The corrosion of underground pipe is a time-variant process, which depends on external factors such as geo-environmental conditions and internal factors such as chemical composition of the transported fluid and could be influenced by temperature and flow rate (Mahmoodian & Li, 2017; Ossai et al., 2015). In the literature, the power law formula as expressed in Eq. (3.45), can be used for representing both localised and general (uniform) corrosion (Sadiq et al., 2004).

$$C_T = kT^n \tag{3.45}$$

Where k and n are empirical constants ($n \leq 1$); and T represents the time of exposure.

The rate of corrosion can be calculated from Eq. (3.45) by differentiating with respect to time. In the literature, the rate of corrosion using Eq. (3.45) has been found to be relatively high at the beginning of the damage process and attenuates gradually as the service age increases (Engelhardt & Macdonald, 2004; Wang et al., 2015). As a result, Engelhardt & Macdonald (2004) suggested a corrosion rate model as shown in Eq. (3.46)

$$\frac{d(C_T)}{dt} = V_0 \left(1 + \frac{T}{T_0}\right)^{n-1} \tag{3.46}$$

Where V_0 denotes the initial corrosion rate, and T_0 represents constant which has the effect on the time interval for reaching a stable corrosion rate.

The rate of corrosion as expressed in Eq. (3.46) considers the early stages of corrosion, and when the metal is exposed to a relatively high concentration of corrosive species (Wang et al., 2015). However, it requires the determination of the initial corrosion rate. The depth and location of a possible indicator of corrosion can be measured and obtained through the use of magnetic flux leakage (MFL) or ultrasonic tools (UTs). Wang et al. (2015) suggested that because of the cost associated with the direct inspection, which is typically scheduled at different times, it is highly impractical to apply the technology to obtain the initial corrosion rate. Rajani et al. (2000) proposed a two-phase model expressed in Eq. (3.47).

$$C_T = aT + b(1 - e^{-cT}) \tag{3.47}$$

Where a is the final pitting rate constant (typical value; 0.009 mm/yr); b represents the pitting depth scaling constant (typical value; 6.27 mm); c is corrosion rate inhibition factor (typical value; 0.14 yr^{-1}) and T is the time.

The effect of corrosion reduces pipe thickness over time. Therefore, pipe thickness expressed in all the considered failure modes are replaced with a residual pipe thickness. The residual pipe thickness is the original pipe thickness minus the corrosion model. In this study, the effect of corrosion is assumed to be uniform over the pipe surface area. Corrosion of buried pipeline is one of the most critical factors that contribute to the failure of buried steel pipe. It can occur both internal and external. External corrosion occurs at the outer surface of the pipe, and it is the most common form of deterioration of the buried pipeline. The level of the impact of external corrosion on buried pipeline depends on the surrounding environmental condition and the material properties of the pipe. Internal corrosion occurs inside the pipe. However, the effect is minimal when compared to the external corrosion. Figure 3.9 shows an example of internal and external corrosion data for a buried iron pipe as defined in (Marshall, 2001). Based on Figure 3.9, it can be deduced that external corrosion is higher than internal corrosion and in both, the rate of corrosion is high at the early stage.

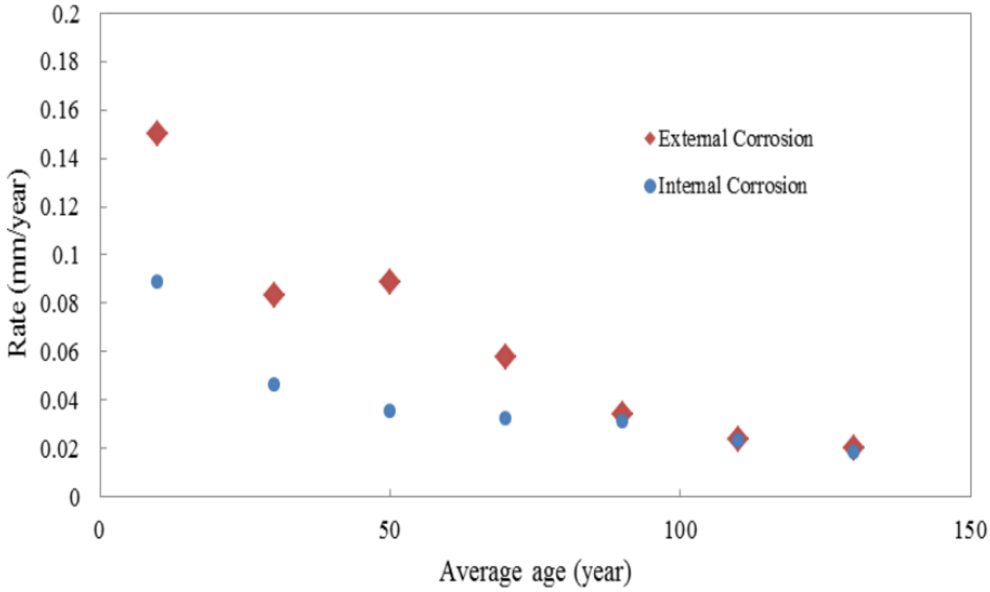


Figure 3.9: Internal and external corrosion rate for iron pipe

Table 3.2: Limit state functions for the failure modes

Failure mode	Limit state
Pipe ovality	$G_{Pipe\ ovality} = 6\% - \frac{\Delta y}{D}$
Through-wall bending stress	$G_{Bending\ stress} = \sigma_y - \sigma_b$
Ring buckling	$G_{Ring\ buckling} = P_{cr} - P_a$
Wall thrust	$G_{Wall\ thrust} = T_{cr} - T_a$
Total circumferential stress	$G_{Total\ circumferential\ stress} = \sigma_y - \sigma_\theta$
Total axial stress	$G_{Total\ axial\ stress} = \sigma_y - \sigma_X$

3.6 Limit State Function

The reliability analysis of an engineering structure requires the limit state function to evaluate the performance of the structure. In this study, the method of reliability analysis is applied to a buried pipeline made of steel and considered to be buried under a roadway. The maximum applied load during the lifetime of the buried pipe is considered to be the traffic wheel load. However, the effect of the cyclic loading is not considered. The reliability analysis is carried out through the study of the failure modes as explained in Section 3.3 and Section 3.4. In all cases, the limit state function that corresponds to the safety of the pipe structure as defined in the literature is shown in Table 3.2. As reported in Table 3.2, the limit state function for a particular failure mode can be expressed as shown in Eq. (3.48). If the outcome of the limit state is positive, that is ($R > S(x)$), then it signifies a safe state and if it is negative, then it indicates a failure state ($R < S(x)$) and the limit state is denoted as $g(x) = 0$.

$$g(x) = R - S(x) \tag{3.48}$$

Where R represents the strength or resistance; $S(x)$ is the load term defined in terms of random variables.

From the limit state function, one can evaluate the failure probability of an engineering structure by running some random samples to generate different pipeline realisations. Then, use a Monte Carlo (MC) technique to estimate the probability of failure. However, the use of the MC approach requires a large number of samples, especially when there is a need to determine a small failure probability. In order to reduce the computational effort, advanced MCS are often used.

3.7 Numerical Example

In this example, a pressurised and underground steel pipe is examined and is considered to be located under a roadway where the groundwater table can rise above or stay below the buried pipe. The buried pipe is considered to be exposed to corrosion and stresses from live and earth loads. The pipeline had a diameter of 1.21 m and the pipe wall thickness of 21.0 mm and considered to be under a heavy traffic condition with a wheel load of 80 kPa. The remaining numerical values of pipe and soil properties used in the analyses are listed in Table 3.3 and Table 3.4. The values of the parameters are based on industry standard and have been acquired from the literature such as Ahammed and Melchers (1994, 1997); Sadiq et al. (2004); and Tee et al. (2014). This example is to illustrate the confidence level in the analysis of buried pipeline under the influence of internal and external stresses and to demonstrate the efficiency of the combined approach.

Table 3.3: Statistical properties of the input parameters

Material properties	Mean	Standard deviation
Elastic modulus of pipe $\boldsymbol{E_p}$	213.74x10^6 kPa (normal)	2.1374x10^6 kPa
Backfill soil modulus $\boldsymbol{E_s}$	10^{3}kPa (normal)	50 kPa
Unit weight of soil $\boldsymbol{\gamma_s}$	18.0kN/m^3 (normal)	0.45 kN/m^3
Wheel load (live load) $\boldsymbol{P_s}$	150 kN (normal)	15 kN
Thickness of pipe *t*	0.021 m (normal)	0.00021
Height of backfill *H*	3.75 m (normal)	0.00375
Internal diameter	0.64 m (normal)	0.01143
Bending moment coefficient $\boldsymbol{K_m}$	0.235 (lognormal)	0.05
Deflection coefficient $\boldsymbol{K_b}$	0.108 (lognormal)	0.0216
Calculation coefficient $\boldsymbol{C_d}$	1.32 (lognormal)	0.20
Surface load coefficient $\boldsymbol{C_t}$	0.12 (lognormal)	0.024
Width of ditch $\boldsymbol{B_d}$	0.5 m (normal)	114.3 m
Pipe effective length $\boldsymbol{A}$	6.1 m (normal)	0.2 m
Concentrated live load	80 kPa (normal)	2.4 kPa
Internal pressure $\boldsymbol{\rho}$	0.45 MPa (normal)	0.12
Multiplying constant $\boldsymbol{k}$	2.0 (normal)	0.1
Exponential constant $\boldsymbol{n}$	0.3 (normal)	0.015

In this study, the relationship expressed in Eq. (3.45) is used to model corrosion. Based on this, the wall thickness *t* which is a variable in the equations for modelling various pipe failure modes is replaced with residual wall thickness. This means as the time of exposure increases, and in consideration of corrosion effect, the thickness of the pipe wall decreases and the reliability of the buried pipe also decreases. The corrosion effect is assumed to be uniform over the entire surface area of the pipe and that the pipe is thinwalled and circular. The bending moment coefficient K_m and deflection coefficient K_b depends on the distribution of the applied stress across the top of the pipe and the distribution of the generated reaction across the bottom of the pipe (Ahammed & Melchers, 1997). The deflection coefficient K_b accounts for the bedding support which varies with the bedding angle.

Table 3.4: Material properties of the input parameters

Material properties	Value	Min	Max
Temperature differential	-	-10.0 (uniform)	0
Frost load multiplier $\boldsymbol{f_{frost}}$	-	0 (uniform)	1
Thermal coefficient of pipe	11 x 10^{-6}	-	-
Height of water above buried pipe	1.0 m	-	-
Unit weight of water $\boldsymbol{\gamma_w}$	9.81 kN/m^3	-	-
Yield strength $\boldsymbol{\sigma_y}$	475 MPa	-	-
Buoyancy factor $\boldsymbol{R_w}$	1.0	-	-
Trench width $\boldsymbol{B_d}$	2.0 m	-	-
Shape factor $\boldsymbol{D_f}$	4.0	-	-
Deflection lag factor $\boldsymbol{D_L}$	1.0	-	-
Capacity modification factor for soil $\boldsymbol{\varphi_s}$	0.9	-	-
Capacity modification factor for pipe $\boldsymbol{\varphi_p}$	1.0	-	-
Live load distribution coefficient $\boldsymbol{C_L}$	1.0	-	-
Poison ratio $\boldsymbol{v_s}$	0.3	-	-
$\boldsymbol{k'}$ value	1.5	-	-
Allowable strain $\boldsymbol{\varepsilon_{cr}}$	0.2 %	-	-

3.8 Results and Discussion

The failure probability of buried pipe is determined based on the total axial stress and the through-wall bending stress due to pipe ovality. The power law formula as expressed in Eq. (3.45) is used in the computation to account for the corrosion effect, which denotes both localised and general (uniform) corrosion. The outcome of the MCS method is referred to as the benchmark and is used to validate the accuracy of the other methods such as LS, IS and a combination of LS and IS. The methods were used to evaluate the reliability of buried pipe by considering the adverse effect of corrosion and the uncertainties that exist with the pipe and soil parameters. For the through-wall bending stress, the concentrated live load effect is obtained using Boussinesq's equation to estimate the pressure of the load on the buried pipe. The failure criterion utilised in this study is based on the yield stress of the steel pipe, and the impact of the seasonal change in the groundwater table is considered in the analysis.

The outcome based on the various methods have been compared with the combined approach, and Table 3.5 shows the result. From the study, the combined method uses a total of $N_T = 500$ samples, while LS uses a total of $N_T = 600$ samples, IS uses a total of $N_T = 10000$ samples and MCS uses a total of $N_T = 100{,}000$ samples, to achieve a small failure probability that is close to 10^{-3}. The number of samples are considered for the purpose of evaluating and validating the failure probability of buried pipeline. Also, the various methods have been compared using a numerical index, which is called the "unitary coefficient of variation δ_u" as defined in Zio (2013). The δ_u can be expressed as $\delta_u = \delta.\sqrt{N_T} = \frac{\sigma}{\hat{P}(F)}.\sqrt{N_T}$, where σ is the standard deviation, δ denotes the coefficient of variation and $\hat{P}(F)$ represent the estimate of the probability of failure. For all structural reliability methods, which is based on MCS technique for estimating the probability of failure, the standard deviation decays with the rate $(1/\sqrt{N_T})$ and δ_u is independent of the total number of sample N_T (Zio, 2013). This means that the smaller the value of unitary coefficient of variation δ_u, the variability of the failure probability estimator will be lower and as a result, the higher the efficiency of the simulation approach. Therefore, the small number obtained using a combination of LS and IS demonstrates the efficiency and robustness of the method. Table 3.5 reports the outcome, which shows the efficiency of the combined approach compared to others. As a result, it can be stated that the combined approach maintains a considerable improvement with regards to efficiency over MCS, IS and LS when used independently.

Table 3.5: Failure probability of buried pipe due to total axial stress

Methods	Failure condition	
	Total axial stress acting on buried pipeline	
	P_f	δ_u
MCS	3.1 x 10^{-3}	1.42
IS	2.7 x 10^{-3}	0.36
LS	2.2 x 10^{-3}	0.073
LS & IS	2.0 x 10^{-3}	0.018

The impact of a seasonal change in groundwater level is performed considering the through-wall bending stress induced on the buried pipe due to pipe ovality. In practice, this effect is often ignored and in most cases assumed to be inconsequential. Herein, the study examines the implications of having the underground water table located below and also, above the buried pipe. Figure 3.10 shows the outcome of this investigation, which is time dependent. As can be seen, having the underground water table above the buried pipeline can increase the possibility of pipe failure. Based on Figure 3.10, the probability of failure started from 25 years when the underground water table is located below the buried pipe, whereas it started from 18 years when the location of the underground water table is above the buried pipe. The result shows that the rise in the underground water table above the buried pipe can affect its performance by increasing the probability of failure.

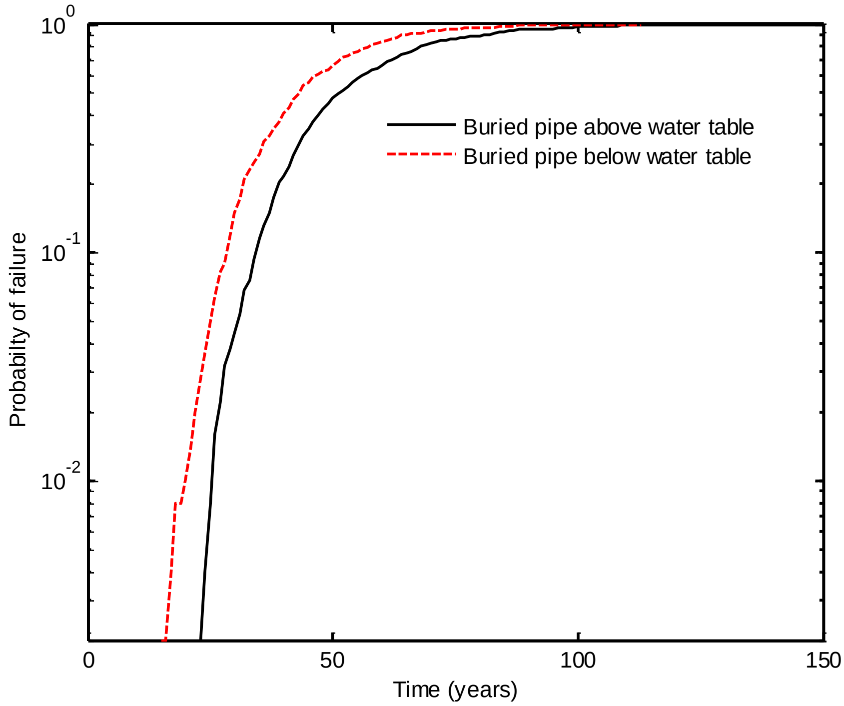


Figure 3.10: Probability of failure by considering water table above and below buried pipe

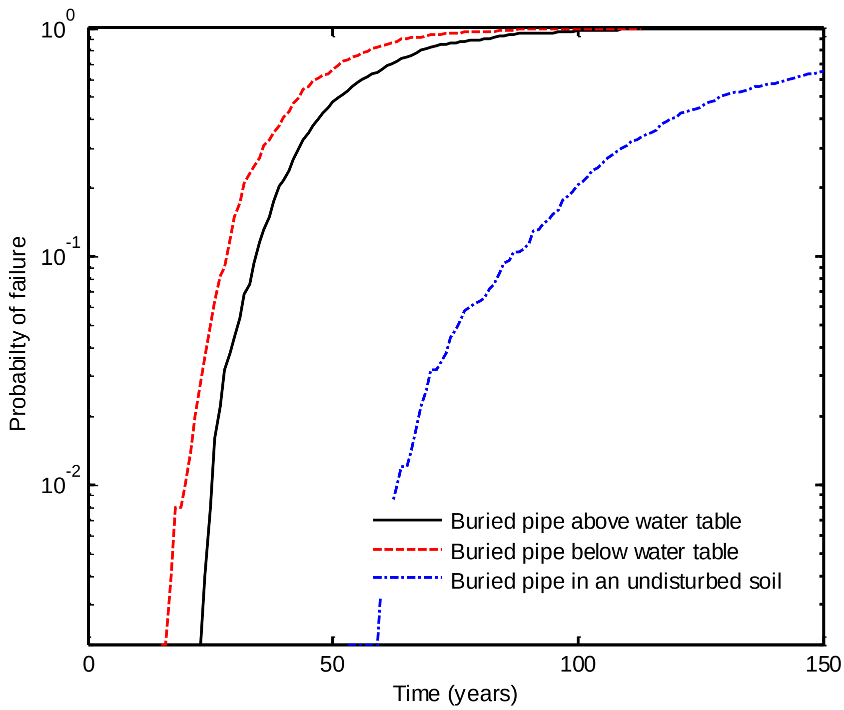


Figure 3.11: Probability of failure by considering undisturbed soil and underground water table

Furthermore, another reliability assessment is performed by considering a situation whereby the buried pipe is jacked into an undisturbed soil as defined by (Moser & Folkman, 2001). In this case, the buried pipe is assumed to be jacked into an undisturbed soil as an alternative to being placed in a trench. As a result, the friction and cohesion of soil on the buried pipe are significantly reduced as against situation where there is a prism load resting on the buried pipe. The result of this and combined with the water table effect is illustrated in Figure 3.11. Again, the result indicates a high reduction in the probability of failure as compared to an open trench where the backfill soil is resting on the buried pipe.

3.8.1 Parametric Studies

The effect of corrosion empirical constants and soil parameters on the performance of a buried pipeline have been investigated through parametric studies based on the failure modes of total axial stress and through-wall bending stress. Sadiq et al. (2004) suggested that the parameters that have the greatest effect could be those for which a decrease in the level of uncertainty, would add to reducing the most significant amount of the uncertainty of the output results. However, this study will assist to identify critical parameters that affect the performance of buried pipe and the parameters used include the multiplying constant k, the exponential constant n, bending moment coefficient K_m and deflection coefficient K_b.

In Figure 3.12 and Figure 3.13, the contribution of the multiplying constant k and the exponential constant n on the failure probability of the buried pipe over time are analysed. The analysis is performed by changing the values of the corrosion parameters (k and n) in order to evaluate their impact on the probability of failure. In Figure 3.12, it can be deduced that any changes which results in an increase in the values of the k (from 1.8 to 2.4) will correspondingly increases the possibility of pipe failure over time. This scenerio can be visualised by considering different service years between 0 to 150 years. This is expected because the higher the values of k, the greater is the degree of corrosion penetration which increases the probability of pipe failure. Similarly, Figure 3.13 shows that a reduction in the values of n (from 0.3 to 0.2) could reduce the possibility of pipe failure over time. Again, this effect is evident by looking at different service years between 0 to 150 years. The two outcome demonstrate the key roles of corrosion empirical constants k and n in estimating the failure probability of a corroded, buried pipeline. Also, the parametric effects of the corrosion empirical constants as reported in Figure 3.12 and Figure 3.13 shows the dynamic and variable nature of corrosion. Thus, a good understanding of the corrosion would provide a useful and better analysis of the reliability of buried pipe.

Figures 3.14 and 3.15 report the impact of the bending moment K_m and deflection coefficients K_b on the reliability of buried pipe over time. In Figures 3.14, the effect of reasonably varing the values of the bending moment coefficient K_m is reported and the outcome shows that the small failure probability increases with an increase in K_m at different service years between 0 to 150 years. This scenerio is expected because if the values of K_m is high, the bending moment could be high and stress that is induced in the buried pipe will result in higher failure probability. For the deflection coefficients K_b, a change in the values results to an insignificant change in the failure probability as shown in Figures 3.15.

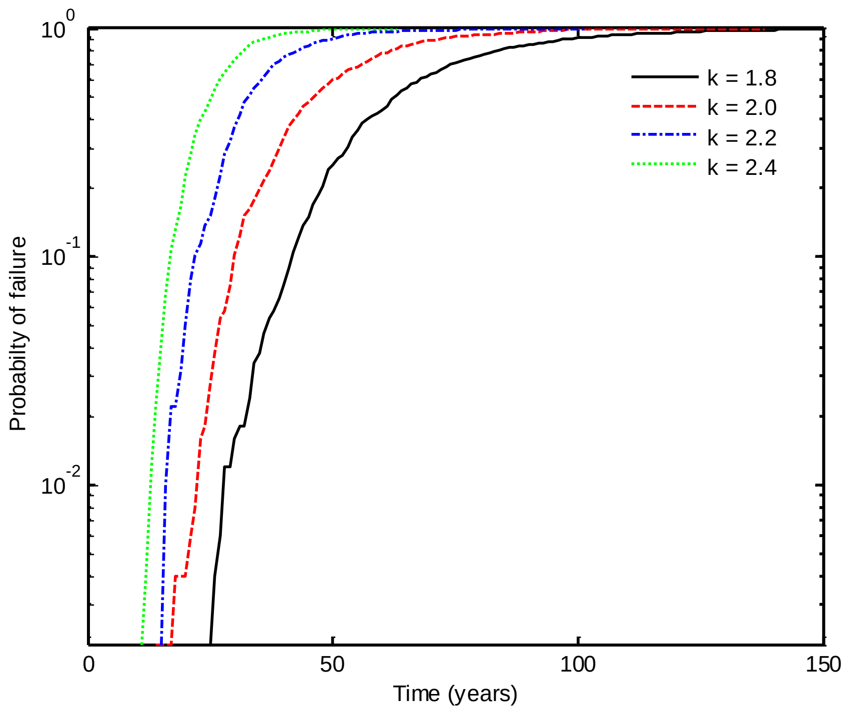


Figure 3.12: The effect of different k values on probability of failure over time

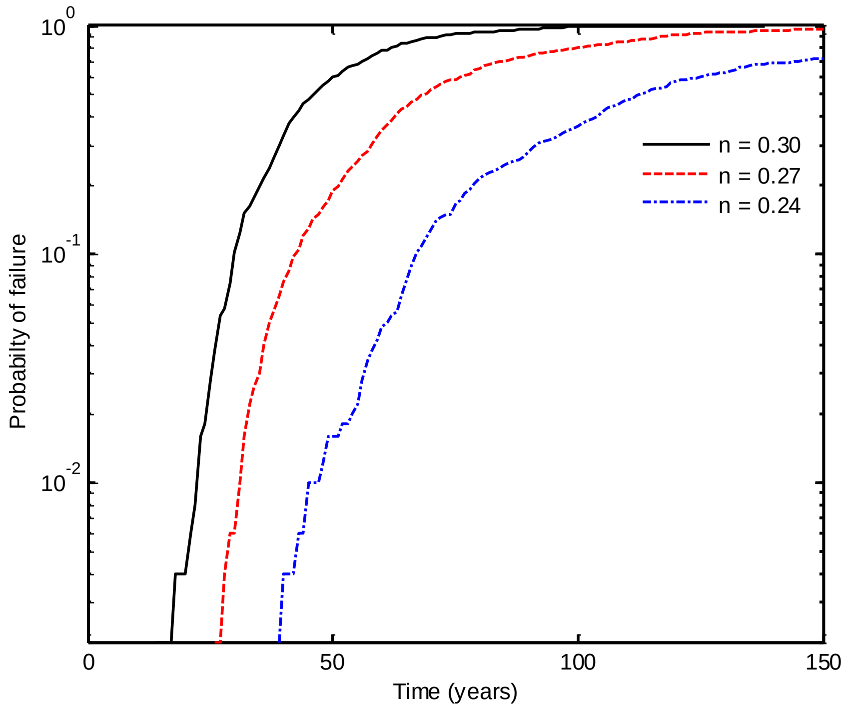


Figure 3.13: The effect of different n values on probability of failure over time

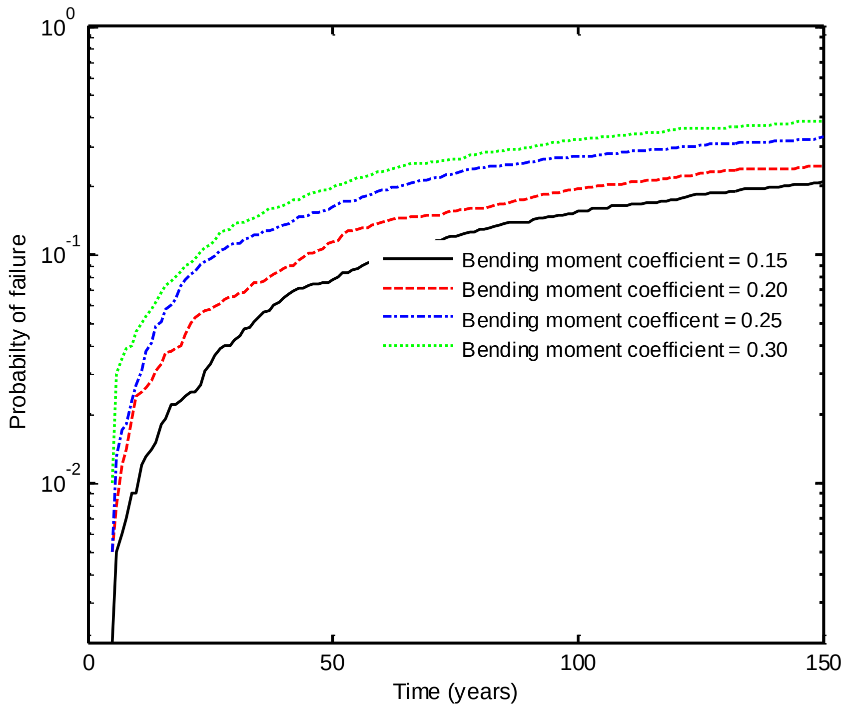


Figure 3.14: The effect of different k_m values on probability of failure over time

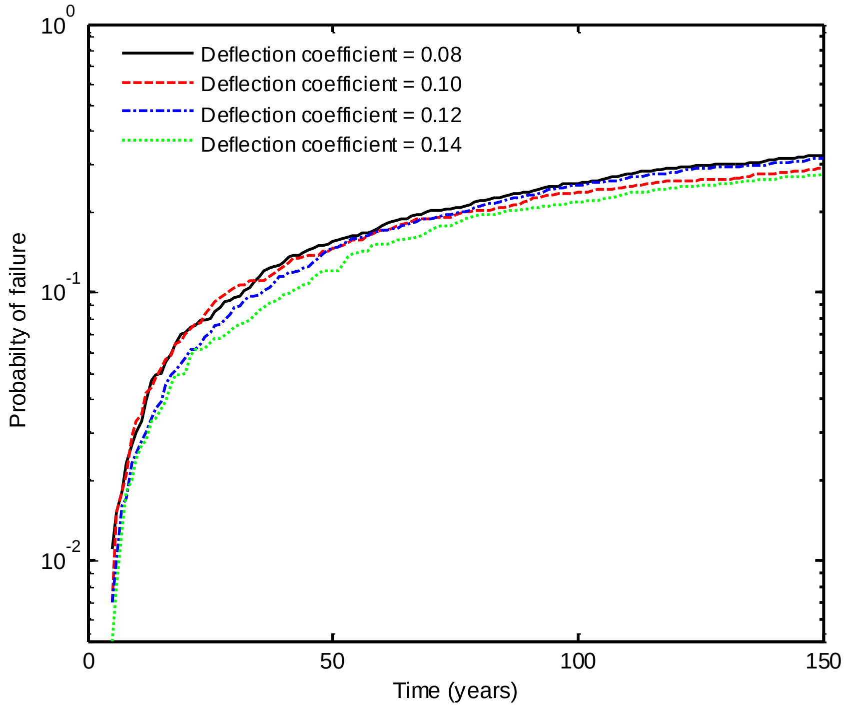


Figure 3.15: The effect of different k_d values on probability of failure over time

3.9 Chapter Summary

In this Chapter, the reliability analysis of buried pipeline is investigated considering the effect of aleatory uncertainty that is associated with pipe, soil and corrosion parameters. The failure probability of buried pipe is estimated using an advanced MCS method such as LS, IS and a combination of LS and IS. The concepts behind the methods are explained, and the procedure for the implementation of the combined approach are outlined. The methods are used to estimate the failure probability of buried pipeline subjected to structural failure modes of total axial stress and through-wall bending stress based on point load considering the impact of corrosion. The results obtained from the methods have been compared with the MCS approach for the purpose of estimating small failure probability. The choice of using the MCS method as a benchmark and for the validation of the results is due to its general acceptance and efficiency in estimating the failure probability of an engineering structure.

Also, the effect of groundwater table located below and above the buried pipe is investigated, and the outcome indicates that undermining this effect could adversely decrease the design life of the pipe. Furthermore, another assessment is performed by considering a situation whereby the buried pipe is jacked into undisturbed soil. In this case, the buried pipe is considered to be jacked into an undisturbed soil where the friction and cohesion of soil on the buried pipe are significantly reduced. The result shows a significant reduction in the probability of failure as compared to an open trench where the backfill soil is resting on the buried pipe. The result from the parametric studies shows the dynamic and variable nature of corrosion empirical constants, which indicates that a slight change in the numerical values can have a significant impact on the pipe failure probability. Considering the impact of uncertain variables, a fuzzy-based robustness assessment is presented in Chapter 4 to analyse the robustness behaviour of buried pipeline. The method is based on the principles of robustness measure, fuzzy set theory, interval analysis, and Shannon's entropy. In Chapter 4, both aleatory and epistemic type of uncertainty are considered.

CHAPTER FOUR

4 FUZZY-BASED ROBUSTNESS ASSESSMENT OF BURIED PIPE

4.1 Introduction

The design of buried pipe structure is associated with uncertainties due to randomness and fuzziness (or vagueness) that exist in the structural parameters. The occurrence of randomness or fuzziness can be due to manufacturing errors, measurement errors, and scarceness of information concerning the determination of the input parameter. The presence of uncertainties has influenced negatively the performance of buried pipe over time. As a result, it is indispensable to evaluate the performance of the buried pipe structure by considering the impact of the associated uncertainties.

In this Chapter, a fuzzy-based robustness assessment of buried pipelines is proposed considering the randomness (aleatory uncertainty) and fuzziness (epistemic uncertainty) that exist in the structural parameters. The approach utilises the principles of robustness measure, fuzzy set theory, interval analysis and Shannon's entropy, which permits the inclusion of random and fuzzy variables in the quantification of the uncertainty associated with the performance of buried pipe. Zhang et al., (2015) suggested that robustness measures analyse robustness as a property of the structure rather than damage. Herein, robustness is used as a measure to assess the ability of buried pipe to sustain damage that may be caused by extreme loads or changes in environmental conditions without disproportionate failure. Therefore, a pipe structure is considered to be robust if it can survive some extreme conditions such as exceptional overloading, unforeseen events, and adverse environmental conditions without any substantial loss of safety and serviceability.

The rest of this Chapter is arranged as follows. Section 4.2 explains an overview of fuzzy set and fuzzy uncertainty. Section 4.3 gives a review of the literature concerning the concepts of robustness measure. Section 4.4 provides the application to buried pipe, which includes the structural failure modes, a numerical example and the damage modelling of buried metal pipe under uniform corrosion. Section 4.5 discusses the results, and significant findings from the study and Section 4.6 provides the Chapter summary.

4.2 Fuzzy Set and Fuzzy Uncertainty

The uncertainty associated with structural parameters and whose uncertain characteristics could be identified as fuzziness can be evaluated using fuzzy set theory (Zadeh, 1965). A fuzzy set is a mathematical tool used in describing an uncertain data whose information may be described as a set of intervals and their associated gradual assignment (Zadeh, 1965). This definition offers a framework for analysing varieties of information associated with uncertain parameters starting from discrete data, continuous data, interval value data and linguistic knowledge. Ross (2010) suggested that a fuzzy set theory allows an ongoing assessment of the elements in relation to a set. However, in modelling the uncertainty of a fuzzy variable, an interval value of the uncertain parameter can be evaluated with the aid of a membership function $\mu_X(x)$. The membership function of a fuzzy variable can be represented graphically using different shapes, which helps to classify the element in the set, whether it is discrete or continuous.

A fuzzy variable with linear membership functions between $\mu_X(x) = 0$ and $\mu_X(x) = 1$ can be represented using fuzzy triangular membership function or a trapezoidal membership function as illustrated in Figure 4.1 and 4.2 (Möller & Beer, 2004; Ross, 2010). The fuzzy triangular numbers are determined by specifying the smallest x_1, mean x_m and the largest x_2 values that belong to the functional value. For the trapezoidal, the interval x_2 and x_3 define the bounds of the interval with the functional value $\mu_X(x) = 1$. In the literature, a triangular membership function is generally used to model epistemic uncertainty. Herein, a triangular membership function is used to describe the uncertain fuzzy variable because it appears more direct and efficient in modelling epistemic uncertainties associated with design parameters.

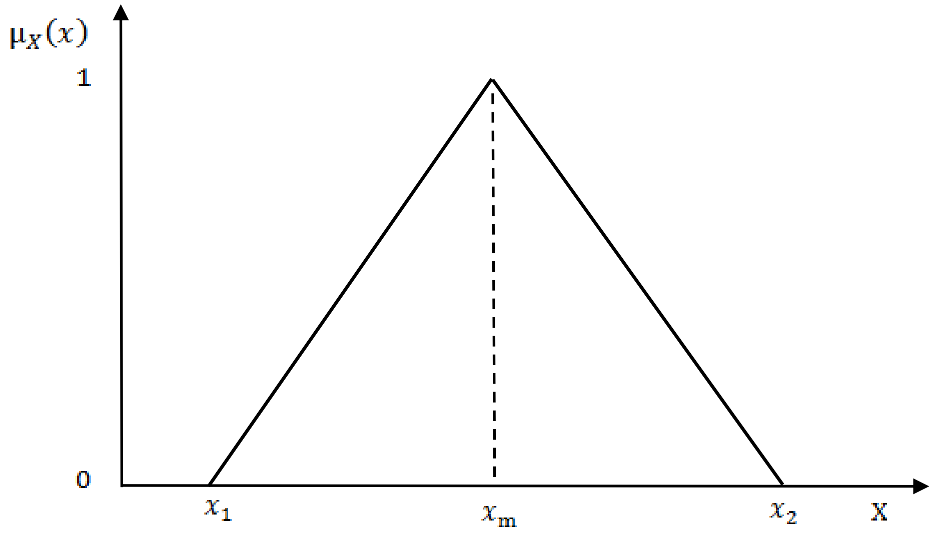


Figure 4.1: Fuzzy triangular membership function

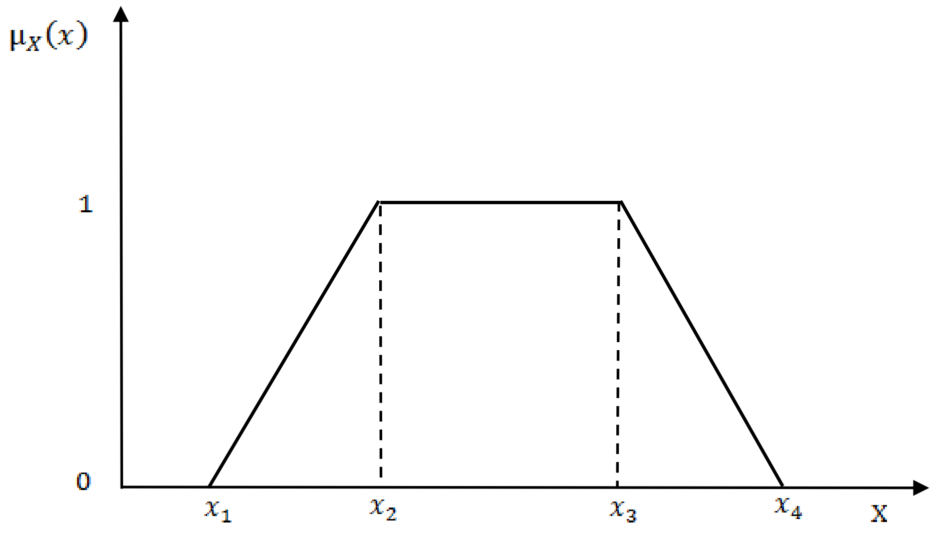


Figure 4.2: Fuzzy trapezoidal membership function

4.2.1 Analysis of Fuzzy Set and α-level Discretisation

Usually, the membership function $\mu_X(x)$ is discretised into ten equal level and denoted using values between 0 and 1 (Möller & Beer, 2004). The values for the membership function could be used to signify several practical meanings. For example, the various level of the membership function of the uncertain parameter could be used to denote the level of variability associated with the parameter. However, the fuzziness associated with a fuzzy variable can be characterised by its normalised membership function $\mu_X(x)$ as expressed in Eq. (4.1).

$$0 \leq \mu_X(x) \leq 1 \quad \forall x \in \mathbb{R} \tag{4.1}$$

Figure 4.3 shows a typical triangular membership function $\mu_X(x)$ of a convex fuzzy variable x. From Figure 4.3, $L_X(x)$ and $U_X(x)$ denote the lower bound and the upper bound of the membership function of the fuzzy variable. The $L_X(x)$ and $U_X(x)$ bound are increasing and decreasing monotonic functions with respect to the fuzzy variable x. Also, the fuzzy variable can be expressed as:

$$\mu_X(x) = \begin{cases} L_X(x) & C_1 \leq x \leq C_m \\ U_X(x) & C_m \leq x \leq C_2 \end{cases} \tag{4.2}$$

Other shapes such as Trapezoidal or Gaussian may be selected if considered appropriate to quantify the uncertainty of a particular structural parameter. As described in the literature Möller & Reuter (2007), the α-level set of a fuzzy variable can be characterised with a family of α-level sets $X(\alpha)$.

$$X(\alpha) = \{[x^l(\alpha), x^u(\alpha)],\ \alpha \in [0,1]\} \tag{4.3}$$

For each α-level, the set $X(\alpha)$ is associated with interval values, that is, $[x^l(\alpha), x^u(\alpha)]$. And for every bound $x^l(\alpha)$ and $x^u(\alpha)$ where $\alpha \neq 0$, the following expressions exist.

$$\begin{cases} x^l(\alpha) = min[x \in \mathbb{R} | \mu_X(x) \geq \alpha] = (L_X)^{-1}(\alpha) \\ x^u(\alpha) = max[x \in \mathbb{R} | \mu_X(x) \geq \alpha] = (U_X)^{-1}(\alpha) \end{cases} \tag{4.4}$$

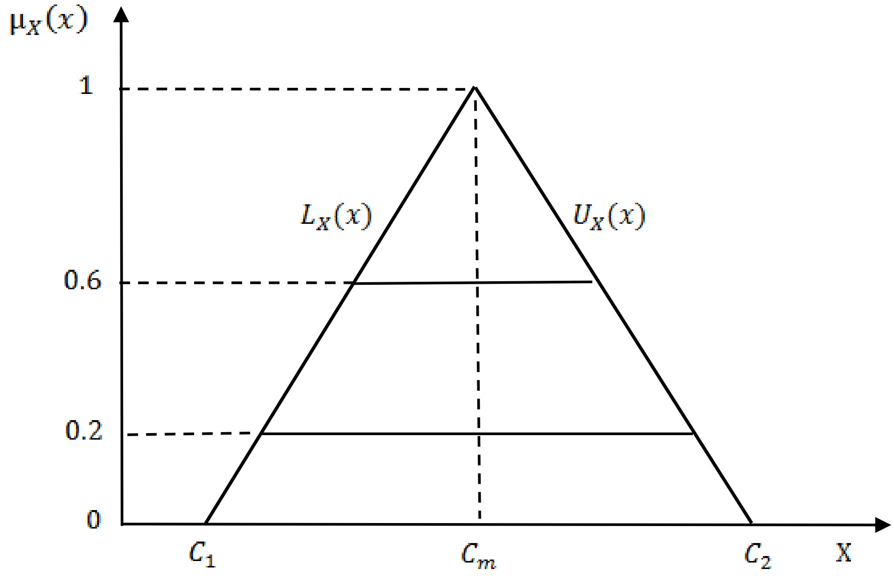


Figure 4.3: The membership function of a fuzzy variable

4.3 The Concept of Robustness Measures

The concept of the robustness measure has been used in different engineering context and applications. An adequate robustness assessment of a structural system requires a measure of its uncertainty (Beer & Liebscher, 2008; Hanss & Turrin, 2010). However, there are no well-established and acceptable criteria for a consistent definition and determination of structural robustness (Starossek & Haberland, 2011). Herein, robustness is considered as a measure to assess the ability of buried pipe to sustain damage that may be caused by extreme loads or changes in environmental conditions without disproportionate failure with respect to the causes of the damage. The variabilities of the load or other design parameters can be modelled using deterministic, probabilistic and non-probabilistic approaches. Based on these methods, the concept of robustness measures is reviewed under the following subsections.

4.3.1 Deterministic Measures

The deterministic measure of the robustness of a structure is developed by evaluating the performance of the structure in both intact and damaged states, using the ultimate strength analysis (Biondini et al., 2008). For the investigated buried pipe structure, the ultimate strength will depend on the non-linear response of the pipe structure and the interaction between the pipe wall, the soil, earth and live loads. However, the concept of reserve strength and residual strength are considered to evaluate the structural robustness associated with the buried pipe based on the failure modes. As defined in Zhang et al. (2015), the reserve strength of a structural system is the ratio between the ultimate resistance of the intact state structure and the environmental design load that is applied to measure the residual strength. This can be expressed as shown in Eq. (4.5).

$$RSR = \frac{ultimate\ resistance\ of\ intact\ structure}{design\ environmental\ load} \tag{4.5}$$

The damage of engineering structures occurs over time. Therefore, Biondini et al. (2008) suggested a general approach to measure the time-variant structural robustness of concrete structures subjected to diffusive attacks from aggressive environmental agents on the ultimate strength analysis. From the expressed measure, the amount of local damage is first obtained at the member level using dimensionless damage index $0 \leq \delta \leq 1$, i.e., associated with the progressive deterioration of the material properties at a spatial point named *x* and time *t*. The global measure of the damaged $\Delta(t)$ at the cross-sectional level can be represented as follows:

$$\Delta(\mathrm{t}) = [1 - \omega(t)]\Delta_c(t) + \omega(t)\Delta_s(t) \tag{4.6}$$

$$\Delta_c(\mathrm{t}) = \frac{\int_{A_c} W_c(x,t)\delta_c(x,t)dx}{\int_{A_c} W_c(x,t)dx} \tag{4.7}$$

$$\Delta_s(\mathrm{t}) = \frac{\sum_m w_{sm}(x,t)\delta_{sm}(x,t)A_{sm}}{\sum_m w_{sm}(x,t)A_{sm}} \tag{4.8}$$

Where $\omega = \omega(t)$, $w_c = w_c(x,t)$ and $w_{sm} = w_{sm}\omega(x,t)$ are the suitable weight functions. A_c is the area of the concrete, and A_{sm} is the area of the m^{th} steel bar.

The cross-section formulation can be extended at the structural level by integration over all the members of the system. Therefore, to account for the uncertainties due to environmental loading and structural resistance for the intact and damaged state, a time-variant measure of the structural system is expressed in Eq. (4.9) (Biondini et al., 2008).

$$\rho(t) = \frac{\lambda_c(t)}{\lambda_c(0)} \tag{4.9}$$

Where $\lambda_c(\mathrm{t})$ is the load multiplier that corresponds to the ultimate capacity in a damaged state and $\lambda_c(0)$ represents the ultimate capacity of the intact state.

4.3.2 Probabilistic Measure

Because of unavoidable uncertainties due to loading conditions and determination of structural parameters, a probabilistic measure of robustness has been developed based on system reliability analysis. The probabilistic measure of system redundancy as proposed in Frangopol & Curley (1987) is based on a reliability index for the full system and the union of the first member failures. This can be expressed in Eq. (4.10).

$$\beta_{Redundancy} = \frac{\beta_{intact}}{\beta_{intact} - \beta_{damage}} \tag{4.10}$$

Where β_{damage} denotes the reliability index of the damaged structural system and β_{intact} represents the reliability index of the intact system. Similarly, Lind (1995) suggested a probabilistic measure called the damage factor of a system as expressed in Eq. (4.11). This will assist to assess the capacity of the structure and to withstand damage without detrimental response. However, these possible approaches are limited to cases in which probabilistic models can be specified for all the variables with sufficient confidence.

$$R_{df} = \frac{P_{f,intact}}{P_{f,damage}} \tag{4.11}$$

4.3.3 Entropy-based Robustness Measure

Entropy-based robustness measure can be used for the assessment of uncertainty specified with the aid of a fuzzy set (Zhang et al., 2015). The robustness assessment of the fuzzy uncertainty of structural parameters can be computed based on Shannon's entropy (Zhang et al., 2015). The Shannon's entropy provided the needed information of the total amount of uncertainty contained in the declared character set (Zimmermann, 2001). Based on Shannon's approach, the uncertainty of a fuzzy variable can be quantified. Shannon's entropy H can be expressed using a probability distribution function $P(x)$ on a finite set as shown in Eq. (4.12).

$$H = -\sum_{x \in X} P(x) \log_2 P(x) \tag{4.12}$$

$$H = -\int_{-\infty}^{+\infty} f(x). \log_2 f(x) dx \tag{4.13}$$

For an infinite set, the expression in Eq. (4.13) can be applied. In assessing the fuzziness of the fuzzy set, the functional values of the membership function $\mu(x)$ are applied as measure values of the elements (Zhang et al., 2015). Therefore, an entropy measure of the fuzziness of an uncertain parameter as defined in Zimmermann (2001) can be expressed as:

$$H(\tilde{A}) = -K. \int_{-\infty}^{+\infty} \{\mu(x). \ln[\mu(x)] + [1-\mu(x)]. \ln[1-\mu(x)]\} dx \tag{4.14}$$

Where $\tilde{A}$ is the fuzzy set which is a subset of the fundamental set X. This entropy measurement equation evaluates the 'steepness' of the membership function μ(x) of $\tilde{A}$.

The coefficient K does not affect the entropy values because entropies appears to be ratios. Therefore K will cancel out. However, K was introduced during the transformation of the dyadic logarithm in Shannon's entropy in Eq. (4.13) into the natural logarithm in Eq. (4.14). Based on the expression in Eq. (4.14) for the entropy, the following properties hold (Zhang et al. 2015):

- $H(\tilde{A}) = 0$ if $\mu(x) = 0$ or $\mu(x) = 1.0$ for all x;
- $H(\tilde{A})$ reaches maximum if $\mu(x) = 0.5$ for all x;
- If $\tilde{A}_i$ denotes any sharpened version of $\tilde{A}_j$ [i.e., if $\mu_{\mathrm{A}_j}(x) \leq 0.5$, then $\mu_{\mathrm{A}_i}(x) \leq \mu_{\mathrm{A}_j}(x)$; and if $\mu_{\mathrm{A}_j}(x) \geq 0.5$, then $\mu_{\mathrm{A}_i}(x) \geq \mu_{\mathrm{A}_j}(x)$], then $H(\tilde{A}_i) \leq H(\tilde{A}_j)$ and
- The symmetry property holds, i.e., $H(\tilde{A}) = H(\tilde{A}^c)$. Where $\tilde{A}^c$ denotes the complement of $\tilde{A}$ and can be defined as $\tilde{A}^c = \{[x, \mu_{A^c}(x)] | x \in X;\ \mu_{A^c}(x) = 1 - \mu_A(x)$.

As defined in Beer & Liebscher (2008), the robustness of a structural system can be defined as the ratio between the entropy of input parameters and the entropy of associated structural responses when the uncertainty of structural parameters is quantified as fuzziness. Using the notation $\tilde{x}$ for the fuzzy input vector for the structural analysis and

$\tilde{z}$ for the fuzzy structural response, the structural robustness measure $R(\tilde{x}, \tilde{z})$, regarding $\tilde{z}$ with respect to $\tilde{x}$ can be expressed as:

$$R(\tilde{x}, \tilde{z}) = \frac{H(\tilde{x})}{H(\tilde{z})} \tag{4.15}$$

Based on the expression for the robustness of a structure, the following properties hold:

- $R(.) \geq 0 \; \forall \; H(\tilde{x}), H(\tilde{z}) > 0$;
- $H(\tilde{z}_2) \leq H(\tilde{z}_1) \Longrightarrow R_2(.) \geq R_1(.) | H(\tilde{x}_1) = H(\tilde{x}_2)$;
- $H(\tilde{x}) \rightarrow 0 \Longrightarrow R(.) \longrightarrow 0 \; | H(\tilde{z}) > 0$; and
- $H(\tilde{z}) \rightarrow 0 \Longrightarrow R(.) \longrightarrow +\infty \; | H(x) > 0$.

Following the properties of the robustness of a structure, the outcome of the robustness measure can lead to a global statement about the degree of variation in the structural output with respect to fluctuation in the structural input (Beer & Liebscher, 2008; Zhang et al., 2015). For example, the second property shows that the smaller the uncertainty associated with the output in relation to the uncertainty associated with the input variables, the higher the robustness of the structure. In practice, Zhang et al. (2015) suggested that this shows that moderate changes applied to structural parameters, e.g. changes in the design parameters and moderate errors, can affect the structural response only marginally. Based on the suggestion of Zhang et al. (2015), entropy-based robustness measure can be assessed at various membership levels with respect to the degree of imprecision in the fuzzy inputs and the associated imprecision in the fuzzy outputs. This is realised by considering each component of the structural system. For instance, for a given fuzzy set $\tilde{A}$ at α-level $\alpha_k \in (0,1]$, a new fuzzy set can be defined as the intersection of fuzzy set $\tilde{A}$ and the corresponding α-level set $\tilde{A}_{\alpha_k}$. This is expressed in Eq. (4.16).

$$\tilde{A}_{\alpha_k} = \tilde{A} \cap A_{\alpha_k} \tag{4.16}$$

Now, the entropy-based robustness assessment can be evaluated at each α-level, as the ratio of the entropy of the fuzzy input to the entropy of the fuzzy structural response. This can be expressed as shown in Eq. (4.17).

$$R(\alpha_k) = \frac{H(\tilde{x}_{\alpha_k})}{H(\tilde{z}_{\alpha_k})} \tag{4.17}$$

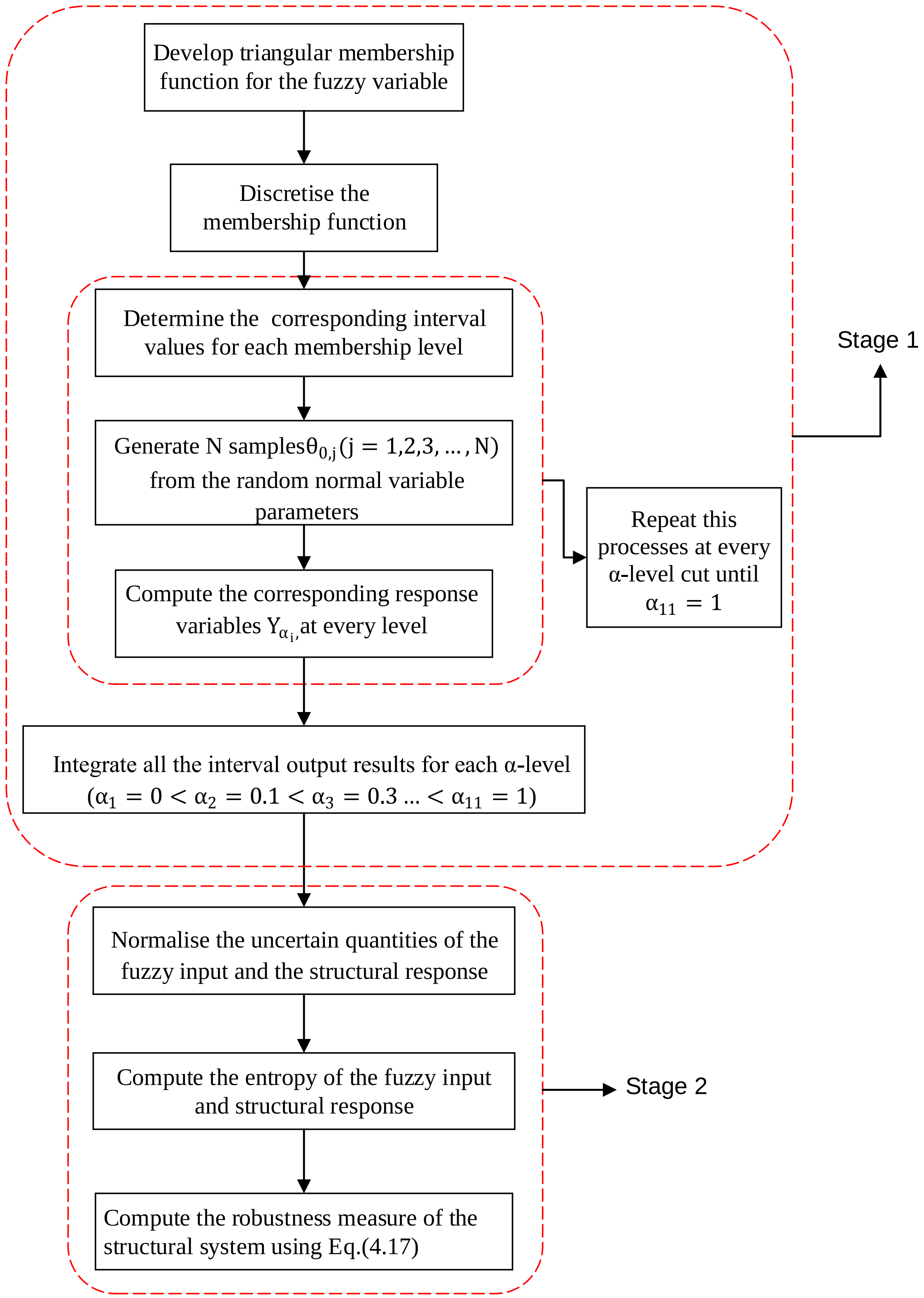


Figure 4.4: Flow diagram for the computation of fuzzy-based robustness measure

4.3.4 Methodology

In Section 4.3.1 to 4.3.3, various approaches for the assessment of the robustness of a structure considering different conditions and uncertainties are reviewed. The entropy-based robustness measure is considered because it provides a potential to assess the robustness in the form of a function that depends on the magnitude of uncertainty that exists in the structure. Therefore, the fuzzy-based robustness assessment is developed based on the concept of the entropy-based robustness measure and the computation is performed in two stages. The first stage deals with interval analysis concept for the solution of the α-level cut. This stage is based on the concept of Dong, Shah, and Wong (DSW) algorithm (Ross, 2004). The method uses the decomposition of a membership function into a series of α-cut intervals and also uses the full α-cut intervals in a standard interval analysis. While the second stage takes care of the robustness assessment that is an analogy to Shannon's entropy based on the concept of Zhang et al. (2015). Figure 4.4 shows the flow diagram for the two stages and the procedures are summarised as follows:

Stage 1

1. Construct the triangular membership function for a fuzzy set model of the corrosion loss.
2. Discretise the membership function into 10 parts between 0 and 1, where the values will be $\alpha_1 = 0 < \alpha_2 = 0.1 < \alpha_3 = 0.3 ... < \alpha_{11} = 1$.
3. For every $\alpha -$ level, determine the corresponding interval values each membership level α_i, find the correspong interval from the fuzzy sets.
4. Generate N samples $\theta_{0,j} (j = 1,2,3, \dots, N)$ from the random normal variable parameters using their original PDF from the example problem.
5. Using standard interval arithmetic, compute the corresponding response variables $Y_{\alpha_{i,}} (i = 0, 0.1, 0.2, 0.3 \dots, 1)$for the output membership function of the selected α-level.
6. Repeat the processes from step 3 to 5 at every α-level cut until $\alpha_{11} = 1$.
7. Integrate all the interval output results for each α-level ($\alpha_1 = 0 < \alpha_2 = 0.1 < \alpha_3 = 0.3 ... < \alpha_{11} = 1$) to obtain the overall results of the solution model.

Stage 2

1. Normalise the uncertain quantities of the fuzzy input and the structural response
2. Compute the entropy of the fuzzy input and structural response for every α-level from the analogy Shannon's entropy using Eq. (4.14)
3. Compute the robustness measure of the structural system using Eq.(4.17)

4.4 Application to Buried Pipe

4.4.1 Structural Failure Mode and a Numerical Example

The numerical example is used to demonstrate the applicability of the method in Section 4.3.4 and the technique is used to assess the structural robustness of a buried pipe while considering the impact of corrosion and uncertain variables. The considered failure modes used in the analysis include pipe deflection, buckling pressure (ring buckling), bending strain and wall thrust as explained in Chapter 3, Section 3.3. The statistical values of the soil and pipe parameters used in the computation are shown in Table 3.3 and Table 3.4. The values are based on industry standard and have been obtained from the works of (Ahammed & Melchers 1994; Sadiq et al., 2004; Tee et al., 2014). As a useful extension, the effect of corrosion on the buried pipe is assessed herein using the intrinsic features of a fuzzy set, and modelling of the damage is explained in the subsequent section.

4.4.2 Damage Modelling of Buried Metal Pipes Under Uniform Corrosion

In this numerical example, the buried metal pipe is assumed to undergo gradual deterioration caused by uniform corrosion. The degradation process can lead to different failure modes such as pipe deflection, buckling pressure, bending strain and wall thrust. The investigation of the corrosion effect was performed using the immersion corrosion data collected by Melchers (2003) as shown in Figure 4.5 to model the corrosion pit depth. A fuzzy corrosion depth associated with the exposure time is derived from the data based on a subjective assessment of deterioration of mild steel coupons as shown in Figure 4.6. Generally, Marano et al. (2008) suggested that it is possible to state that a unitary approach does not exist for the so-called fuzzification, but different procedures can be adapted for each situation. Therefore, the methods for constructing the membership function of a fuzzy variable can be direct or indirect with a single expert or multiple experts (Klir, 2006; Marano et al., 2008).

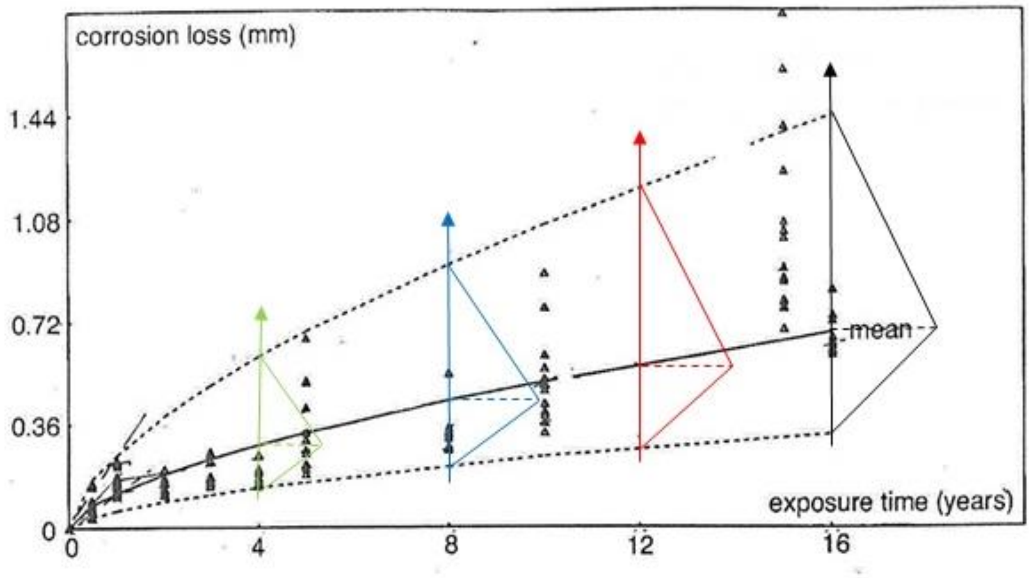


Figure 4.5: Fuzzy input model for corrosion loss based on mild steel coupons pooled from all available data sources until 1994, with 5th and 95th percentile bands.

The membership function for the fuzzy corrosion depth at time T = 4, 8, 12 and 16 years are subjectively constructed according to the data points plotted in Figure 4.5, and the developed membership function is shown in Figure 4.6. The membership function is considered as linear where it connects the 5 percentile, the mean and the 95 percentile values in the experimental data. In this study, the uncertainty of corrosion pit depth is considered for the four failure modes of the buried pipeline. For simplicity, the analysis considers exposure periods of 4, 8, 12, and 16 years (as shown in Figure 4.6). The amount of damage on the pipe wall or cross-sectional area of the buried pipe is evaluated using the concept of (Watkins & Anderson, 1999). Therefore, for a flexible metal pipe, the moment of inertia and the cross-sectional area of the pipe wall per unit length can be obtained using Eq. (4.18) and Eq. (4.19).

Moment of inertia, $I = (t - C_T)^3/12$ (4.18)

Cross-sectional area $A_s = t - C_T$ (4.19)

Where t represents the thickness of the pipe wall, C_T is the pit depth and T is the time of exposure.

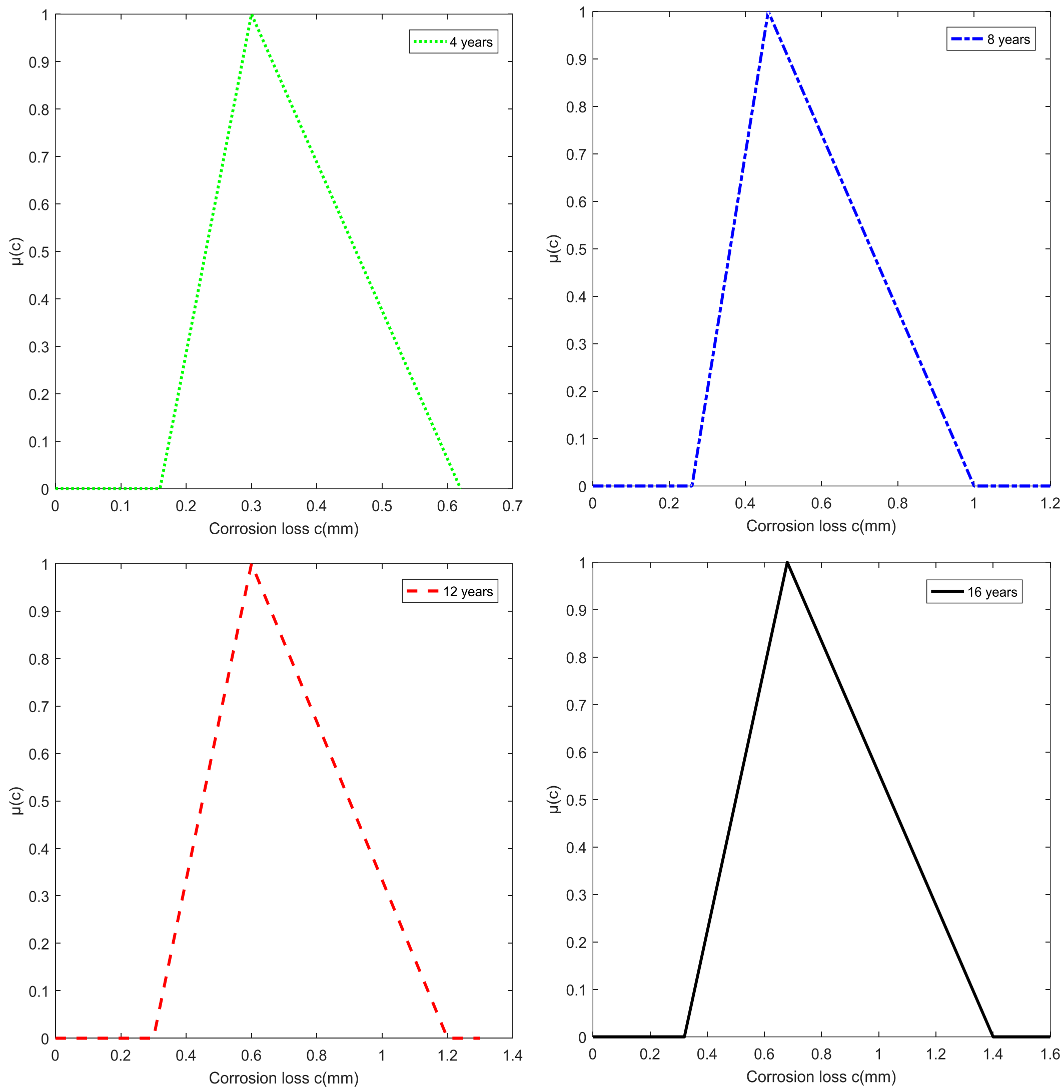
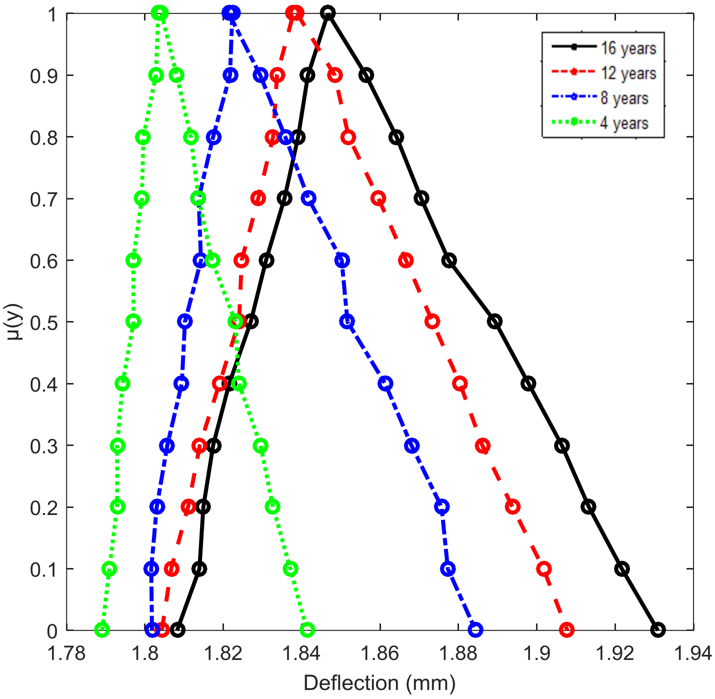


Figure 4.6: Membership functions developed from the immersion corrosion data of mild steel coupons for 4, 8, 12, and 16 years

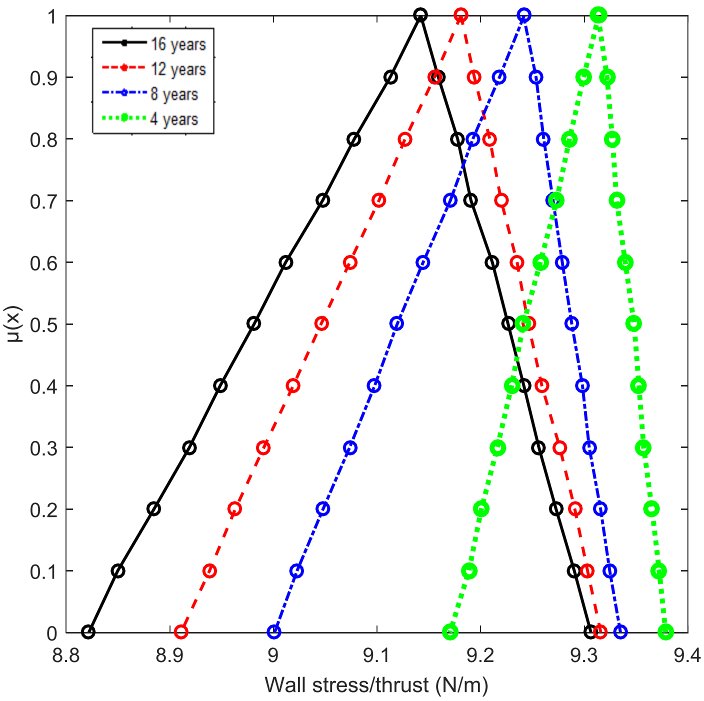
4.5 Results and Discussion

The specified fuzzy variable $\tilde{c}\,(T = 4, 8, 12 \; and \; 16 \; years)$ is employed in modelling the impact of corrosion pit depth and the impact of other uncertain variables for the determination of the structural robustness of a buried steel pipe. The external surface area of the buried pipe wall is considered to suffer corrosion loss that is uniform. Four failure modes are considered in this analysis which includes deflection, wall thrust, bending strain and buckling pressure (see Chapter 3, Section 3.3 for more information). The computed membership function outcome for each failure are shown in Figure 4.7 for the failure modes of pipe deflection and wall stress/thrust, and Figure 4.8 for the failure modes of bending strain and buckling pressure. The results provide clear information about transferring the fuzzy corrosion uncertainty to the pipe failure modes. In each failure mode, the fuzzy model can incorporate and simulate the probabilistic and vagueness associated with pipe, soil and corrosion parameters for the buried pipe. However, the degrees of uncertainty increase as the number of service years increases.

The outcome of the entropy values associated with the α-level of the fuzzy output for different failure modes, normalised by $H(p)$ are reported in Figure 4.9 and Figure 4.10 for an exposure period of 16 and 8 years, respectively. The result clearly indicates a reduction of imprecision in the fuzzy input would lead to a reduction of imprecision in the fuzzy output. It could be noticed from the results that the imprecision associated with the input parameter has a trade-off in reducing the imprecision associated with the computed output for different failure modes. However, for the various failure modes, the entropy states exhibit different characteristics. For example, the imprecision associated with wall thrust and buckling pressure decreases much faster than the imprecision in deflection and bending strain when input uncertainty decreases. This indicates that a small reduction of imprecision in the fuzzy input variable can result in a significant decrease in imprecision in the failure modes of buried pipe for wall thrust and buckling.

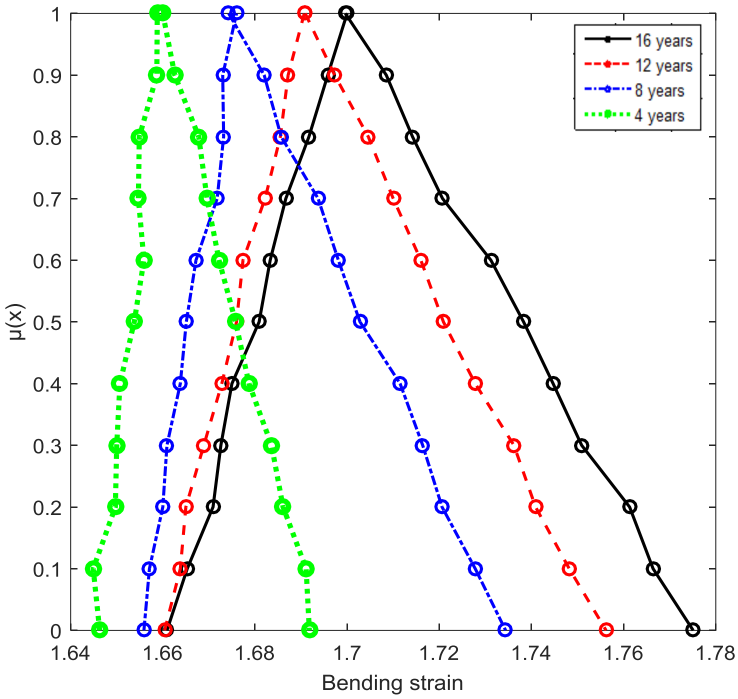


(a) Deflection

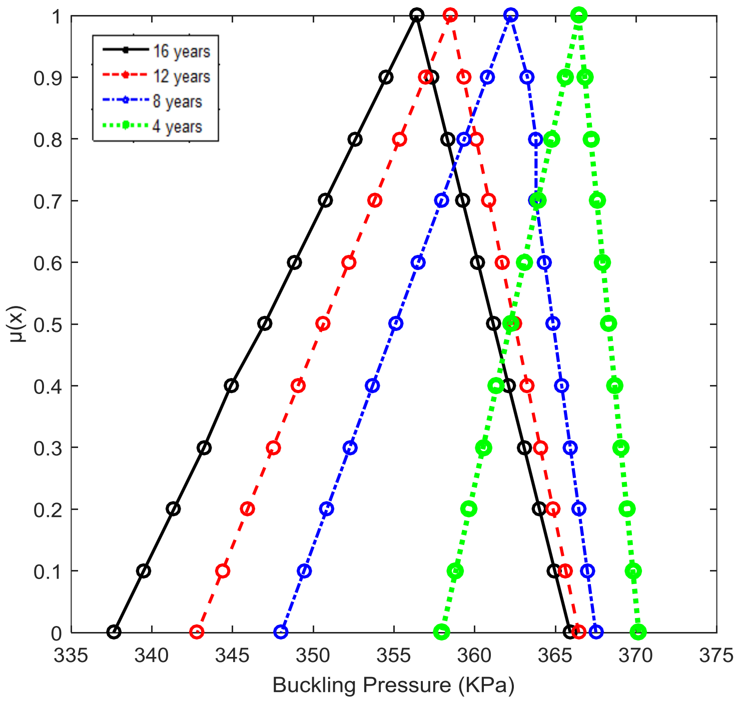


(b) Wall stress/thrust

Figure 4.7: Membership function of pipe failure mode for (a) deflection (b) wall thrust



(a) Bending strain



(b) Buckling pressure

Figure 4.8: Membership function of pipe failure mode for (a) bending strain (b) buckling pressure

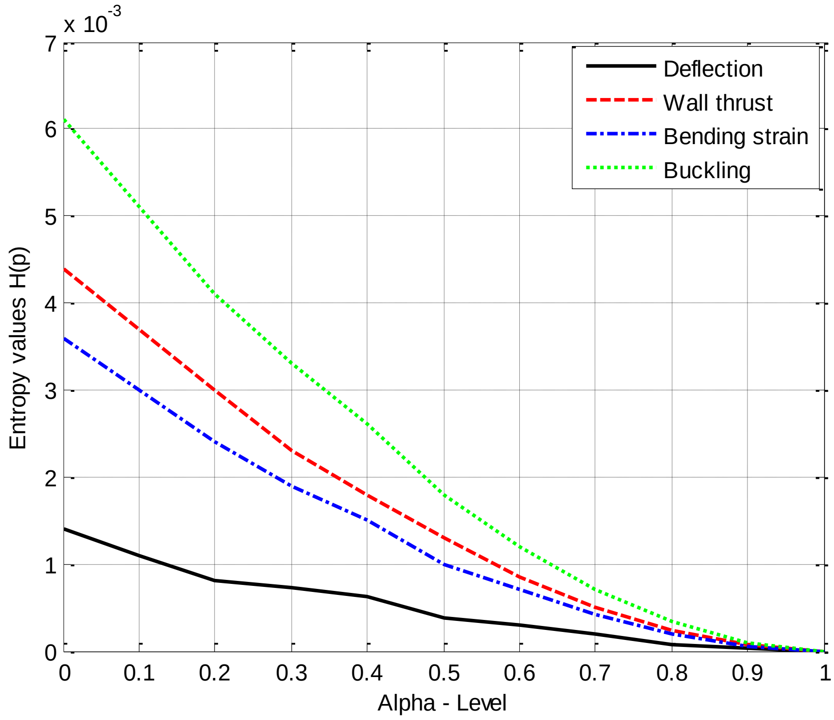


Figure 4.9: Entropy state for different failure modes after 16 years

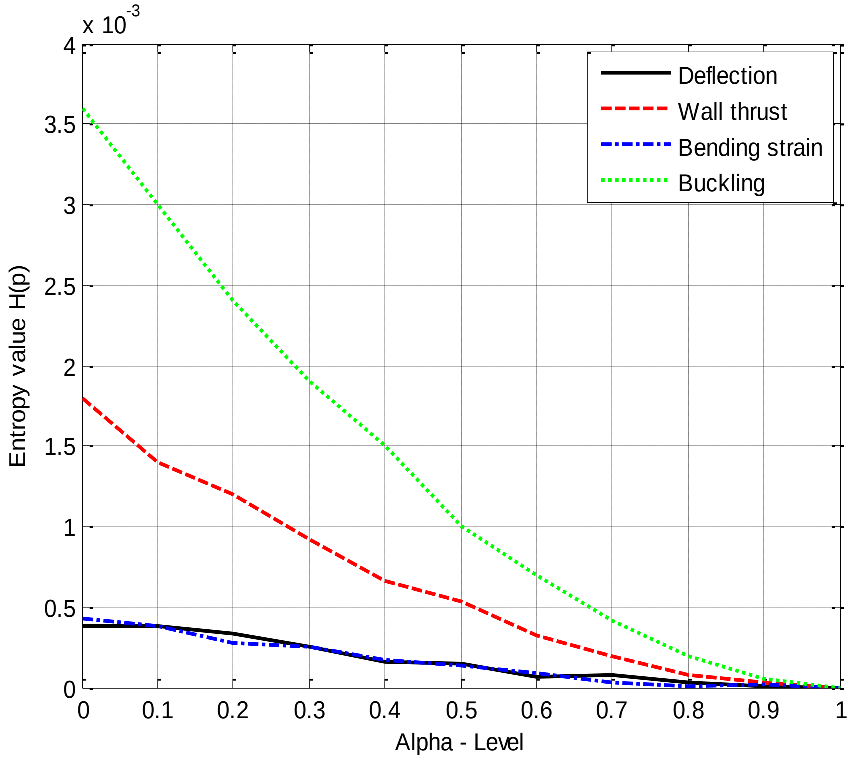
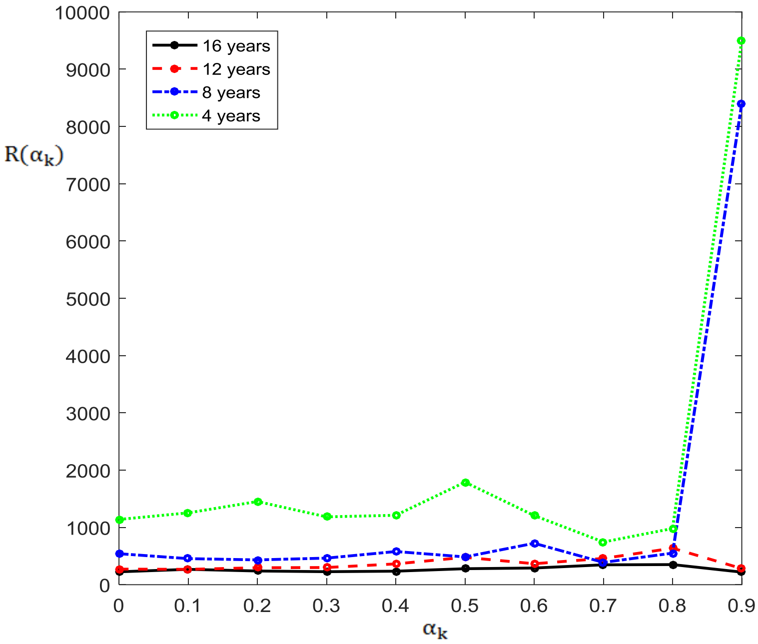


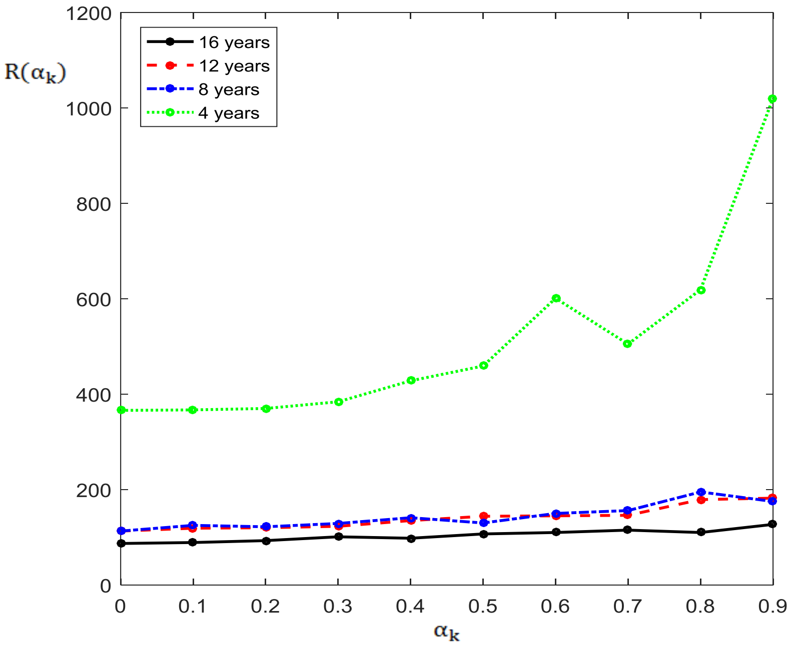
Figure 4.10: Entropy state for different failure modes after 8 years

The entropy state of each failure mode is computed for different $\alpha -$ level with the intersection of characteristic membership functions of both inputs and outputs. The intersection is based on the mathematical operations of fuzzy set theory. The outcome of the corrosion effects of the fuzzy-based robustness measure $R(\alpha_k)$ for different pipe failure modes of buried pipe are reported in Figure 4.11 and Figure 4.12. This is calculated based on Eq. (4.14) and (4.17), which is the ratio between the entropy of the fuzzy input to the entropy of the fuzzy output at each $\alpha - level$. The outcome of the pipe robustness for deflection for the periods of 16 and 12 years demonstrates a close robust behaviour of the buried pipe when $\alpha_k \leq 0.2$.

On the other hand, as the $\alpha - level$ increases, the outcome of pipe deflection for the period of 12 years continues to display a value that is greater than the case for 16 years. For the other years (4 and 8 years), the robustness measure of the buried pipe is quite distinctive. Similarly, for the period of 4 and 8 years, and when the alpha-level $\alpha_k \geq 0.8$, there is a sudden increase in the robustness value. This could mean that the buried pipe under deflection failure modes is more robust when the alpha-level $\alpha_k \geq 0.8$ compared to when the alpha-level $\alpha_k \leq 0.8$. At this level, it is possible that the robustness assessment of pipe deflection would require additional information concerning the corrosion processes. Moreover, as the number of pipe service years increases, the pipe robustness behaviour tends to normalise and shows a similar trend, which illustrates the ductility nature of the pipe material. For the other failure modes, the results show similar behaviour as the number of service years increases

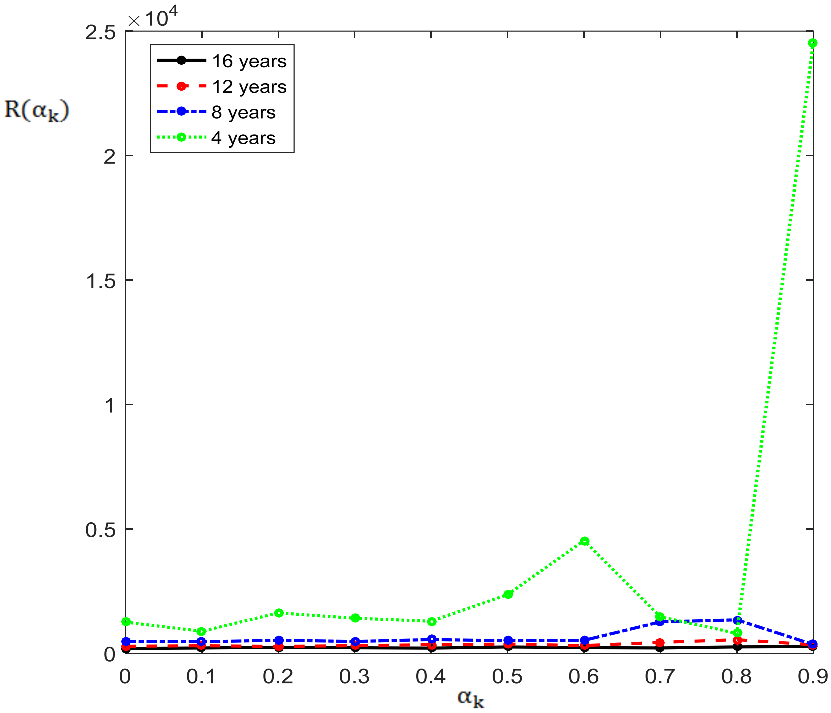


(a) Deflection

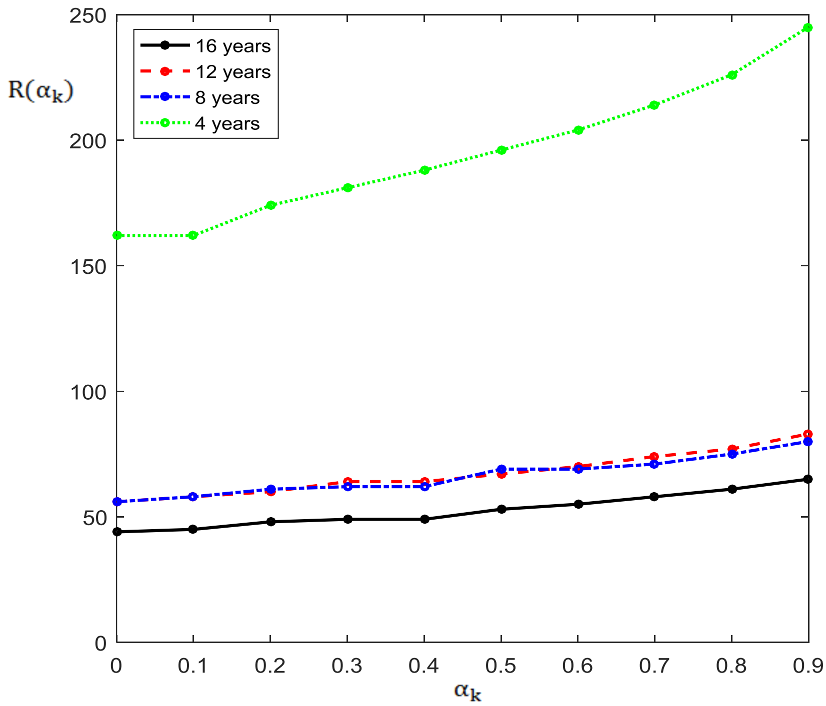


(a) Wall stress/thrust

Figure 4.11: Fuzzy-based robustness assessment of buried pipe (a) deflection (b) wall stress/thrust



(a) Bending strain



(b) Buckling pressure

Figure 4.12: Fuzzy-based robustness assessment of buried pipe (a) bending strain (b) buckling pressure

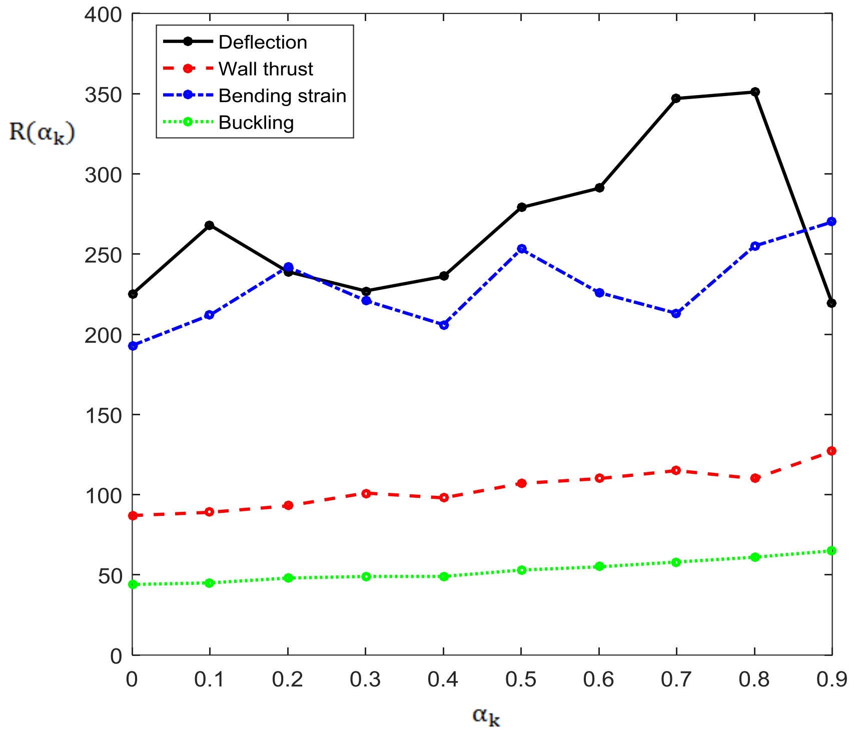


Figure 4.13: Fuzzy-based robustness assessment of buried pipe after 16 years

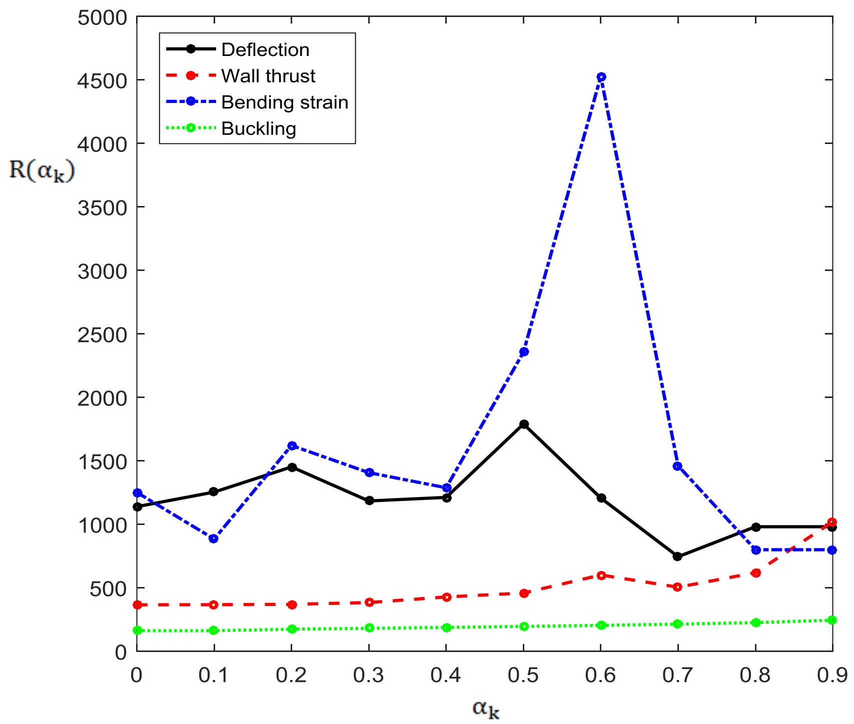


Figure 4.14: Fuzzy-based robustness assessment of buried pipe after 12 years

Consequently, the outcome of the four different years (4, 8, 12, and 16 years) shows that the values evaluated for the pipe robustness measure would continue to decrease as the number of pipe service years continues to increase. For instance, the pipe robustness values for the failure mode of deflection for different alpha levels between α_1 to α_{11} reduces from (1,139, 1,254, 1,452, 1,184, 1,212, 1,790, 1,207, 745, and 981) in 4 years to (225, 268, 240, 228, 237, 279, 292, 347, and 351) in 16 years. This demonstrates that the level of uncertainty based on the adverse effect of corrosion-induced failure could potentially reduce the performance of the buried pipe. In the same way, for an exposure time of 4 and 16 years, the pipe failure modes of deflection and bending strain expresses close behaviour while that of wall thrust and buckling are quite similar. This could mean that the buried pipe shows more resistance against deflection and bending other than wall thrust and buckling as illustrated in Figure 4.13 and Figure 4.14.

4.6 Chapter Summary

In this Chapter, a methodological approach for the assessment of fuzzy-based robustness behaviour of the buried pipe is presented. The concepts behind the method and including the computational procedure are explained. The fuzzy-based robustness problem is formulated based on the failure modes of a buried steel pipe and includes pipe deflection, wall thrust, buckling pressure, and bending strain using the principles of fuzzy set and Shannon’s entropy. The proposed method gains its effectiveness in the assessment of the structure by scrutinising the robustness at every membership level. Other pipe failure modes due to corrosion can be analysed using the proposed method. The fuzziness associated with the corrosion effects at various times in the life of a buried steel pipe are quantified using a fuzzy model and based on the immersion corrosion data collected by Melchers (2003). Corrosion is used as a fuzzy variable in order to account for the uncertainties that characterise the corrosion processes. The estimation of pipe robustness is conducted by considering various levels of uncertainties that affect the performance of the buried pipe, and the modelling of the failure modes based on fuzzy sets, which considers various levels of the α-level cut. The outcome illustrates that evaluating the performance of buried steel pipe using the fuzzy-based robustness measure can deliver a wide-ranging understanding concerning the adverse effect of corrosion uncertainty to the examined pipe failure problems. This result can lead to an optimal decision concerning buried pipe structures where a degree of accuracy is needed. The proposed method can be used to assess any type of corrosion-induced failures for buried pipe and also for other engineering structures. The consequences posed by the uncertain variables for the design of buried pipeline requires an adequate level of reliability. As a result, a multi-objective optimisation of buried pipe based on the expected fuzzy output is proposed in Chapter 5. The formulation is based on fuzzy set and multi-objective optimisation for a robust analysis of a buried pipeline.

CHAPTER FIVE

5 MULTI-OBJECTIVE OPTIMISATION OF BURIED PIPE BASED ON THE EXPECTED FUZZY OUTPUT

5.1 Introduction

Buried pipelines are usually designed based on deterministic parameters and without considering the randomness and fuzziness associated with the design parameters. However, the limitation of the deterministic approach has paved the way for other models in many scientific works. Therefore, the evaluation of the performance of buried pipe based on the deterministic parameter is undoubtedly a simplification because the measurement of pipe or soil parameters such as elastic modulus always shows variability and randomness.

The concept of robust design optimisation (RDO) has been introduced in the literature to deal with the uncertainties that are random, but the occurrence of variables that are vague and cannot be ignored from the practical point of view. Considering the consequences posed by the uncertain variable for the design of buried pipe, an adequate level of reliability on the performance is required for design purpose. However, given the benefit of the fuzzy model approach in modelling uncertainties associated with design parameters, its capability is employed in the multi-objective optimisation of buried pipe. Therefore, this Chapter presents a formulation based on fuzzy set and multi-objective optimisation for a robust analysis of a buried pipe structure. The proposed approach employs the optimal performance of a Hybrid GA-GAM for the optimisation, and the purpose is to optimise the design variable while considering the adverse effect of the uncertain fuzzy variables and variability of the structural performance.

The remaining part of this Chapter is summarised as follows: Section 5.2 presents the concept of robust design optimisation while Section 5.3 describes the fuzzy-based robust multi-objective design optimisation. Section 5.4 explains the Hybrid GA-GAM, which include a GA, Goal Attainment Method (GAM), Hybrid GA-GAM and the methodology. The numerical example is explained in Section 5.5, while Section 5.6 presents the results and the significant findings from the study. Finally, Section 5.7 shows the Chapter summary, which summarises the outcome of the study.

5.2 The Concept of Robust Design Optimisation

Generally, the optimum design of a structural system can be expressed by the following expression in Eq. (5.1).

$$\begin{aligned} \max/\min \quad & F(y) \\ \text{subject to} \quad & g_i(\mathrm{y}, \theta) \leq 0, \quad \mathrm{i} = 1, \dots, \mathrm{I}, \\ & h_j(\mathrm{y}, \theta) = 0, \quad \mathrm{j} = 1, \dots, \mathrm{J}, \\ & s_k(\mathrm{y}) \leq 0, \quad \mathrm{k} = 1, \dots, \mathrm{k} \end{aligned} \tag{5.1}$$

Where y is the vector of the design variable, θ is the vector of the uncertain structural parameter, $F(y)$ is the objective or the cost function, g_i, $\mathrm{i} = 1, \dots, \mathrm{I}$ and h_j, $\mathrm{j} = 1, \dots, \mathrm{J}$, denotes the functions that define a set of inequality and equality constraints, and $s_k, k = 1, \dots, k$, are functions that represent the sets of deterministic constraints.

The design variables can be the structural parameters representing or defining the shape or the dimensions of the structure. The objective and constraint function could represent the limitations of the structural performance. For the buried pipe problem, the solution to the problem relating to Eq. (5.1) can be sensitive to changes that may occur from different sources such as geo-environmental conditions. These include corrosion, temperature variation, pressure and humidity fluctuation, and changes in material properties. Based on these issues, the principal target is to provide an optimal design with a high degree of robustness. The process of finding an optimal solution with some level of robustness is called RDO. For more information, the reader can refer to the works of (Beyer & Sendhoff, 2007; Doltsinis & Kang, 2004; Schuëller & Jensen, 2008).

The design of a structure using the principles of robust design is considered as an optimised design because the technique considered the uncertainties that are explicit in the optimisation process (Schuëller & Jensen, 2008). In the literature, the concept of RDO has been used in different engineering applications. The design of engineering structures always involves a considerable level of uncertainties, and the design engineer needs to take care of it at the design stage. Many approaches, design guides, and codes have been developed for different ranges of engineering problems to support the decision of the designer and also achieve the best solution for a particular case. The structural performance often exhibits high sensitivity to the natural variability of the data. Therefore, conventional robust design can be formulated as:

$$\min_{y} \{\langle f(y,d)\rangle, \sigma[f(y,d)]\} \;\; s.t. \check{h}_j(y,d) \le 0 \;\; j = 1,\ldots,J \quad y^l \le y \le y^u \tag{5.2}$$

Where $f(y,d)$ is the performance or objective function, $\langle . \rangle$ and $\sigma[.]$ are the expected value and the standard deviation operators; y is the design vector and d is the vector of the uncertain variables, y^l and y^u are the lower and upper limits.

5.3 Fuzzy-based Multi-objective Design Optimisation

5.3.1 Fuzzy Design Optimisation

Marano & Quaranta (2008) stated that the expected value and the entropy of the fuzzy variable are often in conflict. As a result, it is ideal to adopt a robust strategy with the intention of solving the Multi-Objective Optimisation Problem (MOOP) and possibly be able to define the equivalent Pareto front. However, searching for the Pareto optimal set for a multi-objective function is the primary goal of the optimisation algorithm. For an engineering problem, finding an optimum solution of a function based on the single objective is limited and does not account for other functions in justifying the outcomes and the evaluation of the optimal design solutions. Therefore, it is important to consider a multi-objective function in the optimisation process so that an accurate representation of the structure is reflected in the evaluation of the Pareto front for the design of an engineering structure.

The use of fuzzy set in the robust design of structures has been studied in the literature (Fang et al., 2016; Marano & Quaranta, 2008). Herein, fuzzy-based multi-objective design optimisation is utilised in the structural analysis of buried pipe. A fuzzy variable can be defined as a function from a possibility space to the set of real numbers (Marano & Quaranta, 2008) and the membership function of every fuzzy variable could be expressed from the possibility measure as explained in (Liu, 2004). The computation of the membership function of a fuzzy variable is one of the challenging factors for a structural analysis using fuzzy set theory. However, different methods have been adopted in the literature to achieve or construct the membership function. For instance, Klir (2006) suggested that the construction of the membership function could be done using direct or indirect information from a single expert or multiple experts. A vector is fuzzy if and only if all the elements is a fuzzy variable (Liu, 2004).

5.3.2 Fuzzy Variable and the Expected Value

The expected value of a fuzzy output variable plays a vital role in the fuzzy-based multi-objective design optimisation. If a fuzzy variable and the membership function are represented as x and $\mu(x)$, then, the corresponding fuzzy set model can be expressed as shown in Eq. (5.3)

$$F = \{((x, \mu(x))| x \in \mathbb{R}, \mu(x) \in [0,1] \ )\} \tag{5.3}$$

Where ℝ is the universal set.

Also, if a fuzzy variable x with assigned membership function $\mu(x)$, is specified, then the following formula in Eq. (5.4), Eq. (5.5), Eq. (5.6) can be utilised to calculate the credibility (Liu, 2004; Marano & Quaranta, 2008). The credibility of a fuzzy variable can be defined as the average between the possibility and the necessity values (Marano & Quaranta, 2008)

$$\mathrm{Cr}\,\{x = \rho\} = \frac{1}{2}(\mu(\rho) + 1 - \sup_{z \neq \rho}\{\mu(z)\}) \quad \forall \mathrm{d} \in \mathbb{R} \tag{5.4}$$

$$\mathrm{Cr}\,\{x \leq \rho\} = \frac{1}{2}(\sup_{z \leq \rho}\{\mu(z)\} + 1 - \sup_{z > \rho}\{\mu(z)\}) \quad \forall \mathrm{d} \in \mathbb{R} \tag{5.5}$$

$$\mathrm{Cr}\,\{x \geq \rho\} = \frac{1}{2}(\sup_{z \geq \rho}\{\mu(z)\} + 1 - \sup_{z < \rho}\{\mu(z)\}) \quad \forall \mathrm{d} \in \mathbb{R} \tag{5.6}$$

Based on this concept of credibility measure, the expected value of a fuzzy variable can be determined using the expression given in Eq. (5.7) (Liu & Liu, 2002).

$$\mathrm{E}[x] = \int_0^{+\infty} \mathrm{Cr}\,\{x \geq \rho\} d\rho - \int_{-\infty}^{0} \mathrm{Cr}\,\{x \leq \rho\} d\rho \tag{5.7}$$

This expression provides a general statement for the expected value of a fuzzy variable. For a continuous fuzzy variable, if the membership function follows a monotonically increasing law in the range of $[-\infty, \rho_o]$ and a monotonically decrease in the range of $[\rho_o, +\infty]$, therefore a more convenient rule could be adopted as shown in Eq. (5.8) (Liu & Liu, 2002; Marano & Quaranta, 2008). This expression can be used to evaluate the expected value of the fuzzy variable.

$$\mathrm{E}[x] = \rho_o + \frac{1}{2}\int_{\rho_o}^{+\infty} \mu(\rho) d\rho - \frac{1}{2}\int_{-\infty}^{\rho_o} \mu(\rho) d\rho \tag{5.8}$$

5.3.3 Entropy Value of a Fuzzy Variable

The concept of fuzzy entropy can be used to analyse and quantify uncertainties associated with the design parameters. The fundamentals of Shannon's entropy could provide the desired information of the total amount of uncertainty contained in the fuzzy set. Therefore, Shannon's entropy can be used as an integral part of information theory to assess the performance of the structural system. The concept of entropy plays a significant role in measuring the fuzzy information such as evaluation of fuzzy degree between two fuzzy sets. In the literature, there are various expressions for computing fuzzy entropy that has been proposed; however, see the work of (Beer & Liebscher, 2008; Liu, 2007; Liu & Liu, 2002) for more information.

From Eq. (5.8), if a continuous variable tends to be a crisp number, its entropy tends towards the minimum value of zero. Herein, the suggestion by Liu (2007) is used, where the entropy of a continuous fuzzy variable is defined as expressed in Eq. (5.10).

$$H(x) = \int_{-\infty}^{+\infty} (-C(\rho) \ln C(\rho) - (1 - C(\rho)) \ln(1 - C(\rho))) \mathrm{d}\rho \tag{5.9}$$

Where $C(\rho) = Cr(x = \rho)$ and for a continuous fuzzy variable x, $C(r) = Cr(x = \rho) = \frac{1}{2}\mu(\rho)$, thus

$$H(x) = -\int_{-\infty}^{+\infty} \left(\frac{1}{2}\mu(\rho) \ln \frac{1}{2}\mu(\rho) + \left(1 - \frac{1}{2}\mu(\rho)\right) \ln \left(1 - \frac{1}{2}\mu(\rho)\right)\right) \mathrm{d}\rho \tag{5.10}$$

From Eq. (5.8) and (5.10), the expectation and the entropy of a fuzzy variable can be computed as soon as the membership function is given.

5.3.4 Formulation of Fuzzy-based Multi-objective Design Optimisation

The design of engineering structure has moved from single objective optimisation to evaluating an optimal solution by considering multi-objective functions. This is because the design of engineering structures requires a resolution of conflicting objectives. Based on the fuzziness of the uncertain parameters for a particular structure, the fuzzy-based multi-objective design optimisation problem can be formulated as expressed in Eq. (5.11).

$$\min_{y} \{E_1[f_1(y, \check{d})], E_2[f_2(y, \check{d})]\}$$
$$Subject\ to\ \check{h}_j(y, \check{d}) \leq 0 \quad j = 1, \dots, J \quad y^l \leq y \leq y^u \tag{5.11}$$

Where $f_1(y, \check{d})$ and $f_2(y, \check{d})$represent the performance function based on design and fuzzy variable for objective 1 and obejective 2; $E_1[.]$ and $E_2[.]$ are the expected values of the fuzzy variable based on objective 1 and obejective 2. $\check{d}$ is the fuzzy vector of the uncertain variable and y is the design vector where $y^l\ and\ y^u$ are the lower and upper values of the design vector. Based on this idea, it is vital to observe that each of the constraints h_j is a fuzzy variable and it is important to extract a specific value $\check{h}_j$ from the fuzzy output variable.

Since most engineering structures are associated with more than one objective, therefore, employing multi-objective optimisation technique becomes a vital aspect for the optimal design (Zhang et al., 2017). Also, it is essential to consider the opportune strategies with the intention of solving the MOOP to obtain the Pareto front. In practice, the decision with regards to the final solution to be used based on the outcome of the Pareto front is formulated by the decision maker. However, a preference-based method which allows preference information to be used in the search to influence the Pareto optimal solution can be used (Coello, 2000). The search for the Pareto optimal set can be determined through the use of any multi-objective optimisation algorithm. Herein, the optimisation is performed using a Hybrid GA-GAM algorithm to determine the Pareto front. This approach is briefly discussed in the next Section.

5.4 Hybrid GA-GAM Approach

5.4.1 Genetic Algorithm (GA)

GA is a population-based metaheuristic algorithm that is widely used for most optimisation problems because of its robust and independent objective function (Li & Lu, 2014; Garg, 2016; Goldberg, 1989; Fonseca & Fleming, 1993). The concept uses the survival of the fittest and a biological mechanism to process a set of solutions iteratively in order to converge and produce an optimum solution. The survival of the fittest which GA adopts is based on Darwinian's theory that begins with a set of solutions denoted as chromosomes, called population. The solutions determined from one population would be used to form another new population, and that population is motivated based on the likelihood that the new population will be preferred when compared to the older population. In addition, the solutions are selected based on their fitness to form a new solution. The computational steps in executing GA is given in Chapter 6, Section 6.3.1.

5.4.2 Goal Attainment Method (GAM)

GAM is usually employed to solve a MOOP. As suggested by Chankong & Haimes (1983), GAM is a powerful optimisation tool that can determine the best possible solution to a multi-objective problem. The GAM approach has the advantage of posing or being converted as a non-linear programming problem (Fonseca & Fleming, 1993) and the characteristic of the problem can be exploited in a non-linear programming algorithm. The GAM method is used as the hybrid solver, and for more information, the reader can refer to (Fonseca & Fleming, 1993).

5.4.3 Hybrid GA-GAM and Multi-objective Design Optimisation

Multi-objective optimisation is an approach to determine a vector of design variables that are located within a feasible region, which minimises the vector of the objective function that could conflict with one another (Cheng & Le, 1997). The optimal solution is called the Pareto front, and this is obtained based on the concept of dominance. The formulation of the multi-objective optimisation takes the form of the expression in Eq. (5.12).

$$\min \{f_1(y), f_2(y), \ldots, f_n(y)\} \ \ subject\ to\ g(y) \leq 0 \tag{5.12}$$

Where y denote the vector of design variables; $f_1(y)$ represents the ith objective function and $g(y)$ is the constraint vector.

The multi-objective optimisation algorithm tries to locate the best sets of solutions that could satisfy the various objective/constraint functions to form the Pareto optimal set. The solution of the multi-objective function is always situated in its Pareto optimal front set (Cheng & Le, 1997; Deb, 2001). The Pareto optimum gives a set of non-dominated solutions, which also varies depending on the search technique. These are solutions for which no objective could be improved without detracting from the other objective functions. The multi-objective programme does not have a unique solution that can simultaneously optimise all the objective functions (Cheng & Le, 1997; Deb, 2001). Therefore, any point located within the Pareto optimal set can become an 'optimum solution,' which invariably depends on the decision of the design engineer. For more details on multi-objective optimisation, the reader can refer to (Cheng & Le, 1997; Deb, 2001; Tang et al., 2011). The rationale behind the introduction of GAM as the hybrid solver for the MOOP is to utilise its efficiency in local search and to enable evaluation of fewer functions in order to achieve convergence. The procedure for evaluating the Hybrid GA-GAM function is described in the following steps.

1. Define the objective functions, and set the operators of the GA, e.g. population size, parent/offspring ratio, selection methods, and mutation rate.
2. Initialise the parameters and generate initial population.
3. Set the solution counter $i = 1$.
4. Calculate the number of solutions n_i that dominates solution i.
5. Compute the rank r of the $i -$ th solution as $r_i = 1 + n_i$. This will increase the number of count of the solutions in rank r_i by one. That is $\mu(r_i) = \mu(r_i) + 1$.
6. If the solution counter i is less than the number of population P_n i.e. $i < P_n$, increase i by one and go to step 2. Otherwise, go to step 7.
7. Identify the maximum rank r_{max} by checking for the biggest r_i which has $\mu(r_i) > 0$. Then, set a rank counter $r = 1$.

8. For each solution i in the rank r, evaluate the niche count nc_i with the other solutions of the same rank.
9. If the rank $r < r_{max}$, increase the rank r by one and go to step 7. Otherwise, go to step 10.
10. Perform a local search on each solution using GAM, compute the corresponding fitness of each new location, and replace the solution if there is a locally improved option.
11. If convergence is achieved, stop the algorithm. Otherwise, got to step 3.

5.4.4 Methodology

Figure 5.1 shows a flow diagram for the computation. Also, the steps used to determine the response of the fuzzy-based multi-objective design optimisation of an engineering structure considering the expected values of the fuzzy output variable based on objective 1 and objective 2 using a Hybrid GA-GAM algorithm are summarised as follows:

- Initialise the input parameters.
- Evaluate the expectation of the fuzzy structural response based on objective 1 and objective 2 using Eq. (5.8).
- Construct the mathematical formulation for the fuzzy-based multi-objective design optimisation as explained in Section 5.3.4.
- Perform the multi-objective optimisation using the Hybrid GA-GAM algorithm as explained in Section 5.4.3.
- Check whether the constrained is satisfied.
- Use the maximum and minimum values in the Pareto front for the computation of the fuzzy structural response and perform the fuzzy entropy-based analysis.

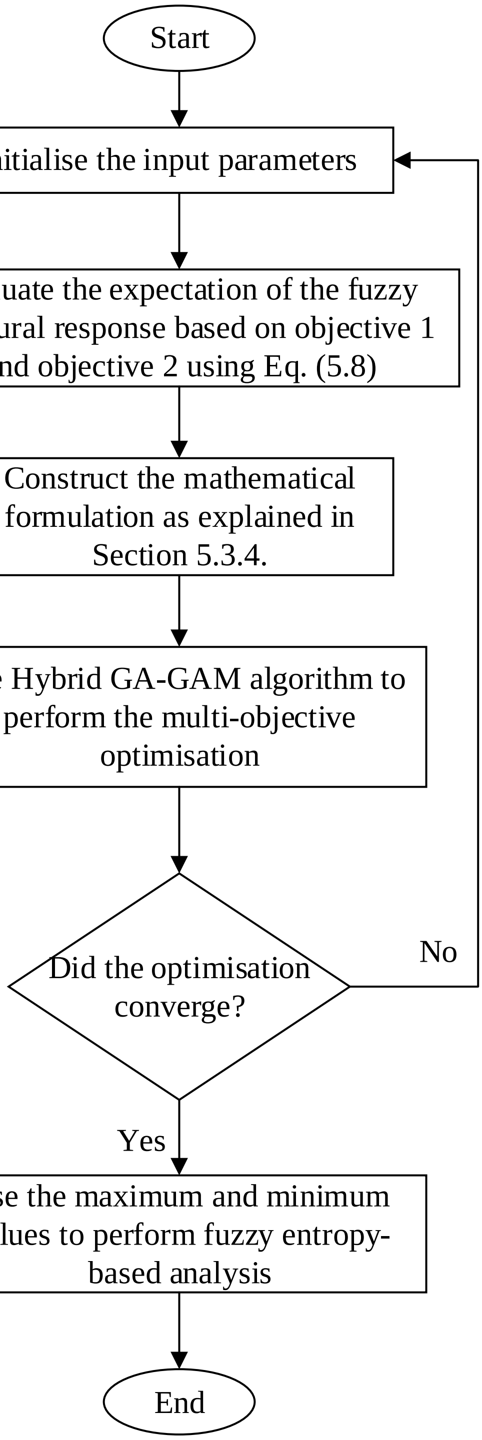


Figure 5.1: Flow diagram of fuzzy entropy analysis using multi-objective optimisation

5.5 Numerical Example

The purpose of this numerical example is to demonstrate the applicability and the confidence level in the design of buried pipeline by incorporating a multi-objective optimisation approach. The method is used to analyse the performance of buried pipe structure based on multi-objective functions considering the design variables and the uncertain fuzzy variables. The possible pipe failure modes used in the analysis include (i) ovality of pipe, and (ii) buckling pressure. For details concerning the pipe failure, see Chapter 3, Section 3.3. The statistical values of the soil and pipe parameters used in the computation are given in Table 3.3 and 3.4. The values are based on industry standard and have been obtained from the works of (Ahammed & Melchers 1994; Sadiq et al. 2004; Tee et al. 2014).

As a useful extension, the effect of corrosion on the buried pipe is assessed herein using the intrinsic features of a fuzzy set to develop the membership function. In this case, the sensitivities of the responses with respect to the uncertainties associated with the empirical constants are analysed, and an acceptable interval size determined and used to construct the membership function as illustrated in Figure 5.2 and for the exposure period of 25, 50 and 100 years. This approach provides the possibility to consider a gradual assessment of the uncertainties in relation to interval values. Generally, Marano et al. (2008) suggested that it is possible to state that a unitary approach does not exist for the so-called fuzzification, but different procedures can be adopted for each situation. Therefore, the methods for constructing the membership function of a fuzzy variable can be direct or indirect with a single expert or multiple experts (Klir, 2006; Marano et al., 2008). For more information, see (Klir & Yuan, 1995; Klir, 2006). Herein, the reason for treating corrosion as a fuzzy variable is to account for the uncertainties in the values of the parameters that characterise the environment, variables that affect the time to corrosion initiation, and the rate of corrosion propagation (Anoop & Balaji, 2007; Marano et al., 2008).

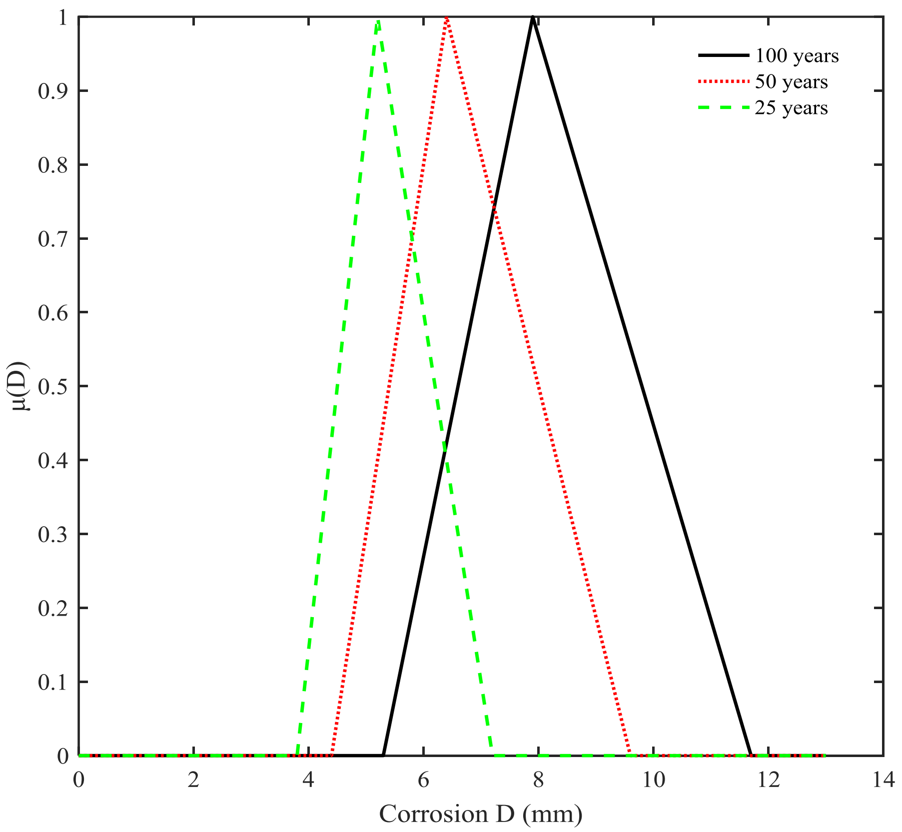


Figure 5.2: Corrosion pith depth at T = 25 years, 50 years and 100 years

5.6 Results and Discussion

The applicability and the usefulness of the proposed method are demonstrated using the numerical example in Chapter 3, Section 3.7. The output of the multi-objective optimisation is the Pareto front as shown in Figure 5.3. In this work, a Hybrid GA-GAM as explained in Section 5.4.3 is used for the multi-objective optimisation, and the outcome has been compared with the GA. It is clear from Figure 5.3 that the performance of the two methods is very close. However, for the Hybrid GA-GAM approach, a total of 7255 function evaluations was needed to converge while the GA used a total of 10051 function evaluations. The two optimisation algorithms have been measured running on a central processing unit (CPU) time using a 1.60 GHz Pentium 4 computer. The time taken for the former to converge is 23 minutes while the latter used about 35 minutes. Based on the execution time, it can be concluded that the difference in time is not significant. However, the introduction of the Hybrid GA-GAM has enabled evaluation of fewer functions to achieve convergence. The GA is performed independently for the assessment of the optimal solution from the multi-objective function. The rationale behind this is to act as a verification and validation of the results from the Hybrid GA-GAM approach. Herein, the primary aim of using the Hybrid GA-GAM for the multi-objective optimisation is to find the minimum pipe thickness that could satisfy the design intent by considering the possible failure conditions. The multi-objective optimisation is considered in order to ascertain the trade-offs between the failure conditions of the buried pipe. The purpose of applying a Hybrid GA-GAM algorithm is to perform the optimisation with the goal of finding a set of Pareto front values for the pipe thickness that can withstand the adverse effect of corrosion.

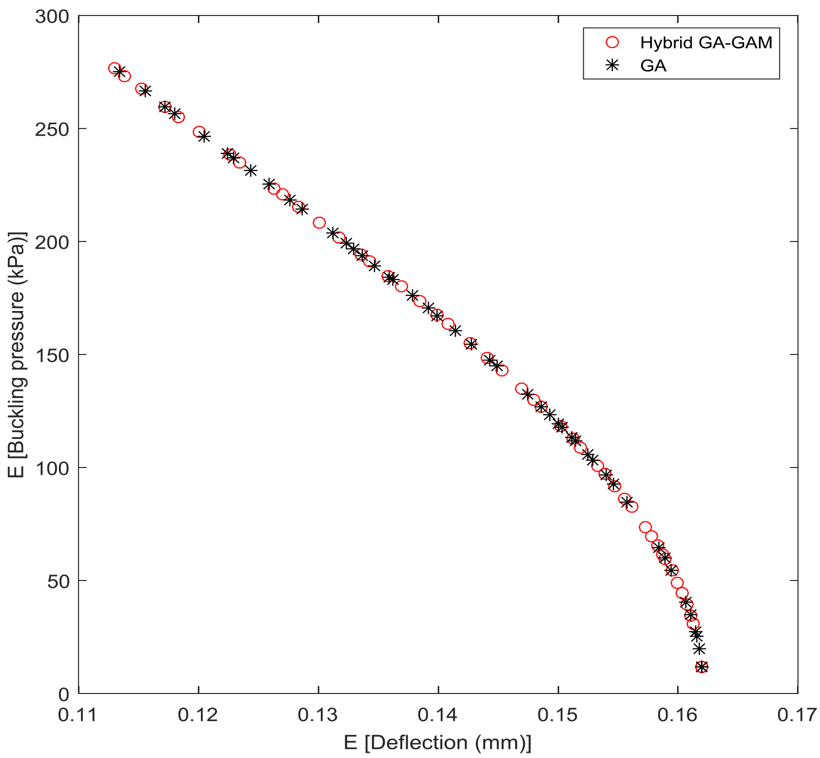


Figure 5.3: The Pareto front for pipe design based on GA and Hybrid GA-GAM

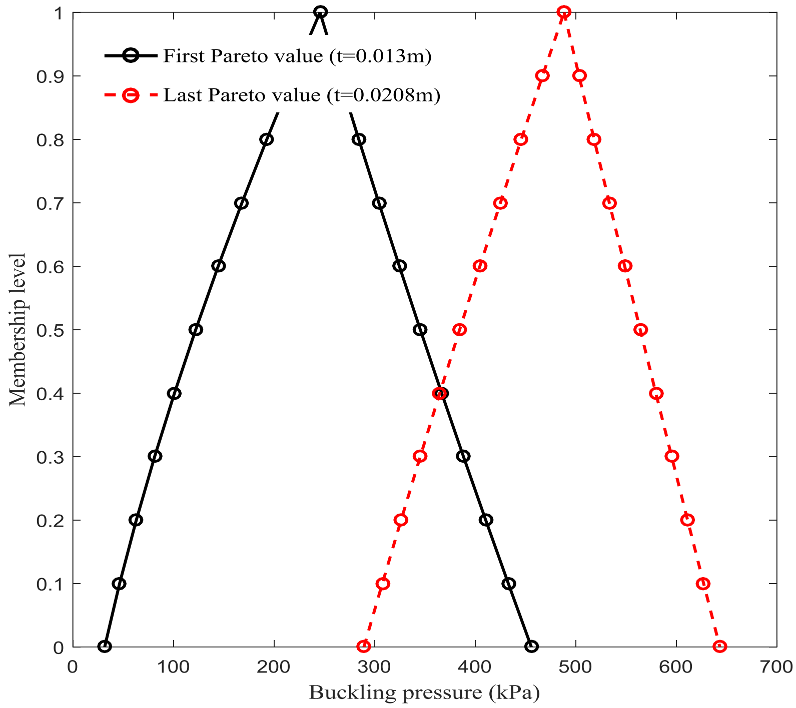


Figure 5.4: Performance of buried pipe due to buckling pressure after 100 years

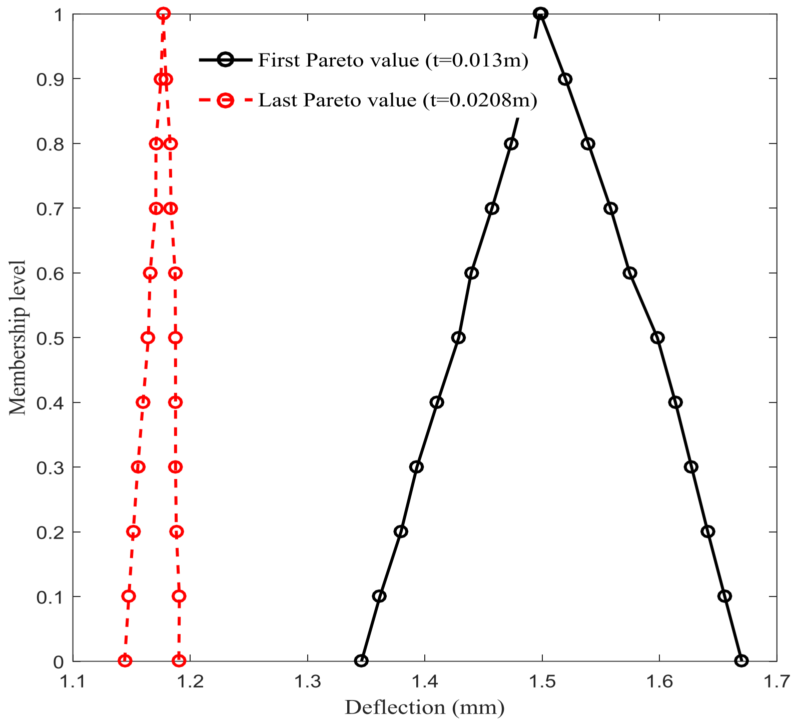


Figure 5.5: Performance of buried pipe due to deflection after 100 years

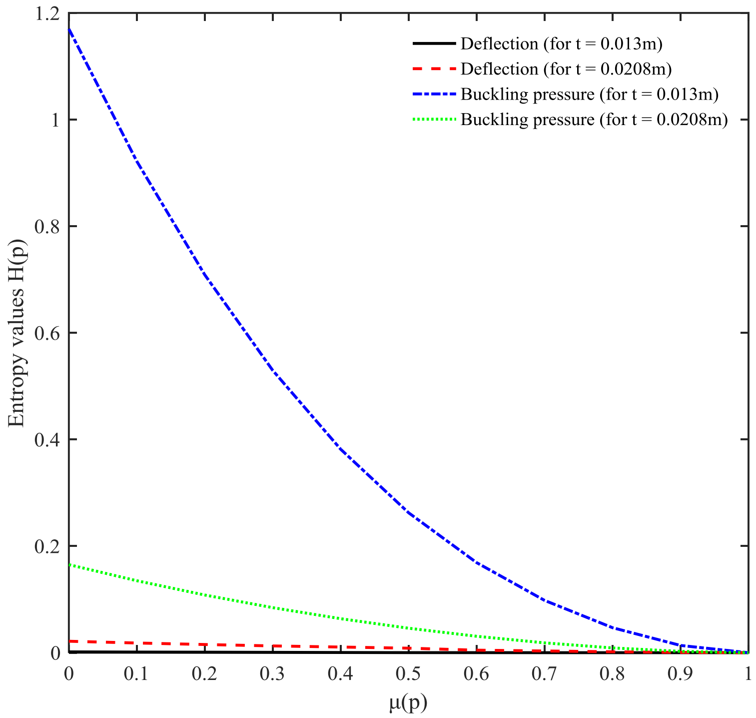


Figure 5.6: Fuzzy entropy state of buried pipe after 100 years

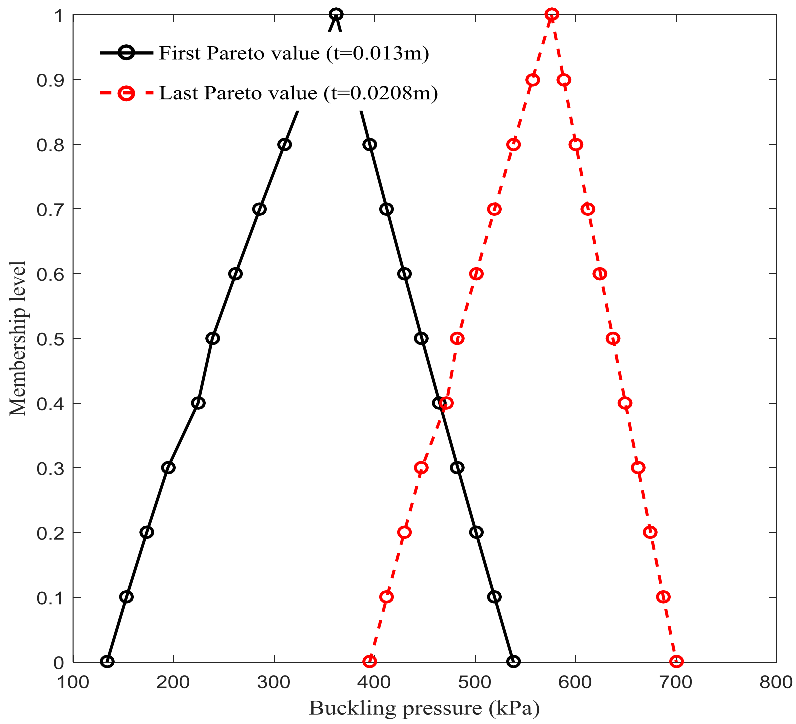


Figure 5.7: Performance of buried pipe due to buckling pressure after 50 years

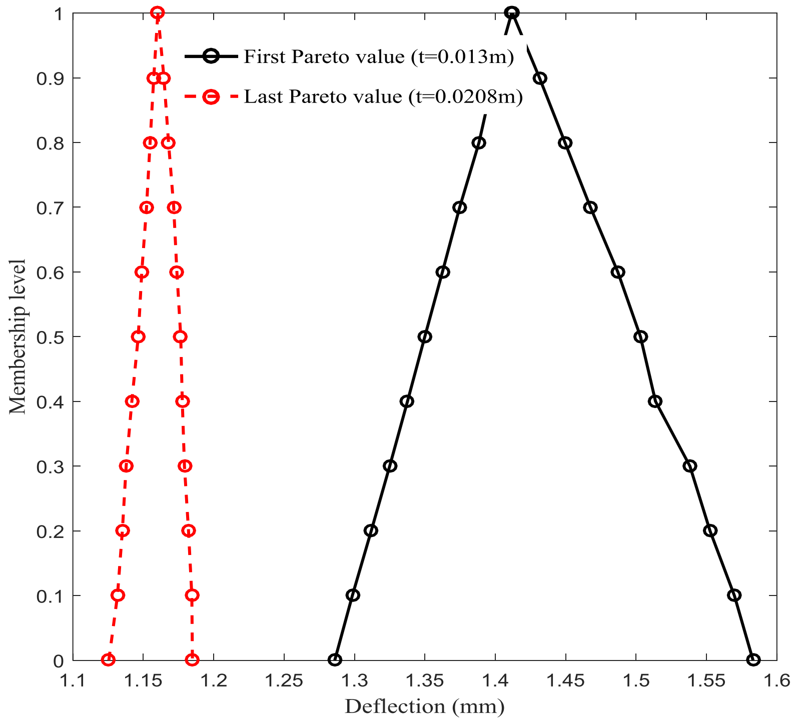


Figure 5.8: Performance of buried pipe due to deflection after 50 years

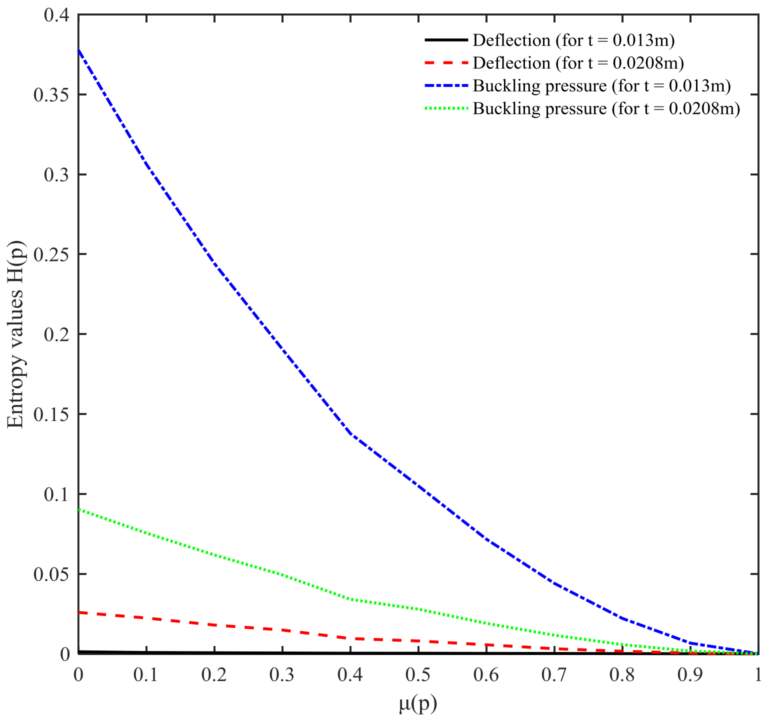


Figure 5.9: Fuzzy entropy state of buried pipe after 50 years

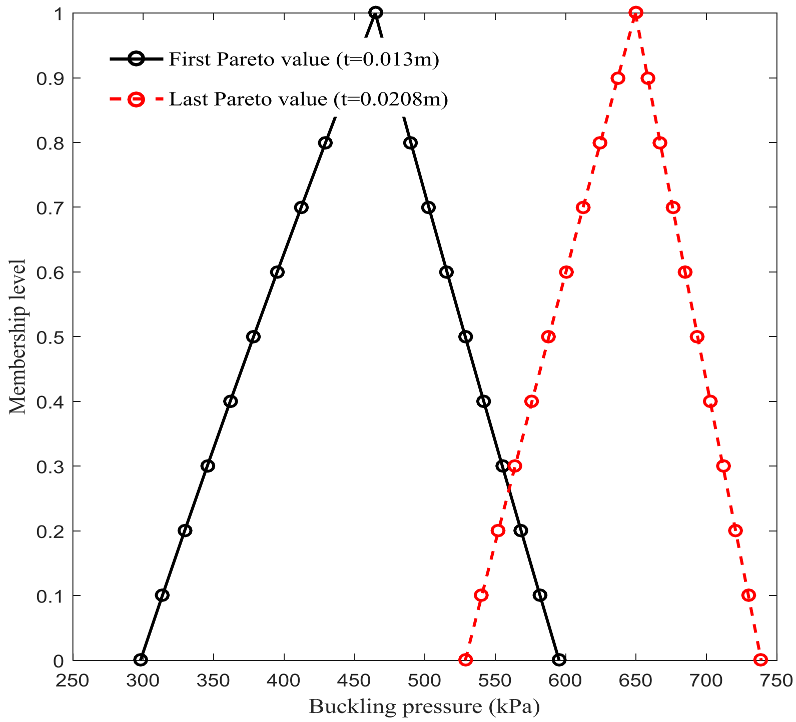


Figure 5.10: Performance of buried pipe due to buckling pressure after 25 years

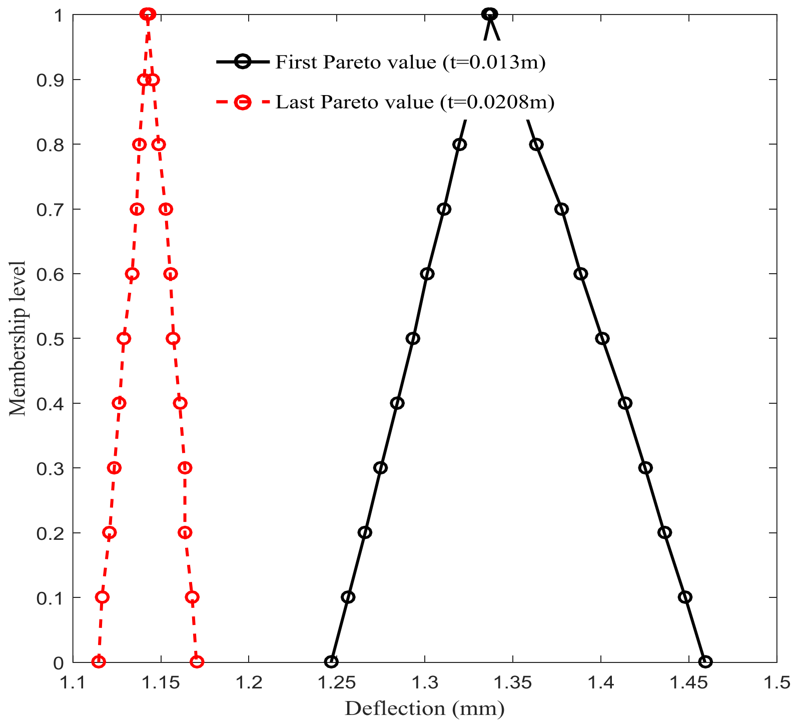


Figure 5.11: Performance of buried pipe due to deflection after 100 years

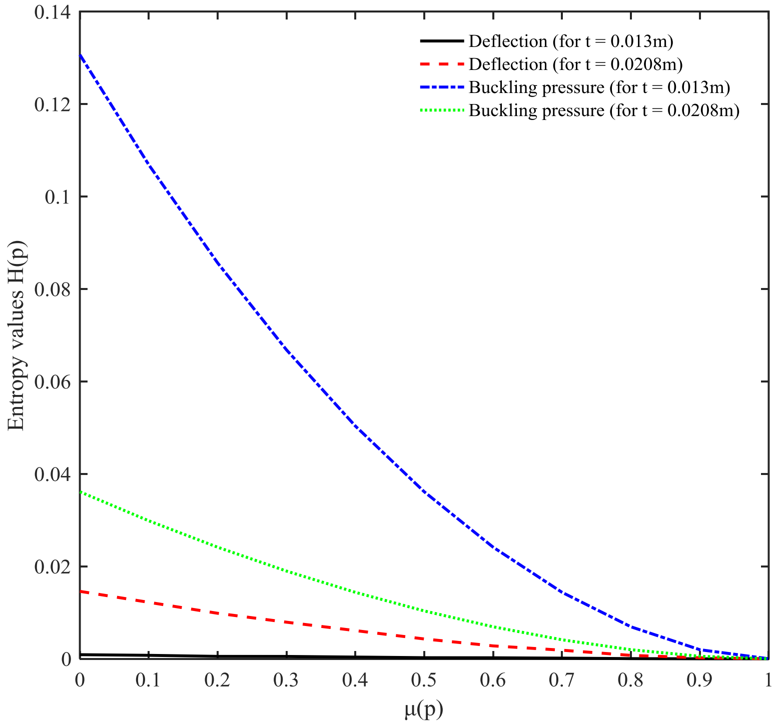


Figure 5.12: Fuzzy entropy state of buried pipe after 25 years

From the Pareto front, the two extreme values were used in the computation of the fuzzy structural response of buried pipe, and the results are shown in Figures 5.4 and 5.5 for the failure mode of buckling pressure and pipe deflection respectively. The first extreme value of the optimal solution set (black line and circle markers) is characterised by less performance, less robustness, and more significant variability. The investigated pipe failure conditions give a small value of the fuzzy output as against the second extreme value, but also a substantial value of the fuzzy entropy for buckling pressure as shown in Figure 5.6. Similarly, the second optimum outcome is used in the computation of fuzzy structural response for the same number of years. The result from this is characterised by best performance, greater robustness, and less variability. Figures 5.4, 5.5, and 5.6 demonstrate how the expected value of the fuzzy variable and the fuzzy entropy values vary with regards to the maximum and minimum values for the design variable. The outcome of this investigation shows that the two failure conditions of the pipe are in mutual opposition with regards to design variables and the expected entropy values. Evidently, on the grounds of Figures 5.3, 5.4, 5.5, and 5.6, the designer or decision maker could have the opportunity to decide on the final solution for a buried pipe having 100 years of design life.

Subsequently, for the design life of 50 years and 25 years, a similar analysis was performed to determine the optimal solution set. Again, the two extreme values were employed in the computation of the fuzzy structural response of buried pipe and the outcomes are shown in Figures 5.7, 5.8, 5.10 and 5.11. The first extreme value of the optimal solution set (black line and circle markers) is characterised by less performance, less robustness, and more significant variability. Similarly, the second optimum outcome is used in the computation of fuzzy structural response of buried pipe for the same number of years. The result from this is characterised by best performance, greater robustness, and less variability. Again, the investigated pipe failure conditions give a small value of the fuzzy output as against the second extreme value, but also a significant value of the fuzzy entropy for buckling pressure as shown in Figures 5.9 and 5.12.

The engineering application of fuzzy-based multi-objective design optimisation has proved to be an instrumental and vital part of pipe design, especially with corrosion uncertainty. It is worth stating that the results reported in this study are the primary motivation. Another contribution of this approach is the importance of analysing the fuzzy variables. By comparing the results of the fuzzy-based multi-objective design optimisation for different years of fuzzy variables and their corresponding impact on the failure conditions, the design engineer would be able to gauge the negative impact on the safety of the structure. Therefore, reducing the variability of the fuzzy variable, e.g., by performing more test or collecting additional information, could help to mitigate structural failure. In addition, a suggestion by Liu (2007) is used to compute the fuzzy entropy of a structural system. The approach is evaluated along the membership level, which permits the assessment of the variability and sensitivity of the structural response concerning various failure modes.

5.7 Chapter Summary

In this Chapter, an approach is presented for the optimum design of buried pipes involving design variables and fuzzy variables, using multi-objective optimisation algorithm. The method is based on the expected value of a fuzzy output variable for the pipe failure modes. The concepts and the processes of the proposed algorithm are introduced, and a numerical example is used to demonstrate its applicability and usefulness in the design of buried pipe structure. The outcome demonstrates that the uncertainty of the fuzzy variables for the input parameters could be propagated for the optimal design of buried pipe structure by employing a multi-objective optimisation algorithm for finding the optimal solution set. The fuzzy-based multi-objective design optimisation problem has been expressed by using the expected value of a fuzzy output variable for the pipe failure modes. The outcome of the expected value controls the performance of the optimal solution and the entropy deals with the variability and sensitivity of the structural problem.

Furthermore, a multi-objective optimisation is considered because it offers the potential to consider several mutually conflicting design requirements that are associated with pipe failure modes. Based on this, it is essential to locate the Pareto optimal set which plays a vital role for a pipe designer to decide, because of the opportunity of having a trade-off kind of analysis. Also, to improve the approach, other improved optimisation and multi-objective optimisation methods with better computational efficiency and require a lower number of function evaluations with regards to achieving convergence may exist in practice and could be used to improve the methodology. The possibility of using up to four and five objective functions can be included in the optimisation process. In practical design of buried pipeline, it is possible for fuzzy variables with membership functions and random variables with PDFs to co-occur. Based on this, the reliability analysis of buried pipeline based on fuzzy and subset simulation is proposed in Chapter 6. The method is based on the fuzzy set, subset simulation, and GA. The approach considers deterministic, random and fuzzy variables.

CHAPTER SIX

6 RELIABILITY ANALYSIS OF BURIED PIPE BASED ON FUZZY AND SUBSET SIMULATION

6.1 Introduction

The impact of uncertain variables can be propagated using the probabilistic method (e.g. MCS, IS, LS, and FORM) or non-probabilistic method (e.g. interval modelling and fuzzy set). Beer et al. (2013) suggested that the use of the probabilistic technique can be difficult because the data needed for the estimation of the mathematical statistics are always not available to a large extent. Therefore, the characterisation of the uncertain parameters based on PDFs may be subjective due to none availability of the required data in most cases. Also, the scarcity of information and partial knowledge of design parameters characterises the design of most engineering structures. Oftentimes, expert knowledge is usually used to quantify this type of vague information, rather than rigorous analysis.

In most practical engineering design, where there are various parameters involved, fuzzy variables with membership functions and random variables with PDFs could co-occur. This type of situation can be found in the design of buried pipes considering different loading and environmental conditions. As a result, the fuzzy reliability analysis of buried pipeline considering deterministic, random and fuzzy variables using optimisation based fuzzy-subset simulation approach is proposed in this Chapter. The approach relies on the performance function, which involves deterministic values, random and fuzzy variables. The rationale is to locate a failure domain or region where the objective function is minimised or maximised and compute the reliability using subset simulation.

The rest of this Chapter is organised as follows: Section 6.2 presents the propagation of uncertain input variables. Section 6.3 explains optimisation based fuzzy-subset simulation approach which includes the GA, Subset simulation, Markov Chain Monte Carlo, the proposed method and the applicability. In Section 6.4, the numerical example is presented, which includes investigation 1 for pipe ovality, investigation 2 for through-wall bending stress, and discussion. Section 6.5 presents the Chapter summary.

6.2 Propagation of Uncertain Input Variables

Usually, the uncertain input variables can be dependent or independent normal or non-normal random variables. The dependent normal random variables can be systematically transformed into the independent ones, and the dependent non-normal random variables can also be numerically transformed into the independent normal ones using Rosenblatt or Nataf transformation (Li & Lu, 2014).

The number of input variables $\boldsymbol{\theta} = (\theta_1, \theta_2, \dots, \theta_n)$ is denoted as $n = n_d + n_r + n_f$ where n_d denotes the number of deterministic parameter; n_f represents the number of fuzzy parameter; and n_r is the number of random parameter in a structural system. Therefore, the number of deterministic parameter n_d with values $\boldsymbol{\theta_d} = \theta$ can be described in the computational process using their corresponding values. The number n_r of input parameter (random variable) $\boldsymbol{\theta_r} = (\theta_1, \theta_2, \dots, \theta_{nr})$ are independent and random variables with PDFs $f_{\theta_i}(\theta_i)(i = 1, 2, \dots, n_r)$. Similarly, the number n_f of fuzzy parameter (fuzzy variable) $\boldsymbol{\theta_f} = (\theta_{n_r+1},\ \theta_{n_r+2}, \dots, \theta_n)$ are independent fuzzy variables, which are defined by their associated membership function $\mu_{\theta_j}(\theta_j)(j = n_r + 1, n_r + 2, \dots, n)$. The performance function $G(\theta_d, \theta_R, \theta_F)$ of the structure is the function of $\theta = (\theta_d, \theta_R, \theta_F)$, which involves deterministic values, fuzzy variables and random variables. Since the performance function of the engineering structure is associated with deterministic values, fuzzy and random variables, therefore the reliability would be fuzzy and it depends on the fuzziness of the fuzzy input variables. Consequently, the reliability of the structure is expressed as $P_r = P\{G(\theta) > 0\}$.

Figure 6.1 shows the propagation of the input variables based on fuzzy uncertainty in the determination of fuzzy reliability. For the membership function, the variation of a fuzzy variable is defined using lower and upper bounds, i.e. $\theta_F(\alpha) \in (\theta_F^l(\alpha), \theta_F^u(\alpha))$ for every $\alpha -$ level. $\alpha -$ levels are used to represent the discretised membership function of a fuzzy variable i.e. $\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_{10}$. Therefore, by mapping $P_r = P\{g(\theta_R(\alpha), \theta_F(\alpha)) > 0\}$ between $\theta_F(\alpha)$ and P_r, and the fuzzy reliability of the structure can be determined using any of the reliability method in the reduced random variable space at the bounds. The structural reliability can be computed at the bounds on $\theta_F(\alpha)$ for every membership level, which would lead to $P_r^l(\alpha)$ and $P_r^u(\alpha)$. So different membership levels would produce different bounds of reliability.

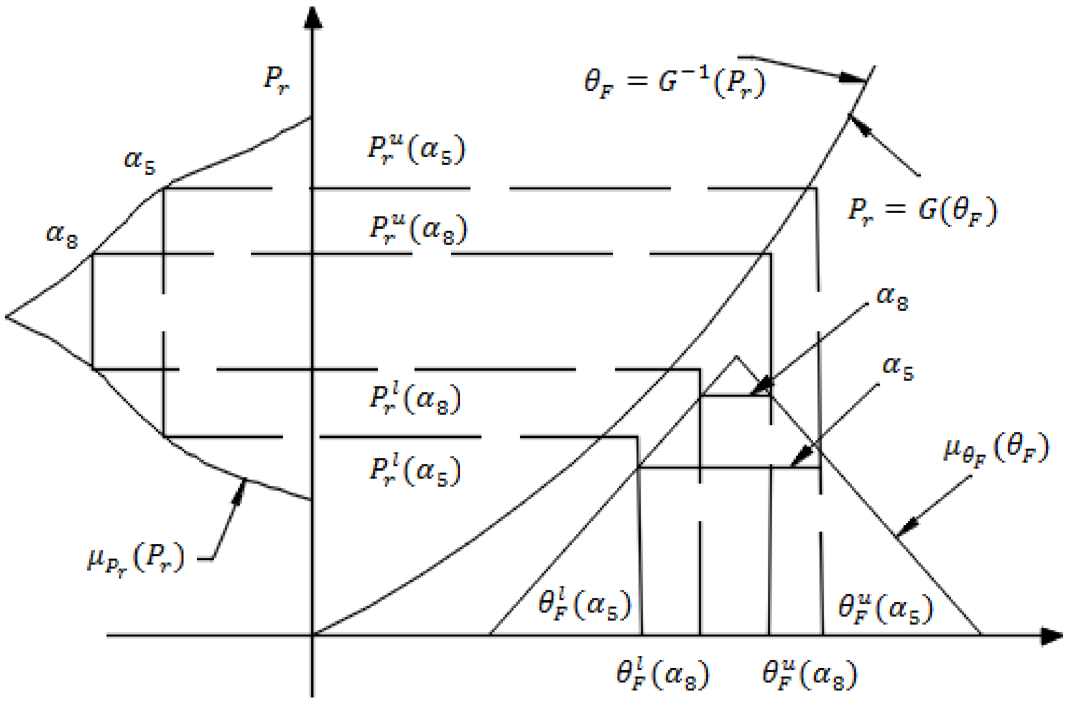


Figure 6.1: The propagation of input variables based on fuzzy uncertainty

6.3 Optimisation Based Fuzzy-subset Simulation Approach

Following the discussion on the propagation processes of the input parameters, it is evident that at every $\alpha - level$, the values of the fuzzy variables turn into sets of intervals. This means that the challenge of propagating the uncertainties of the fuzzy input variables becomes an interval analysis. The outcomes are bounding functions and consequently, an interval for the reliability of the structure. The combination of the interval nature of the uncertainty and the random parameters is carried out by performing a probabilistic assessment on every bound of the $\alpha - level$ set. As a result of this, the minimum and maximum values of the membership function of the fuzzy reliability of a structure can be estimated for every $\alpha - level$. The propagation of the uncertainty of the fuzzy input variables for the determination of the membership function of fuzzy reliability at every membership level can be seen as a double loop method, where the inner loop evaluates the fuzzy failure probability and the outer loop searches for the bounds at various alpha levels. A direct optimisation approach is employed to estimate the extreme values. Herein, a GA is used to compute the outer loop sampling, which would evaluate the desired interval outcome directly. On this basis, the structural reliability problem can be seen as a function of the random variable, the lower and upper values of the fuzzy variables and the deterministic values. Therefore, similar to the works of Eldred et al. (2011) and Li & Lu (2014), the computation of the fuzzy reliability can be seen as two optimisation problems and could be expressed as shown in Eq. (6.1) and Eq. (6.2).

$$\min P_R(\alpha) \qquad \text{subjected to} \quad \boldsymbol{\theta}_F^l(\alpha) \leq \boldsymbol{\theta}_F(\alpha) \leq \boldsymbol{\theta}_F^u(\alpha) \tag{6.1}$$

and

$$\max P_R(\alpha) \qquad \text{subjected to} \quad \boldsymbol{\theta}_F^l(\alpha) \leq \boldsymbol{\theta}_F(\alpha) \leq \boldsymbol{\theta}_F^u(\alpha) \tag{6.2}$$

6.3.1 The Outer Loop: Genetic Algorithm (GA) Approach

GA is a population-based metaheuristic algorithm that is widely used for most optimisation problems because of its robust and independent form of the objective function (Li & Lu, 2014). The concept uses the survival of the fittest and a biological mechanism to process a set of solutions iteratively in order to converge and produce an optimum solution. The survival of the fittest which GA adopts is based on Darwinian's theory that begins with a set of solutions denoted as chromosomes, called population. The solutions determined from one population would be used to form another new population, and that population is motivated based on the likelihood that the new population will be preferred when compared to the older population. In addition, the solutions are selected based on their fitness to form a new solution. This process of selection would happen at every iteration of the algorithm, and this would continue until all the conditions are satisfied and the best individual is generated. The procedure of GA employed in this study is summarised below (Haupt & Haupt, 2004; Li & Lu, 2014):

The computational process of GA is outlined below:

- Set the solution counter $l = 0$, initialise the parameters and generate an initial population of the chromosomes $\varphi_i^{(l)}$ randomly based on the population size N.

- Define the objective function $f\left(\varphi_i^l\right)$ and evaluate the fitness of each chromosomes in the population. The outcome is used to find the optimum solution (φ^{best}) in the current population.
- Create a new sequence of population $\varphi_i^{l+1} \epsilon\ \Omega(\mathrm{i} = 1,2, \dots, N)$ by repeating steps a to d. The algorithm uses individuals from the current generation to create the next population.
  a. Select two parent chromosomes from the population $\varphi_i^l \epsilon\ \Omega(\mathrm{i} = 1,2, \dots, N)$ according to their fitness $f(\varphi_i^l)\ \epsilon\ \Omega(\mathrm{i} = 1,2, \dots, N)$. The better the fitness, the more chances it will have to be the parent.
  b. Perform a cross-over probability over the parents to form a new offspring. However, if there is no cross-over of the offspring by the parent, then offsprings becomes the exact copy of the parents.
  c. Perform mutation probability of the new offsprings at each locus.
  d. Place the new offsprings in the new population
- If the condition is satisfied, stop the algorithm and return the best individual in the current population. Otherwise, let $l = l + 1$ and start the process again from step 2.

6.3.2 The Inner Loop: Subset Simulation (SS)

Subset simulation (SS) method is an adaptive stochastic simulation approach developed for estimating efficiently the small failure probabilities of a structural system (Au & Beck, 2001). In the literature, the use of the SS method has shown to be a powerful technique in structural analysis over the years and it has been successfully applied in different fields like aerospace, geotechnical engineering and buried pipelines (Schuëller et al., 2004; Tee, et al., 2014; Zio, 2013). The fundamental concept of SS is to express the failure probability as a product of conditional probabilities on the intermediate failure events. To achieve this, the SS approach probes the input space of the structural system by generating a set of a small number of independent and identically distributed samples and evaluating the equivalent system response.

Based on the framework of subset simulation, Markov Chain Monte Carlo (MCMC) and Splitting techniques can be used in the conditional sampling of the nested subsets. For the splitting techniques, the conditional sampling in the nested subsets is determined by splitting the trajectories that reach each subset instead of using them as seeds to generate more samples from Markov chains in their stationary state. Therefore, in generating the number of samples at a level, the splitting technique is slightly more efficient than the MCMC approach using the Modified Metropolis Algorithm (MMA) because when the conditional samples are generated, the input offspring trajectories already have available the first part of the corresponding output trajectories (Beck & Zuev, 2017). However, as suggested in Beck & Zuev (2017), splitting technique cannot handle parameter uncertainty in the model since the offspring trajectories must use the same parameter values as their mothers. As a result, the splitting can only be applied to dynamic problems, while the MCMC version can be applied to both static and dynamic uncertainty problems and can handle parameter uncertainty. So, the conditional samples of the target distribution are generated using a Markov chain. Markov chain is designed in a way that the limiting stationary distribution would become the conditional distribution of the adaptive failure event. This would allow the conditional samples to progressively populate the successive intermediate failure domain and up to the final target failure domain (Schuëller et al., 2004).

The use of SS simulation approach overcomes the ineffectiveness of direct MC method in assessing the small failure probability of a structure. The failure probability P_F can be expressed as a product of larger conditional probabilities. This is realised by defining a reducing sequence of failure events F; let $F_1 \supset F_2 \supset F_3 \supset \cdots \supset F_m = F$ be the decreasing sequence of failure event, so that $F_k = \bigcap_{i=1}^{k} F_i,\ \ k = 1, \dots,\ m$. If the failure of a structural system is defined as the exceedance of an uncertain demand D over a given capacity C, that is, $F = \{D > C\}$, then a sequence of decreasing failure events can simply be defined as $F_i = \{D > C_i\}$, where $C_1 < C_2 < \cdots < C_m = C$. The following expressions can be derived by considering the definition of conditional probability.

$$P_F = P(F_m) = P(\bigcap_{i=1}^{m} F_i) \tag{6.3}$$

$$= P(F_m | \bigcap_{i=1}^{m-1} F_i) P(\bigcap_{i=1}^{m-1} F_i) \tag{6.4}$$

$$= P(F_m|F_{m-1})P(\cap_{i=1}^{m-1} F_i) \quad (6.5)$$

$$= P(F_i) \prod_{i=1}^{m-1} P(F_{i+1}|F_i) \quad (6.6)$$

Eq. (6.6) expresses the failure probability of a structure as a product of a sequence of conditional probabilities. The conditional probabilities can be made very large, so that the simulation approach could be employed to evaluate the failure probability (Au & Beck, 2001). To evaluate the probability of failure based on the conditional failure probability, there is a need to calculate the probabilities of $P(F_i)$ and $\{P(F_{i+1}|F_i): i = 1, \ldots, m-1\}$. The $P(F_i)$ can be estimated using the expression in Eq. (6.7)

$$P(F_i) \approx \bar{P}_1 = \frac{1}{N}\sum_{k=1}^{N} I_{F_1}(\theta_k) \quad (6.7)$$

Where the set of values $\{\theta_k: k = 1, \ldots, N\}$ are independent and identically distributed (i.i.d.) samples simulated according to their corresponding PDF q. Similarly, the conditional probability $P(F_{i+1}|F_i)$ can also be evaluated based on the estimated probability of failure in Eq. (6.7). It is not efficient to use the same approach because it takes $1/_{P(F_i)}$ samples before one of another sample occurs. However, this can be by-passed by the use of MCMC simulation, which is explained in Section 6.3.3. The reliability of the structure can be expressed as shown in Eq. (6.8).

$$P_R = 1 - P_F \quad (6.8)$$

The following steps summarise the subset simulation approach as described in (Au & Beck, 2001; Au & Wang, 2014)

a) Initialise the parameters and generate samples N from the original PDF. At this stage, the subscript ‘0’ represents the samples which correspond to the conditional level 0 and set $i = 0$.
b) Compute the corresponding response values $\{\tilde{Y}_k^0 = h(\boldsymbol{X}_k^0): k = 1, \ldots, N\}$ from the structure.
c) Sort the response values $\{\tilde{Y}_k^0: k = 1, \ldots, N\}$ in ascending order to give the list $\{\tilde{b}_k^0: k = 1, \ldots, N\}$. The values from the list $\tilde{b}_k^0$ would give the estimate of the exceedance fuzzy probability $\widetilde{P}_k^0 = P(Y > b)$ where $\widetilde{P}_k^0 = \frac{N-k}{N}; K = 1, \ldots, N$

d) The value of $\tilde{b}_{k+1}$ is chosen as the $(1-p_0)Nth$ value in the ascending order of $\{\tilde{b}_k^0 : k = 1, \dots, N\}$. This would allow the sample estimate of $\tilde{P}_{(F_{i+1})} = P(\tilde{Y} > \tilde{b}_{k+1})$ to be always equal to p_0. p_0 and N are chosen so that the product $p_0 N$ is always an integer.

e) If $\tilde{b}_{k+1} \geq b_m$, proceed to step g. Otherwise, if $\tilde{b}_{k+1} \leq b_m$ identify the $p_0 N$ samples whose response $\tilde{Y}$ lies in the $(F_{i+1} = P(\tilde{Y} > \tilde{b}_{k+1})$. These samples are at conditional level $k+1$ and distributed as $q(.|F_{k+1})$.

f) Use one of the samples $\theta_k^u (u = 1, 2, \dots, p_0 N)$ as the starting point and generate $(1-p_0)N$ additional conditional samples distributed as $q(.|F_{k+1})$ using MCMC simulation. So, there would be a total of N conditional samples at conditional level $k+1$. Details of the MCMC is given in Section 3.3.

g) Stop the algorithm.

6.3.3 Markov Chain Monte Carlo (MCMC)

The use of MCMC simulation is on the increase, especially the Metropolis approach which is a robust technique for simulating samples according to their PDFs (Hastings, 1970; Metropolis et al., 1953). In assessing the probability of failure of interest, MCMC simulation provides an efficient way of generating samples from the multidimensional conditional PDF $\theta_k(k)$. To demonstrate the algorithm of MCMC simulation method with reference to a generic failure region F_i, let $\theta^{-u} = \{\theta_1^{-u}, \theta_2^{-u}, \dots, \theta_j^{-u}, \dots, \theta_n^{-u}\}$ be the Markov chain sample drawn. Also let $P_j^*(\xi_j|\theta_j^u), j = 1,2, \dots, n$, become a 1-dimensional "proposal PDF" for ξ_j, which is centred at the value θ_j^u and satisfy the symmetry property in Eq. (6.9) (Au & Beck, 2001).

$$P_j^*(\xi_j|\theta_j^u) = P_j^*(\theta_j^u|\xi_j) \tag{6.9}$$

The following steps can be used to generate parameter samples from the Markov chain.

1. Generate a candidate from the parameter sample $\bar{\theta}^{u+1} = \{\bar{\theta}_1^{u+1}, \bar{\theta}_2^{u+1}, \dots, \bar{\theta}_j^{u+1}, \dots, \bar{\theta}_n^{u+1}\}$ for each parameter $\theta_j, j = 1,2,3, \dots, n$, followed by:

- Sample a pre-candidate value ξ_j^{u+1} from the proposed distribution $P_j^*\left(.\,|\theta_j^u\right)$
- Compute the acceptance ratio using Eq. (10) below.

$$r_j^{u+1} = \frac{q_j(\xi_j^{u+1})}{q_{j(\theta_j^u)}} \tag{6.10}$$

- Then set the new value $\bar{\theta}_j^{u+1}$ of the jth element $\bar{\theta}^{u+1}$ as follows:

$$\bar{\theta}_j^{u+1} = \begin{cases} \xi_j^{u+1} & with\,probability \quad \min(1, r_j^{u+1}) \\ \theta_j^u & with\,probability \quad 1 - \min(1, r_j^{u+1}) \end{cases} \tag{6.11}$$

2. Then the candidate samples would be accepted/rejected if:

- $\bar{\theta}_j^{u+1} = \theta^u$ (There are no pre-candidate values accepted), therefore set $\bar{\theta}_j^{u+1} = \theta^u$. Check if the sample $\bar{\theta}_j^{u+1}$ belongs to the failure sample space, i.e. $\bar{\theta}_j^{u+1} \in F_i$: if the generated sample belongs to the sample space, then accept the candidate $\bar{\theta}_j^{u+1}$ sample as the next state, i.e. $\theta_j^{u+1} = \bar{\theta}_j^{u+1}$; otherwise, reject the sample candidate and take the current sample as the next one, i.e. $\theta_j^{u+1} = \theta^u$.

The candidate sample $\bar{\theta}^{u+1}$ is generated from the current sample θ^u. However, the candidate sample $\bar{\theta}^{u+1}$ or the current sample θ^u is used as the next sample, but depends on whether the candidate sample $\bar{\theta}^{u+1}$ lies in the failure domain or not.

6.3.4 Proposed Method

For an optimisation problem, finding the maximum or minimum optimum of a function using MCS is not efficient and involves substantial computational cost (Robert & Casella, 2004). This inefficiency could be attributed to the evaluation of the functions that are performed in regions which are not close to the maximum. The notion behind the use of interval optimisation based subset simulation approach of the membership function is to estimate the corresponding membership interval of the fuzzy variable for structural reliability assessment. In the value space of fuzzy variable, the lower and upper values of the reliability problem would be gradually searched by employing the concept of GA and the highly efficient subset simulation in the reduced domain of the random variables.

Figure 6.2 shows the computational steps, and the procedure for computing the membership function for the failure probability of a structural system based on the proposed method can be summarised as follows:

Steps

1. Initialise the design variables for deterministic parameters, random and fuzzy variables and use it to solve the membership function of the structural system. To achieve this, the fuzzy variable will be developed into a membership function and then discretise into ten $\alpha -$ level cut. The vector of the fuzzy variables $\tilde{\boldsymbol{\theta}}$ could be expressed as:
$$\tilde{\boldsymbol{\theta}} = \left[\tilde{\theta}_1, \tilde{\theta}_2, \dots, \tilde{\theta}_{n_f}\right] = \left[\tilde{\theta}_1^1, \tilde{\theta}_1^2, \dots, \tilde{\theta}_1^N;\ \tilde{\theta}_2^1, \tilde{\theta}_2^2, \dots, \tilde{\theta}_2^N; \dots, \tilde{\theta}_{n_f}^1, \tilde{\theta}_n^2, \dots, \tilde{\theta}_{n_f}^N\right] \tag{6.12}$$
Where n_f denotes the number of fuzzy variables for the vector $\tilde{\boldsymbol{\theta}}$ and N is the number of samples for every $\tilde{\theta}_i$ used in the computation. The membership interval $\tilde{\boldsymbol{\theta}}_F(\alpha) \in \left(\tilde{\boldsymbol{\theta}}_F^L(\alpha), \tilde{\boldsymbol{\theta}}_F^U(\alpha)\right)$, which corresponds to a particular membership level of a fuzzy variable and can be solved using an inverse function of the fuzzy variable.
2. Compute the boundaries of performance function at every $\alpha -$ level for the lower and upper bounds of the structural reliability using GA based SS simulation in each case for $\tilde{\boldsymbol{\theta}}_F(\alpha) \in \left(\tilde{\boldsymbol{\theta}}_F^L(\alpha), \tilde{\boldsymbol{\theta}}_F^U(\alpha)\right)$. This will lead to the formulation of the limit state function $Y(\alpha) = g_i(\tilde{\boldsymbol{\theta}}_F^L(\alpha))$ and $Y(\alpha) = g_i(\tilde{\boldsymbol{\theta}}_F^U(\alpha))$ for every $\alpha -$ level cut. The outcome from the limit state function $Y(\alpha)$ is an interval variable because $\tilde{\boldsymbol{\theta}}_F(\alpha)$ is an interval variable.
3. Compute the fuzzy probability bounds and the corresponding structural reliability from the real-valued probabilities associated with the originals $\tilde{\boldsymbol{\theta}}^j(\alpha)$. Now, at every alpha-level $\boldsymbol{\theta}_F(\alpha) \in \left(\boldsymbol{\theta}_F^L(\alpha), \boldsymbol{\theta}_F^U(\alpha)\right)$, the equivalent reliability would satisfy $P_R^L(\alpha) \leq P_R(\alpha) \leq P_R^U(\alpha)$, which is described in this study as two optimisation problems as expressed in Eq. (6.1) and Eq. (6.2). The minimum $P_R^L(\alpha)$ of $P_R(\alpha)$ can be determined using GA and taking $\left(\boldsymbol{\theta}_F^L(\alpha), \boldsymbol{\theta}_F^u(\alpha)\right)$ as the solution domain for every alpha-level. Therefore, during the optimisation, the SS simulation is called to estimate the reliability whenever the objective function is

required in the computational process. However, for the GA, the initial solutions would be generated uniformly in the solution domain $\left(\boldsymbol{\theta}_F^L(\alpha), \boldsymbol{\theta}(\alpha)\right)$ and these would be used to form a new set of solutions for the next generation. This process will continue until the global minimum value of the reliability is converged. Similarly, to estimate the maximum reliability, that is, $P_R^u(\alpha)$ of $P_R(\alpha)$, the objective function expressed in Eq. (6.2) is transformed into a minimum using $-P_R(\alpha)$. Then, the minimisation process of GA is applied to search for the minimum value of $-P_R(\alpha)$, which eventually produce the maximum $P_R^u(\alpha)$ of $P_R(\alpha)$.

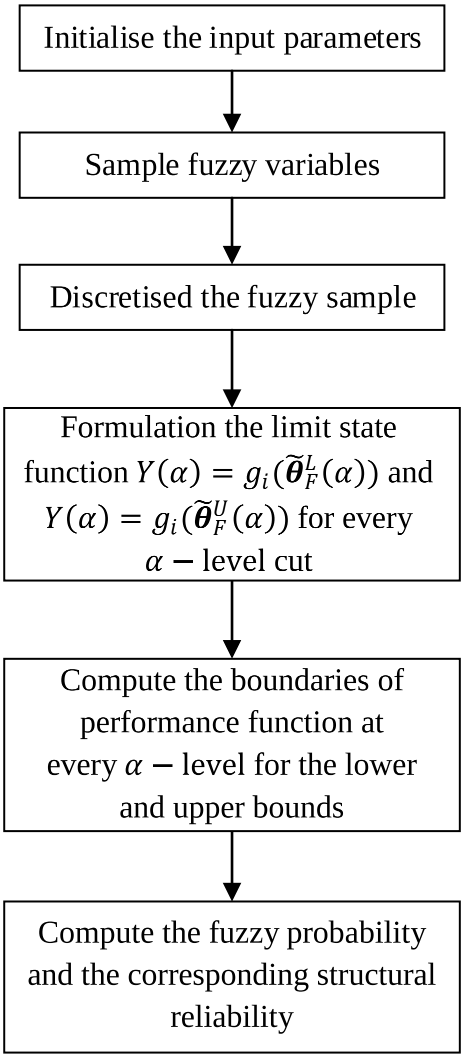


Figure 6.2: Flow diagram for the optimisation based fuzzy subset simulation approach

6.3.5 Applicability of the Proposed Method

The proposed method in this study is generally applicable to any engineering structure associated with parameters such as fuzzy variables, random variables, and deterministic values. The efficiency of this approach does not depend on a large number of samples when compared to MC. This feature makes it specially suitable for reliability analysis of structures and in particular to solve real engineering problems. For a structure that is characterised by a large number of failure modes, the proposed strategy can be used to efficiently estimate the fuzzy structural reliability associated with each of the failure modes. Therefore, the entire system reliability can be evaluated by integrating the individual failure probability to assess the safety of the structure.

6.4 Numerical Example

The applicability and computational performance of the proposed approach in Section 6.3.4 is demonstrated with a structural failure problem of buried pipes. The random variable parameters and deterministic values are reported in Table 3.3 and Table 3.4, which are based on industry standard. These values are obtained from the literature as reported in (Ahammed & Melchers, 1997; Babu & Srivastava, 2010; Tee et al., 2014; Sadiq et al., 2004). In this example, corrosion-induced failures for pipe ovality and through-wall bending stress are considered and for a design life of 25, 50, 75 and 100 years. The proposed approach is employed to capture the impact of uncertain variables (random and fuzzy variable) on the performance of buried pipelines, where some probabilistic information is considered not adequate for standard probabilistic analysis. Two different failure modes as stated earlier are used in this Section to investigate and demonstrate the performance of the presented approach, which is based on GA, fuzzy set, and subset simulation. The outcomes of these investigations are validated and compared with that of the MCS method to ascertain the efficiency of the presented model. To guarantee and achieve good convergence of the failure probability using the MCS approach, a large sample size (10^6) is used at each realisation of the fuzzy variable. The above-mentioned failure modes are further discussed with the result outcomes as investigation 1 (Section 6.4.1 for pipe ovality) and investigation 2 (Section 6.4.2 for through-wall bending stress).

6.4.1 Investigation 1 (Pipe Ovality)

A buried steel pipe would tend to ovalise under the action of earth and live load as shown in Figure 3.5. The modified Iowa equation according to Alliance (2001) and expressed in Eq. 3.33 is used to analyse the ovality of the buried pipe under the influence of live and earth load. Table 3.1 shows the PDFs for live load, the elastic modulus of pipe material E, backfill soil modulus E_s, and pipe thickness. Other parameters include the pipe deflection lag factor D_L; the pipe deflection coefficient K_b and the mean diameter D and are defined as certain deterministic values. The corrosion parameters for final pitting rate constant a (Eq. (6.13)), pitting depth scaling constant b (Eq. (6.14)), and corrosion rate inhibition factor c (Eq. (6.15)) are modelled using triangular fuzzy membership function. The reason for treating corrosion as fuzzy variable is to account for the uncertainties in the values of the parameters that characterise the environment, variables that affect the time to corrosion initiation, and the rate of corrosion propagation (Anoop & Balaji, 2007; Marano et al., 2008). The fuzzy variables for the corrosion parameters are combined into a joint membership function using transformation technique and interval arithmetic. The study is carried out for the design life of 25, 50, 75, and 100 years.

$$\mu_a(a) = \begin{cases} (a - 0.001)/0.008\,; & 0.001 \le a \le 0.009 \\ (a - 0.015)/(-0.006)\,; & 0.009 \le a \le 0.015 \end{cases} \tag{6.13}$$

$$\mu_b(b) = \begin{cases} (b - 2.5)/3.77\,; & 2.5 \le b \le 6.27 \\ (b - 7.5)/(-1.23)\,; & 6.25 \le b \le 7.5 \end{cases} \tag{6.14}$$

$$\mu_c(c) = \begin{cases} (c - 0.01)/0.09 & 0.01 \le c \le 0.1 \\ (c - 0.18)/(-0.17) & 0.1 \le c \le 0.18 \end{cases} \tag{6.15}$$

For the computation of fuzzy reliability of the membership function of buried pipe, the probabilistic and fuzzy alpha-level with GA is applied. Figures 6.3, 6.4, 6.5, and 6.6 shows the membership function of the fuzzy-based reliability of buried pipe after 25, 50, 75 and 100 years, respectively. These results are obtained using the procedure as explained in Section 6.3.4. It can be deduced from the results (Figures 6.3, 6.4, 6.5 and 6.6) that the performance of the proposed method, shows a good match with that of the MCS. This illustrates and demonstrates the correctness and applicability of the proposed method.

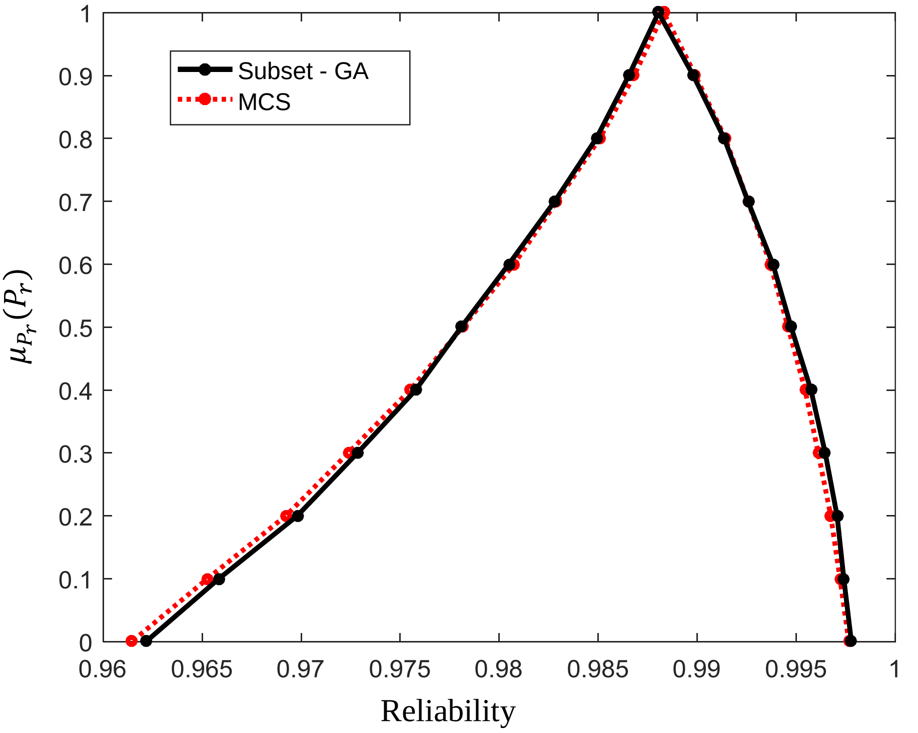


Figure 6.3: Reliability of buried pipe after 25 years due to pipe ovality

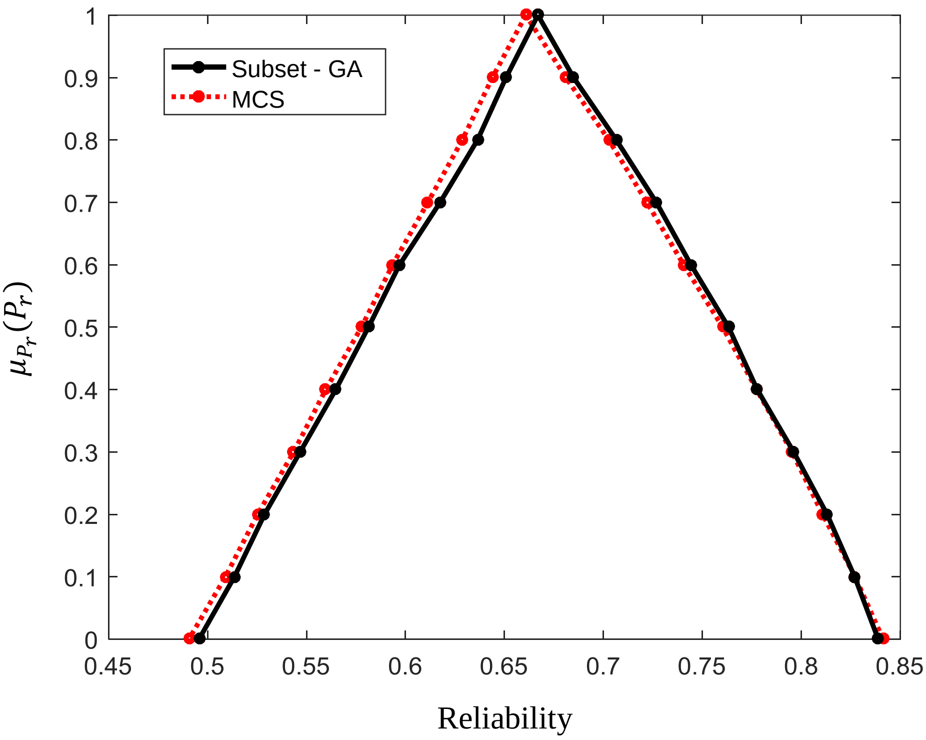


Figure 6.4: Reliability of buried pipe after 50 years due to pipe ovality

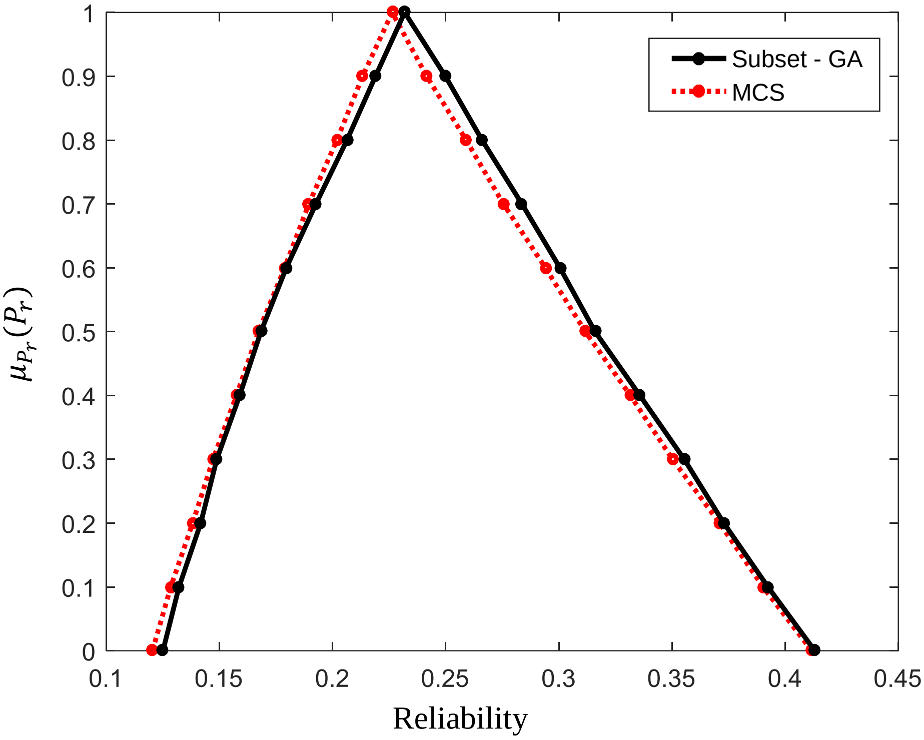


Figure 6.5: Reliability of buried pipe after 75 years due to pipe ovality

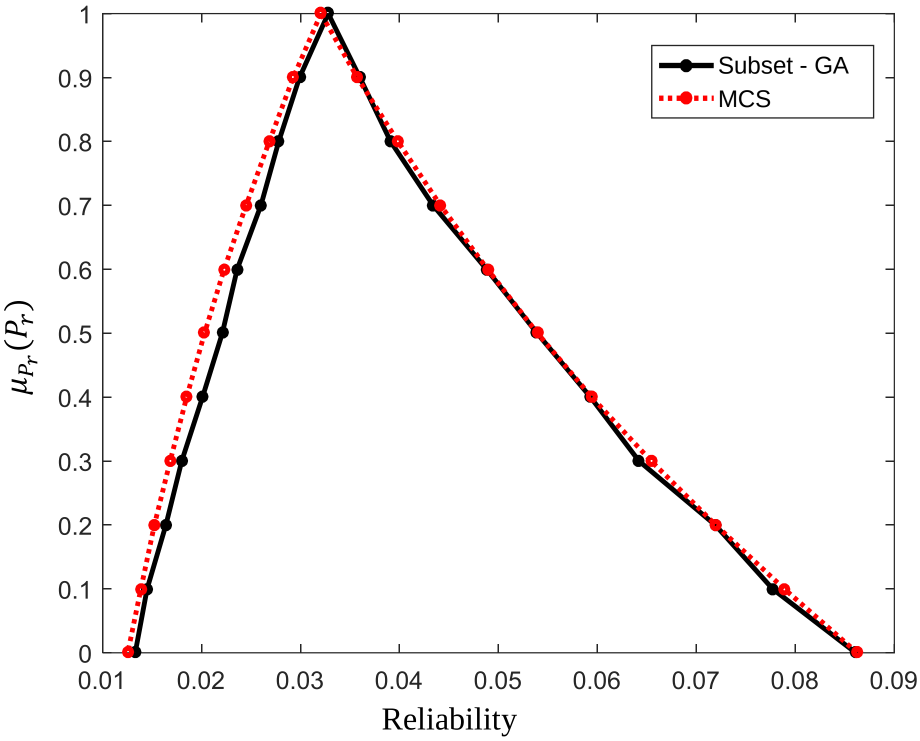


Figure 6.6: Reliability of buried pipe after 100 years due to pipe ovality

6.4.2 Investigation 2 (Through-wall Bending Stress of Buried Pipe)

Figure 3.34 shows the schematic diagram for the through-wall bending stress. The through-wall bending stress is developed under the impact of earth and the surface load acting on the buried pipe. The properties of soil and pipe required for this failure condition are given in Table 3.3 and Table 3.4. Similarly, Figures 6.7, 6.8, 6.9, and 6.10 illustrate the performance function of the buried pipe for investigation 2 after 25, 50, 75 and 100 years, respectively. These results are obtained using the procedure as explained in Section 6.3.4. The fuzzy reliability of the membership function of the buried pipe is evaluated using the proposed method and compared with the MCS method. The outcome based on the proposed method shows satisfactory results with the MCS and demonstrates the efficiency of the approach in analysing structural engineering problems.

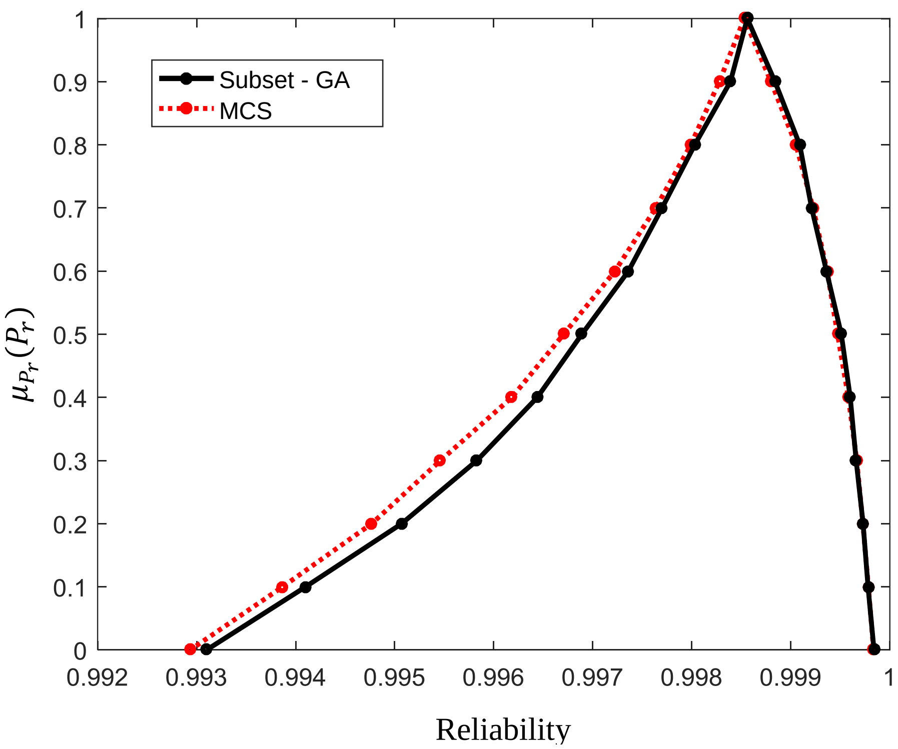


Figure 6.7: Pipe reliability after 25 years due to through-wall bending stress

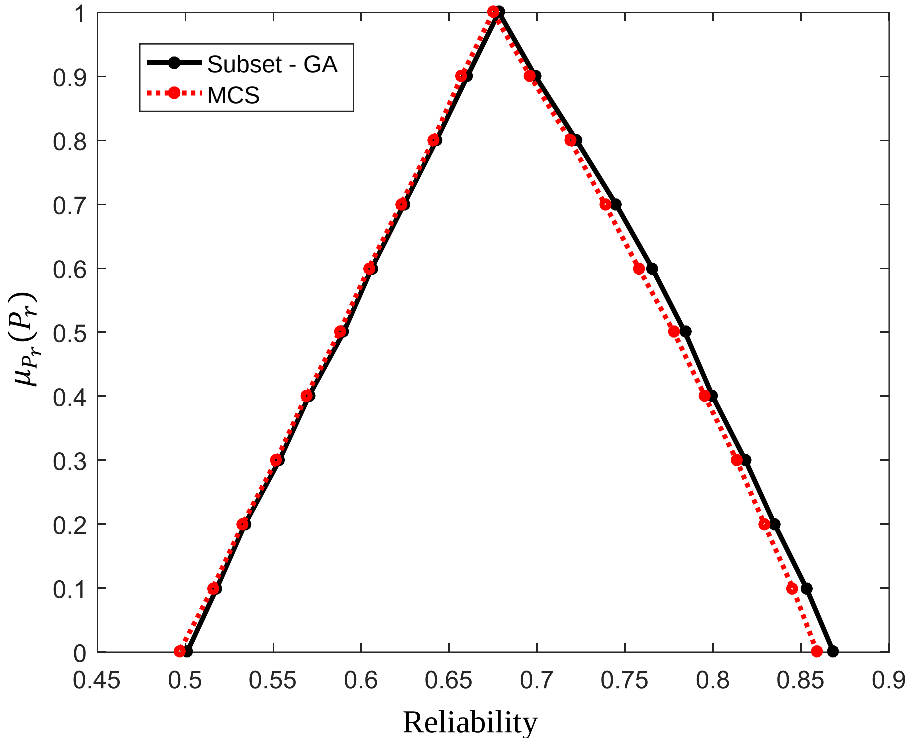


Figure 6.8: Pipe reliability after 50 years due to through-wall bending stress

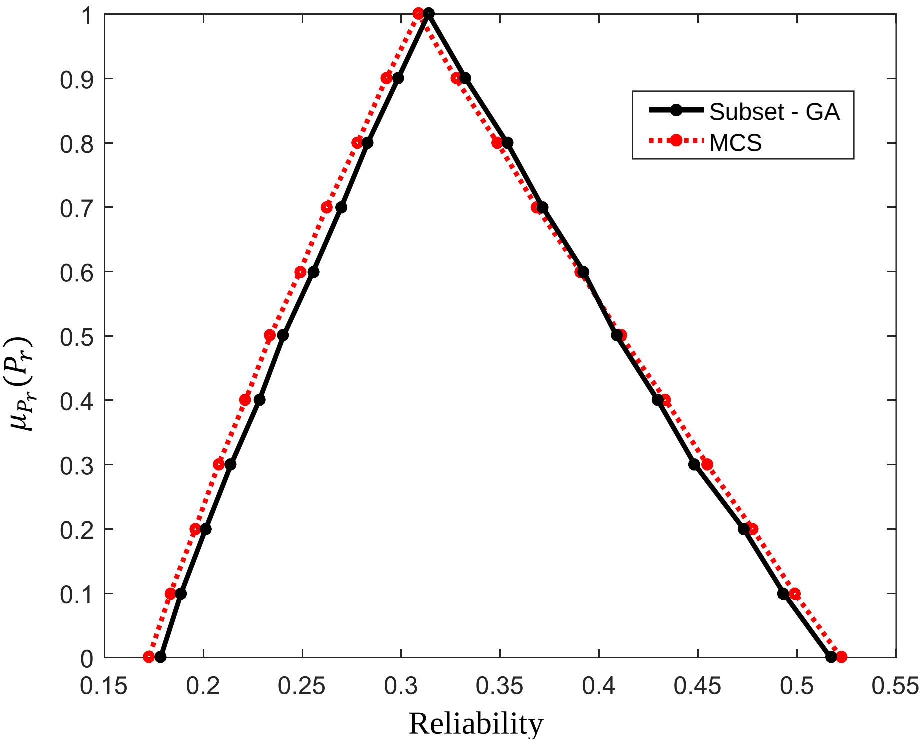


Figure 6.9: Pipe reliability after 75 years due to through-wall bending stress

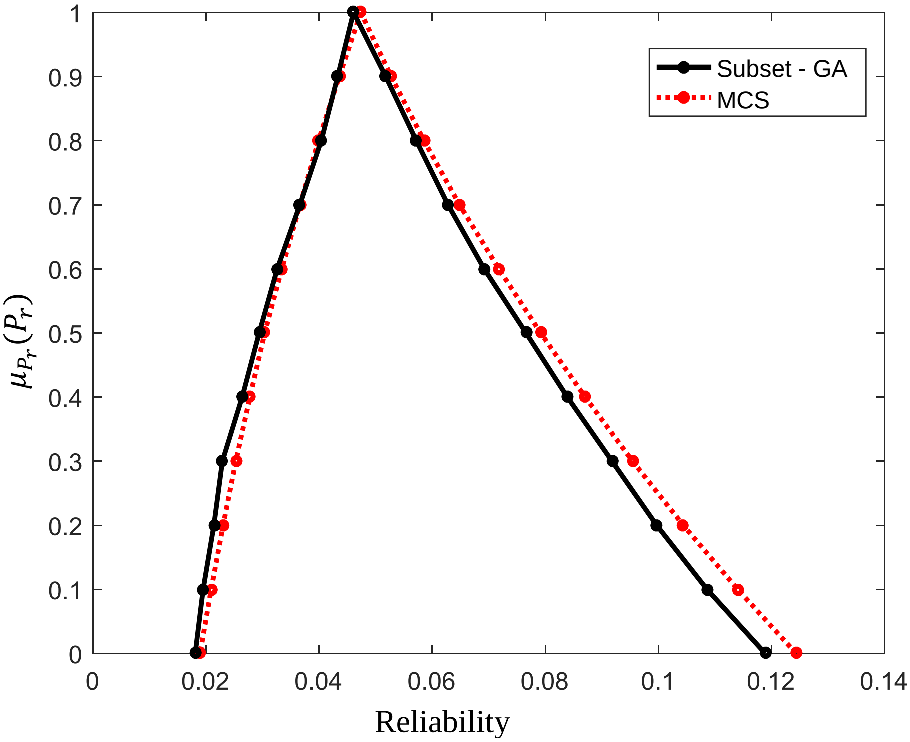


Figure 6.10: Pipe reliability after 100 years due to through-wall bending stress

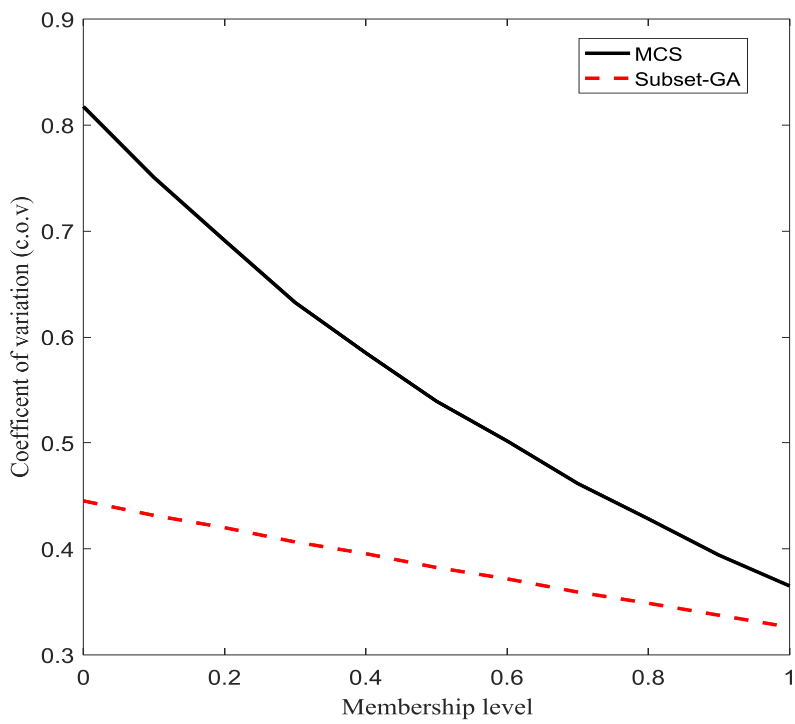


Figure 6.11: COV versus membership level

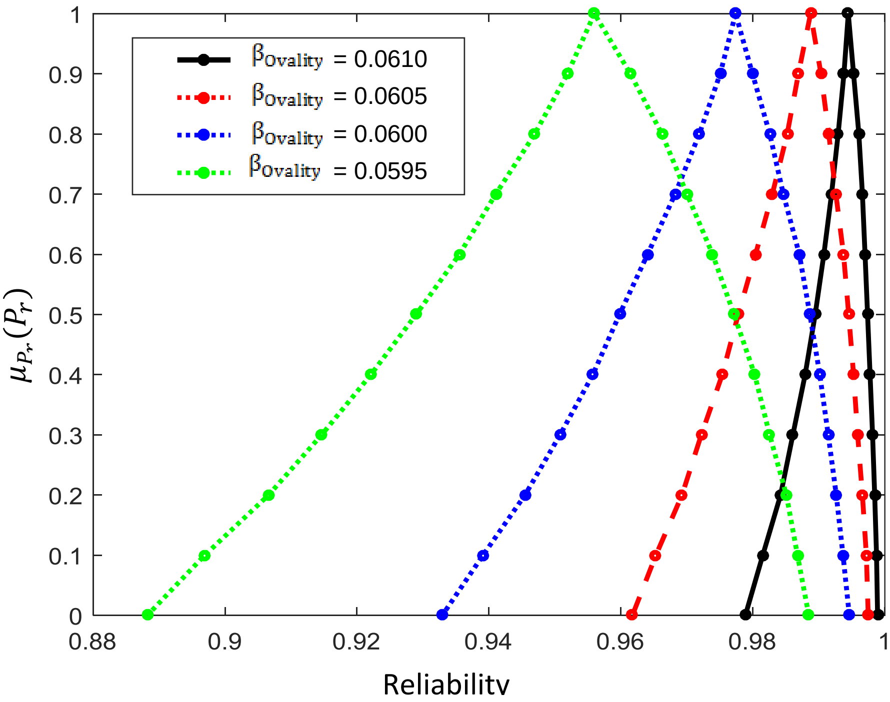


Figure 6.12: Sensitivity test for pipe performance at 25 years design life (pipe ovality)

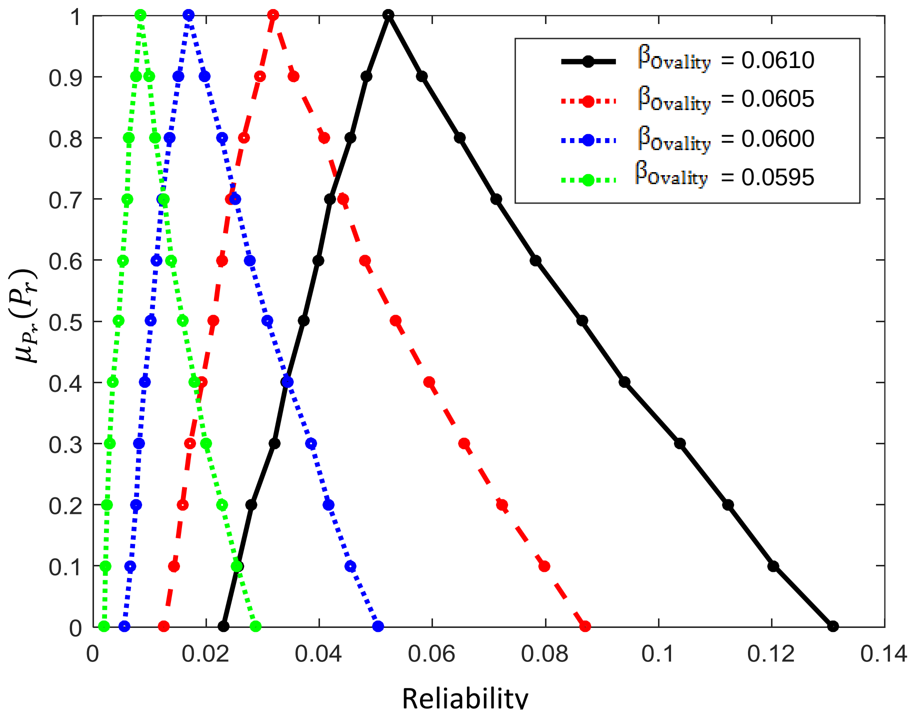


Figure 6.13: Sensitivity test for pipe performance at 100 years design life (pipe ovality)

6.4.3 Discussions

As shown in Figures 6.3 - 6.6 and Figures 6.7 – 6.10, the proposed model has been compared with the MCS approach and the outcome demonstrates that the proposed approach is robust, reliable and efficient for analysis of engineering structures. The optimised subset simulation algorithm for the estimation of fuzzy reliability of an engineering structure has helped to directly solve the reliability problem by focussing on the maximum of the objective function. In the computation, for each realisation of fuzzy variables, a total of 10^6 performance function evaluation counts are required to estimate the reliability of the structure at each bound when using the MCS, while a total of 650 performance function evaluation counts are needed when using the optimised subset simulation approach. This clearly demonstrates the computational efficiency of the proposed method. Also, the computational time for the two methods is assessed, and in both cases, the expressions are defined in analytical form, which makes the computational process fast. The two techniques have been measured running on a CPU time using a 1.60 GHz Pentium 4 computer. The computational times required for MCS approach is 281 minutes, while the proposed method is 264 minutes. However, a further computational assessment based on the COV is reported in Figure 6.11. The COV for MCS is computed using the expression in Eq. (6.16) and for subset-GA approach, it is estimated using Eq. (6.17) (Au & Beck, 2001).

$$\sqrt{(1-P_f)/NP_f}, \tag{6.16}$$

$$\sqrt{\left(\log(P_f)\right)^2(1-P_0)(1+\overline{\gamma}\,)/(\log(P_0))^2NP_0} \tag{6.17}$$

Where $\overline{\gamma}$ represents the correlation factor. In Figure 6.11, the assessment is performed on every membership level, and the result shows that the proposed method can lead to a substantial improvement in computational efficiency over MCS when estimating small failure probabilities. However, this advantage begins to narrow down as the probability of failure approaches unity.

Table 6.1: Failure probability of buried pipe after 25-years

α level	Subset-GA			
	Lower bound		Upper bound	
	P_F	CoV	P_F	CoV
0	0.002106	0.445403	0.03688	0.2385
1	0.002547	0.431663	0.033118	0.246276
2	0.002987	0.420146	0.029339	0.255033
3	0.003602	0.406616	0.026285	0.262976
4	0.004196	0.395584	0.023155	0.27214
5	0.005029	0.382497	0.020671	0.280341
6	0.005829	0.371828	0.018137	0.289792
7	0.006928	0.359345	0.016133	0.298254
8	0.008018	0.348784	0.014114	0.307917
9	0.009374	0.337492	0.012431	0.317093
10	0.010957	0.326215	0.010957	0.326215

It is worth mentioning that the engineering application of the proposed model is vital to structural engineering problems, especially where there are fuzzy and random variables. Figures 6.12 and 6.13, show the parametric analysis of pipe performance at 25 years and 100 years design life based on pipe ovality failure mode by critically analysing the level of imprecision on the pipe strength. For instance, the maximum allowable value of pipe ovality (β_{ovality}) is changed using values such as $0.0610, 0.0605, 0.060$ and 0.0595. It can be deduced that after the first 25 years (Figure 6.12), the impact of the changes in imprecision is insignificant compared to the 100 years (Figure 6.13) design life for fuzzy reliability assessment. The practical implication of this could mean that the uncertainty level is high and therefore minor changes in imprecision could lead to a notable change in the reliability of the structure. Similarly, as shown in Table 6.1, a 3% level of increase in imprecision leads to upper bound reliability of 0.03688 and lower bound reliability of 0.002106, which is slightly more than one order of magnitude larger than the standard analysis. Also, in Table 2, as the $\alpha - level$ increases, the corresponding failure probability for the lower and upper bound increases. This feature also demonstrates, how sensitive the interval-based reliability analysis is with respect to the level of imprecision of the input variables. However, the $\alpha - level$ gains its usefulness by examining the reliability of the structure at different level, which can represent a different degree of imprecision. Based on this, a better understanding of the impact of uncertainty associated with the failure of buried pipe can be evaluated. This feature helps to capture and quantify the negative effects of uncertain variables on the performance of an engineering structure with regards to estimating the reliability of the structure.

6.5 Chapter Summary

This Chapter analysed the reliability of buried pipe based on fuzzy-subset simulation approach and considering the effect of uncertain variables. The underlying ideas behind the proposed algorithm are explained, and an example problem based on the buried pipeline is used to analyse the applicability and efficiency of the proposed model. The approach relies on the performance function of the buried pipe, which involves random and fuzzy variables for the modelling of the pipe structure. The values of the fuzzy variables for every alpha-level are first obtained using the membership function. Therefore, the set values of the fuzzy variable bound the reliability of the structure, and this is evaluated using optimisation and efficient subset simulation approach. The rationale behind the proposed strategy is to locate a failure domain or region where the objective function is minimised or maximised and compute the reliability using subset simulation. The presented approach illustrates that the fuzzy uncertainty of the input variables could be propagated to determine the fuzzy reliability of the membership function of a structural system. For the full evaluation of the random variables, the approach utilised the efficiency and capability of subset simulation. MCS is used to validate the applicability of the proposed method, and the result shows a very good agreement. The developed model can accommodate a various degree of uncertainty in the computation of the fuzzy reliability and can easily be applied to other engineering structures. Because of the deteriorating condition of the buried pipeline, it is essential to develop a maintenance strategy in other to keep the risk under control. As a result, determining the optimal time for maintenance of the buried pipe becomes an important aspect of this study. Therefore, a maintenance strategy is proposed in Chapter 6 and is designed at evaluating the performance of a buried pipeline using fuzzy reliability, risk, and cost to predict the optimal time interval for maintenance.

CHAPTER SEVEN

7 MAINTENANCE OF DETERIORATING BURIED PIPE USING OPTIMISATION INVOLVING FUZZY RELIABILITY, RISK AND COST

7.1 Introduction

In this Chapter, a maintenance approach is proposed and is aimed at examining the performance of a buried pipeline using fuzzy reliability, risk, and total maintenance cost to predict the optimal time interval for maintenance. The goal is achieved using a multi-objective optimisation where the first objective is the minimisation of the total cost of maintenance, while the second objective involves the maximisation or minimisation of one of the performance indicators (e.g., fuzzy reliability or risk). The maintenance of the deteriorating pipe segment is considered so that when replaced, there will be a total restoration of the performance of the pipe segment to the original condition. The pipe segment with the highest repair priority will be determined using performance indicator, considering maximum reliability and minimum risk.

The performance of underground pipe network influenced by adverse environmental effects (e.g., corrosion) and the associated induced failure possibility and risks increases as the impact of the effects increases. Corrosion effect has affected the safe operation of most engineering structures over the years. For a buried pipeline, corrosion has gradually reduced the resistance of the mechanical and the structural properties, which has increased the possibility of failure over time. Due to the deteriorating condition of the buried pipeline, the assessment and maintenance would require a proper inspection and maintenance activities to keep the risk under control. As a result, the evaluation and determination of the optimal time for maintenance of the buried pipe become an important research area.

Considering the safe operation of the buried pipe, Hong (1999) stated that the optimal maintenance programme should be defined based on a minimum acceptable level of failure probability. Similarly, regarding cost Laggoune et al. (2010) suggested that the optimal maintenance planning should be defined based on the minimum expected cost. The two viewpoints play a vital role in regards to when maintenance should be carried out. Also, Barone & Frangopol (2014a) suggested that the increase in the number of systems that reached critical conditions, due to deterioration of the structural resistance, has directed the attention of researchers to the development of a method that would provide cost-effective maintenance approach. However, this Chapter presents the development of a cost-effective strategy that would assist the decision-makers with the tool to know the appropriate time interval to carry out maintenance within the design life of the buried pipe.

The rest of this Chapter is organised as follows: Section 7.2 presents the maintenance of buried pipe and performance indicators. Section 7.3 explains methods for evaluating performance indicators and the procedure for estimating the structural reliability. In Section 7.4, the numerical example is presented, and Section 7.5 explains the performance indicators and total cost using multi-objective optimisation. Also, the outcome of the annual fuzzy reliability and total maintenance cost, and the annual risk and total maintenance cost is presented. Section 7.6 presents a parametric study and Section 7.7 explains Chapter summary.

7.2 Maintenance of Buried Pipe and Performance Indicators

The buried, ageing and deteriorating pipeline network is maintained to ensure safe operation within the service life. The benchmark for a new service design life of pipeline is commonly set as 50 years, although other pipe products and design methods under certain conditions may provide a service life of around 100 years (Najafi, 2011). Also, to successfully achieve the purpose of pipe maintenance, factors such as the history of the pipe, possible causes of failure (corrosion, concentrated load, or nearby blasting), leakage, failure modes, and the nature of the transported fluid should be adequately considered. Without a proper and detailed understanding of the overall pipeline failure conditions, it is difficult to select a maintenance approach that would mitigate the problem appropriately. However, in this study, a corrosion-induced failure is considered based on the structural failure mode of a buried pipeline. A replacement of a pipe section is deemed to based on the optimal time and whenever a maintenance action is required relying on the outcome of the pipe reliability and the associated risk. The objective of pipe replacement design involves a set of equations that is based on limit state functions and considering factors such as pipe material properties, soil, traffic loads, and other loading conditions.

Various techniques considered in assessing the structural performance of buried pipe throughout the design life may involve the use of performance indicators such as reliability, and risk or lifetime distribution such as hazard function. However, the use of life cycle maintenance is a fundamental requirement for sustaining and ensuring that the performance of the engineering structure is above a specific safety level (Barone & Frangopol, 2014b; Biondini & Frangopol, 2009). Therefore, it is vital for any maintenance approach to take account of the optimal time for maintenance interventions. The inspection of the buried pipe during the design life would assist to identify any structural defects, evaluate the structural performance and, update the structural models established in the design stage while maintenance interventions are required to maintain, improve, or restore the structure to the initial state. Barone & Frangopol (2014b), suggested that the maintenance interventions aimed at slowing down the structural deterioration process or restoring the resistance of one or more component of the structure when a specific condition is reached. Slowing down the deterioration process is more of the preventive maintenance while the restoring the resistance of the part of a structure is called the essential maintenance (Barone & Frangopol, 2014b). The essential maintenance is usually performed when one or more of the performance indicators reach a predefined level.

In the literature, essential maintenance of a structure based on a probabilistic approach is used for the evaluation of structural reliability as illustrated in Figure 7.1. Herein, the essential maintenance approach is analysed based on a non-probabilistic method for the assessment of the structural safety as shown in Figure 7.2. Corrosion is evaluated as fuzzy variable because of the uncertainty associated with the corrosion parameters. This approach has helped to capture the variabilities related to corrosion process, which cannot be obtained using the probabilistic method. The essential maintenance approach assumed that the reliability of the structure returns to the original condition after repair as illustrated in Figure 7.1 and Figure 7.2. The time interval used to perform the maintenance is not considered, and for this reason, the reliability of the structure would suddenly increase at the time of repair.

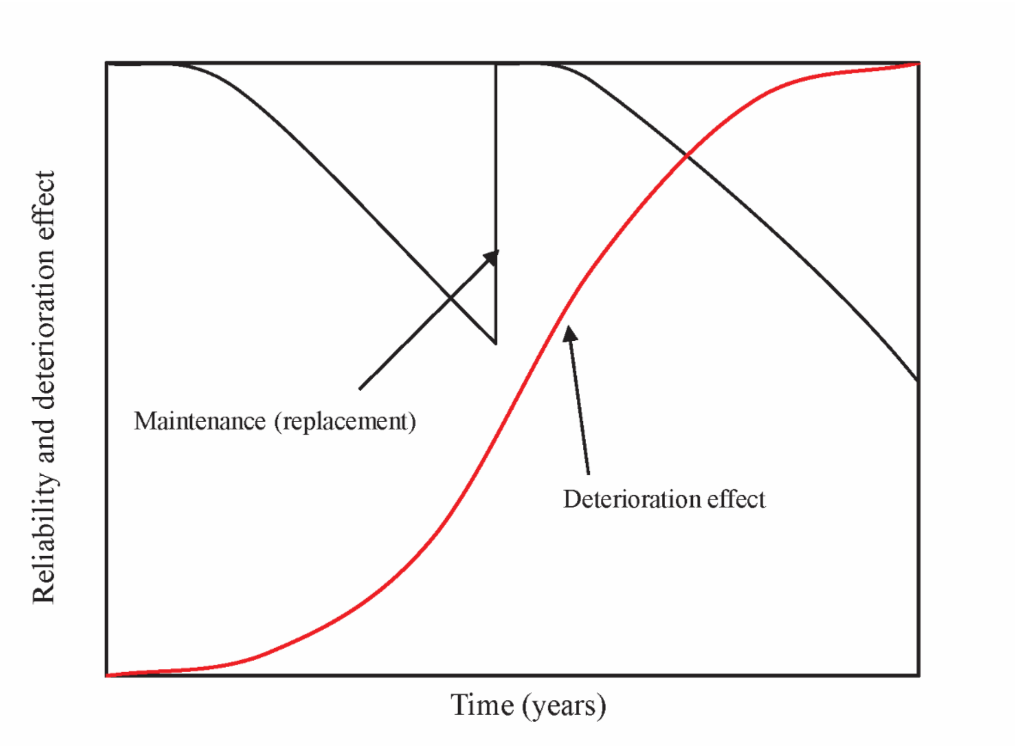


Figure 7.1: Reliability and maintenance cost over time (probabilistic method)

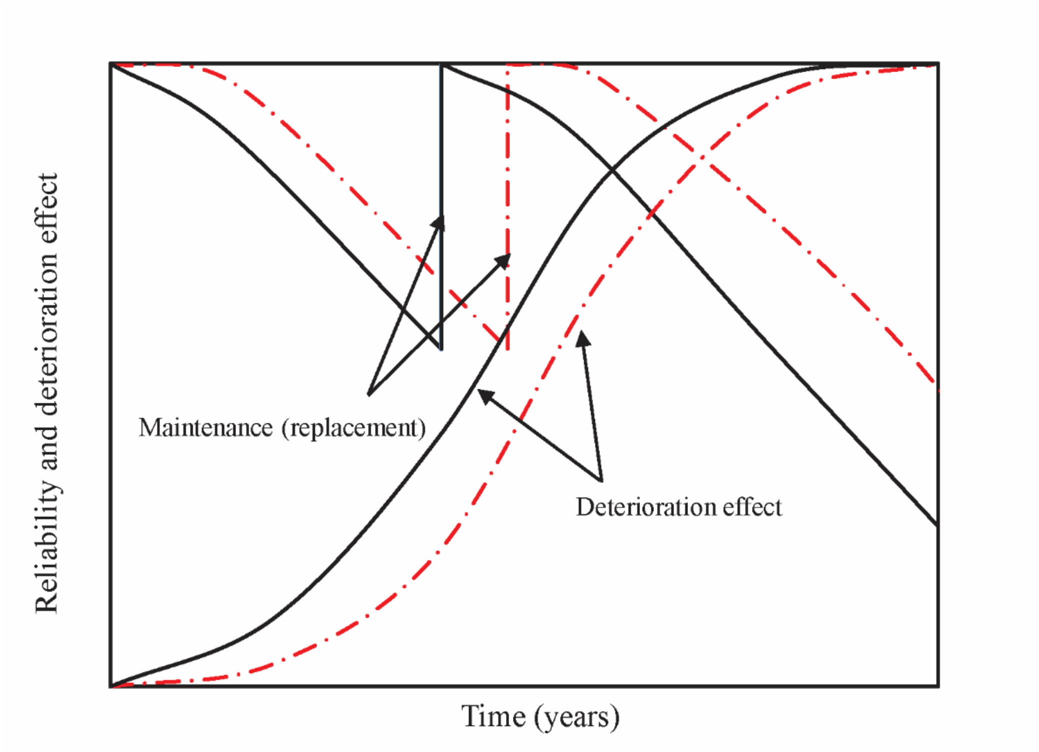


Figure 7.2: Reliability and maintenance cost over time (non-probabilistic method)

Buried pipes are usually affected by corrosion over time, for example, continuous reduction of pipe walls can lead to failure. Maintenance carried out through replacement of corroded part would return the pipe segment to its original state, which would enhance the performance of the pipe network. In some cases, a repair priority can be assigned to one or more pipe sections, based on their likelihood and consequences of failure. The decision to carry out a maintenance using different repair options and time will depend on the performance indicators considered in the analysis.

Maintenance of buried pipeline system requires continuous upkeep of every segment and components to ascertain a suitable functionality. The terms preventive and essential maintenance are used to describe different types of maintenance. Preventive maintenance ensures that the structure does not deteriorate to a critical state before essential maintenance is carried out. Preventive maintenance is usually performed during the life cycle before the safety state of the structure is dangerous. Essential maintenance is needed when the structure has reached suggested performance thresholds, which could threaten the safety of the structure and cause an environmental hazard (Barone & Frangopol, 2014a). Barone & Frangopol (2014a), suggested that the use of essential maintenance actions plan provide rescue of the structural performance of engineering structure. On the other hand, the cost-efficiency of maintenance can be maximised by carrying out maintenance at an optimal time before failure occurs. Therefore, maintenance of buried pipeline structure should be formulated as an optimisation problem. A multi-objective optimisation approach, which uses performance indicator and total maintenance cost as objective functions are proposed for the maintenance of buried pipe.

7.3 Annual Fuzzy Reliability and Risk as Performance Indicators

There are several probabilistic and non-probabilistic methods that have been proposed to analyse the performance of deteriorating structures while considering the effect of uncertain variables. These proposed methods aimed at the assessment of the structure over the life cycle to ensure the reliability of the structure. While considering the effect of randomness and fuzziness, a rational way to treat these uncertain variables is to consider an approach that can simulate the two types of uncertainty. In this context, the failure probability of a structure can be defined as the probability of violating the limit state associated with the failure mode of the structure as explained in Chapter 3.

For a buried pipe, the deterioration process due to corrosion occurs with time, so the performance indicator is analysed at a time t. In this study, the performance indicator for reliability and risk associated with the failure of the buried pipe is performed annually. The determination of the failure probability of a structure involving fuzzy and random variables using optimisation is usually a challenging task because of the computational cost. For this reason, a simplified approach is proposed as shown in Section 7.3.1

Risk assessment of an engineering structure has been recognised in recent time as a crucial part of decision making (Barone & Frangopol, 2014a). As a result of this, several performance indicators have been proposed to evaluate a time-dependent structural performance of deteriorating buried pipeline (Ahammed & Melchers, 1997; Sadiq et al., 2004; Tee et al., 2014). Due to the need of taking into account, the consequences associated with the failure of buried pipeline, making of decisions based on risk has become an essential tool for optimising the time for maintenance. The assessment of risk can be either qualitative or quantitative. According to Arunraj & Maiti (2007), qualitative risk assessment deals with simple descriptions of the types of hazards, their consequences and likelihood, which are reported in an opportunely built risk matrix In this study, a quantitative risk assessment is considered, and it is the risk associated with a particular failure mode of buried pipe. It is defined as the product of the failure probability and the associated consequences.

Over the years, optimisation algorithms are used while considering maintenance times as design variables, which allow the identification of possible opportunity for maintenance during the design life cycle. In this Chapter, two different optimisation problems based on reliability, risk, and total maintenance cost are utilised for the determination of the optimal maintenance time of a buried pipe. The failure modes considered herein for the analysis are briefly described in Chapter 3, Section 3.3. The structural failure modes of buried pipe have been modelled as a series-series system so that failure will occur when either of the failure conditions exceeds the safety threshold.

7.3.1 Procedure for Estimating Reliability

The propagation of the random and fuzzy variables for the maintenance of a buried pipe system was performed using fuzzy reliability. Möller et al. (2003) suggested that the determination of the fuzzy reliability of a structure requires a fundamental stochastic solution, which means in principle any probabilistic algorithm could be used for this purpose. In this study, a subset simulation approach is employed and the procedure is summarised below:

1. Initialise the design parameters and sample random variables and develop the membership of the fuzzy parameters.
2. Discretise the membership function into ten $\alpha -$ level cut. The vector of the fuzzy variables $\tilde{\theta}$ could be expressed as:

$$\tilde{\theta} = [\tilde{\theta}_1, \tilde{\theta}_2, \dots, \tilde{\theta}_n\ ] = [\tilde{\theta}_1^1, \tilde{\theta}_1^2, \dots, \tilde{\theta}_1^N;\ \tilde{\theta}_2^1, \tilde{\theta}_2^2, \dots, \tilde{\theta}_2^N; \dots, \tilde{\theta}_n^1, \tilde{\theta}_n^2, \dots, \tilde{\theta}_n^N] \qquad (7.1)$$

   Where n denotes the number of fuzzy variables for the vector $\tilde{\theta}$ and N is the number of samples for every $\tilde{\theta}_i$ used in the computation. For every $\alpha - level$ the fuzzy variable can be decomposed into $\tilde{\theta}_F^L(\alpha)$ and $\tilde{\theta}_F^U(\alpha)$. Where $\tilde{\theta}_F^L(\alpha)$ denotes the lower and $\tilde{\theta}_F^U(\alpha)$ is the upper value of every $\alpha -$ level cut. The membership interval $\tilde{\theta}_F(\alpha) \in \left(\tilde{\theta}_F^L(\alpha), \tilde{\theta}_F^U(\alpha)\right)$, which corresponds to a particular membership level of a fuzzy variable.
3. Compute the boundaries of performance function at every $\alpha -$ level for lower and upper bounds of the structural response in each case for $\tilde{\theta}_F(\alpha) \in \left(\ \tilde{\theta}_F^L(\alpha), \tilde{\theta}_F^U(\alpha)\right)$. This will lead to the formulation of the limit state function $Y(\alpha) = g_i(\tilde{\theta}_F^L(\alpha))$ and $Y(\alpha) = g_i(\tilde{\theta}_F^U(\alpha))$ for every $\alpha -$ level cut.
4. Calculate the reliability of the structure for lower $R_L$and upper R_U using subset simulation (SS) (see Chapter 6, Section 6.3.2). Based on the relationship between the outcomes of subset simulation with the effect of corrosion, the reliability of the structure considering the lower and upper values for every $\alpha -$ level cut can be expressed as shown in Eq. (7.2) and Eq. (7.3)

$$R_L(\alpha_L;T) = 1 - \left[P(\tilde{\theta}^L) \prod_{i=1}^{N-1} P(\tilde{\theta}_{i+1}^L|\tilde{\theta}^L)\right]\Big|_{\alpha_L} \tag{7.2}$$

$$R_U(\alpha_U;T) = 1 - \left[P(\tilde{\theta}^U) \prod_{i=1}^{N-1} P(\tilde{\theta}_{i+1}^U|\tilde{\theta}^U)\right]\Big|_{\alpha_U} \tag{7.3}$$

7.4 Case Study

The investigated problem and the numerical values are obtained from the literature (Khan & Tee, 2016; Rahman & Vanier, 2004). The total length of the flexible metal pipe is approximately 789 km, and the pipe network comprises of medium size steel and ductile iron materials. However, one Section of the medium size steel was used to test the applicability and the usefulness of the fuzzy-based optimal maintenance approach. The approach utilised fuzzy reliability and GA to evaluate the optimal time interval to carry out maintenance of buried pipe network. The pipe material, location, and statistical properties for the considered segments are reported in Table 7.1 and Table 7.2, with an assumption that the pipe network is constructed above the underground water table. Therefore, the effect of subsurface water table was not considered in the analysis. The corrosion parameters for final pitting rate constant a, pitting depth scaling constant b and corrosion rate inhibition factor c are modelled as fuzzy variable and the values are expressed in Eq. (7.4), Eq. (7.5), and Eq. (7.6).

$$\mu_a(a) = \begin{cases} a - 0.001/0.008; & 0.001 \le a \le 0.009 \\ a - 0.015/(-0.006); & 0.009 \le a \le 0.015 \end{cases} \tag{7.4}$$

$$\mu_b(b) = \begin{cases} b - 2.5/3.77; & 2.5 \le b \le 6.27 \\ b - 7.5/(-1.23); & 6.25 \le b \le 7.5 \end{cases} \tag{7.5}$$

$$\mu_c(c) = \begin{cases} c - 0.01/0.09; & 0.01 \le c \le 0.1 \\ c - 0.18/(-0.17); & 0.1 \le c \le 0.18 \end{cases} \tag{7.6}$$

In this example, corrosion-induced failures modes as explained in Chapter 3 with limit state functions are used to evaluate the optimal time for maintenance. The effect of a continuous reduction of pipe thickness over time due to corrosion is considered over the service life. Loads acting on the buried pipe are as a result of live and soil load, and they are considered in the analysis. The failure probability of the pipe segment has been estimated using fuzzy-subset simulation approach. The approach is employed to capture the impact of corrosion uncertainty on buried pipes, where the probability information is considered not adequate for standard probability analysis. The reliability and the failure probability results based on $\alpha -$ levels 1, 5 and 8 of the membership function of a fuzzy variable are reported in Figures 7.3 and Figure 7.7. The various $a -$ level sets may denotes different opinion of engineering judgement or expert knowledge based on the uncertain fuzzy variables in other to gauge the effect of uncertainties. However, $a -$ levels 8 is used herein to plan the maintenance of buried pipe.

Optimal maintenance plans for the buried pipeline are investigated based on two different approaches, and these include reliability and risk associated with pipe failure. The maintenance plans involve essential maintenance actions on any of the pipe segment and are considered new after repair. The maintenance cost (cost of replacement) is assumed to be £25,000, and a discount rate r of 2% is used in the analysis. The cost of injuries and fatalities, environmental damages, and cost of deferred supply during the pipe maintenance are assumed to be £10,000,000. These costs are obtained based on the case study of Rahman & Vanier (2004) and Davis et al. (2008) report.

Table 7.1: Statistical properties

Properties	Mean value	Coefficient of variation %	Distribution
Elastic modulus of steel pipe $\boldsymbol{E}$	210 GPa	1.0	Normal
Modulus of soil reaction $\boldsymbol{E'}$	2 MPa	5.0	Normal
Unit weight of soil $\boldsymbol{\gamma_s}$	18.0 kN/m3	2.5	Normal
Backfill soil modulus $\boldsymbol{E_s}$	10^3kPa	5.0	Normal
Deflection coefficient $\boldsymbol{K_b}$	0.11	1.0	Lognormal
Buoyancy factor, $\boldsymbol{R_w}$	1.0	-	-
Yield stress, $\boldsymbol{\sigma_y}$	475MPa	5.0	Normal
Deflection lag factor, $\boldsymbol{D_L}$	1	-	-

Table 7.2: Pipe materials and location properties

Pipe segment	A
Material	Steel
Location	Commercial
Embedment soil	Clay
Length (km)	150
Mean diameter (mm)	600
Thickness (mm)	9
Soil height above soil invert (m)	2.0
Wheel load (live load), $\boldsymbol{P_s}$	100

7.5 Performance Indicators and Total Cost Using Multi-objective Optimisation

The annual performance indicators for buried pipe usually assumes numerical values, which represents the performance condition of the buried pipe at a given time during its life cycle. Traditionally, this can be computed annually, that is a one-year interval. The performance of an underground pipeline over the design life is evaluated with regards to a specific limit state. However, this will depend on the design intent of the assessment, the function and strategic importance of the structure. The soil and pipe parameters are associated with uncertainties that affect the ultimate performance of pipe structure over time. Therefore the performance indicators provide a measure of the likelihood of pipe failure within the service life.

Most engineering parameters associated with a significant amount of uncertainties are as a result of lack of information or knowledge on how to efficiently estimate the values of the parameter. In numerical analysis, uncertainties are usually accounted for through the use of the traditional probabilistic model (Baecher & Christian, 2005). The probabilistic modelling approach is associated with challenges because of lack of information particularly with geotechnical engineering parameters (Beer, Zhang, et al., 2013). Also, the data required for the computation of mathematical statistics are often not available in sufficient quantity and quality. With the lack of information concerning the design parameters, a non-probabilistic approach, e.g., fuzzy modelling provides the needed method to capture the impact of the uncertain parameter on the performance of the structure. In this study, a fuzzy-based model as explained in section 7.3.1 is used to determine the annual reliability and probability of failure that produces a lower and upper bound as illustrated in Figure 7.3 and Figure 7.7.

In the literature, annual performance indicators have been used to assess the maintenance of engineering structure based on reliability index, risk and cost (Dong & Frangopol, 2015; Khan & Tee, 2016). Herein, a non-probabilistic approach is utilised for the determination of the optimal maintenance time of a buried pipeline. The fuzzy method is considered in computing the structural reliability so that the effect of the uncertain fuzzy variable on the overall performance of buried pipeline can be captured. The annual reliability and risk based on the $\alpha -$ level of the membership function associated with buried pipe performance are studied. The former is considered due to its direct definition regarding estimating the failure probability, and the latter due to its increasing importance in decision making and also, research field.

7.5.1 Annual Fuzzy Reliability and Total Cost of Maintenance

The first method discussed in this study is based on the use of fuzzy annual reliability for the optimal pipe maintenance. In this approach, a multi-objective optimisation procedure is used to analyse the optimal maintenance planning of a buried pipeline, and a numerical application dealing with a series-series connection of the pipe structural failure mode. The aims of this optimisation approach are (a) to maximise and determine the minimum annual structural reliability of buried pipe over a 125 years life cycle, and (b) to minimise the total cost required to carry out maintenance within the design life. This will help to keep the buried pipe in a safe working condition throughout the design life. The fuzzy structural reliability-based on lower and upper bounds for the performance of buried metal pipe is shown in Figure 7.3 for the condition where there are no maintenance actions. The values of the structural response for the annual reliability have been obtained using a fuzzy approach that utilised subset simulation for estimating structural reliability.

The failure of the buried pipeline will involve a direct economic loss and other financial consequences as a result of the incident. However, a maintenance action would be required, and this would be carried out on the pipe segment with the lowest reliability at the time maintenance is required. The present total cost of maintenance C_{To} for keeping the each segment of buried pipe in safe working condition is expressed in Eq. (7.7).

$$C_{To} = \sum_{i=1}^{N} \frac{C_F}{(1+r)^T} \tag{7.7}$$

Where N denotes the total number of sections that require replacement during the time for maintenance; C_F represents the future cost of carrying out the replacement of each component of the pipe network; and r is the annual discount rate.

The formulation of the multi-objective optimisation is described by using the following minimisation problem.

Given:	$g(T), C,\ r,$	(7.8)
Find	$T_{opt} = \{T_1, \dots, T_n\}$	(7.9)
To minimise:	$\begin{cases} P_r^L(\mathrm{T}) \\ C_{To} \end{cases} \quad 0 \le \mathrm{T} \le 125 \text{ years}$	(7.10)
	And	
	$\begin{cases} P_r^U(\mathrm{T}) \\ C_{To} \end{cases} \quad 0 \le \mathrm{T} \le 125 \text{ years}$	(7.11)
Such that:	$\{0 \text{ years} \le T_{\mathrm{opt}} \le 125 \text{ years}\}$	(7.12)

Where $g(T)$ represents the limit state functions associated with the structural pipe failure modes; C_{To} denotes the cost of carrying out maintenance for each of the pipe segment; r is the annual money discount rate; n is the total number of designed years for the structure; $T_{opt} = \{T_1, \dots, T_n\}$ represents the vector of the repair times; $P_r^L(\mathrm{T})$ is the minimum lower bound value of the reliability of pipe over its life cycle, $P_r^U(T)$ denotes the minimum upper bound value of the pipe reliability over its design life and $\mathrm{C_T}$ is the total cost of the maintenance plan, evaluated using Eq. (7.7).

The goal of Eq. (7.8) and Eq. (7.11), has been defined regarding the fuzzy annual reliability for the lower and the upper bound of the buried pipe system, so that a minimisation problem can be achieved with respect to the two objectives. The optimal solution of the functions is obtained using a GA, and a single cross-over has been adopted, using an initial population of 200 trial solutions. The formulation and cross-over functions have been adapted to comply with constraints defined in Eq. (7.12).

Figure 7.3 shows the fuzzy annual reliability for the lower and upper bound of pipe segment A with no maintenance action, while the Pareto front obtained from the optimisation is given in Figure 7.4. The first set of the maintenance activities associated with Figure 7.4 for the pipe segment is characterised by two renewal actions occurring at different times, for the lower and upper bound reliability. The optimal time determined based on the optimisation outcome occurred at 60 years and 66 years. However, the maintenance plan involves essential maintenance, which requires replacement of the pipe segment with the lowest reliability at the time when pipe maintenance is needed. Because the failure modes are considered to be connected in series, which means one failure mode will affect the other and cause the buried pipeline to fail. Therefore, replacement of pipe segments would provide the needed reliability for the pipe network at the time of maintenance. By considering Eq. (7.7), the cost of the maintenance plan at 60 years and 66 years will be £82,025 and £92,374 respectively. Also, the fuzzy reliability profile associated with the optimal time for maintenance of the pipe segment is shown in Figure 7.5. In this case, two maintenance actions time are provided for the maintenance of the buried pipe.

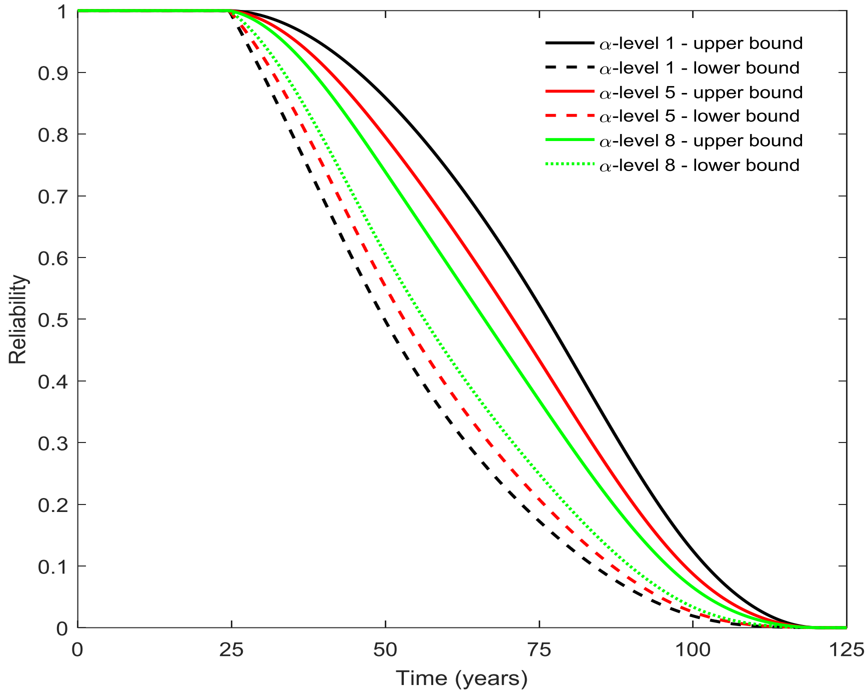


Figure 7.3: Pipe reliability with no maintenance action

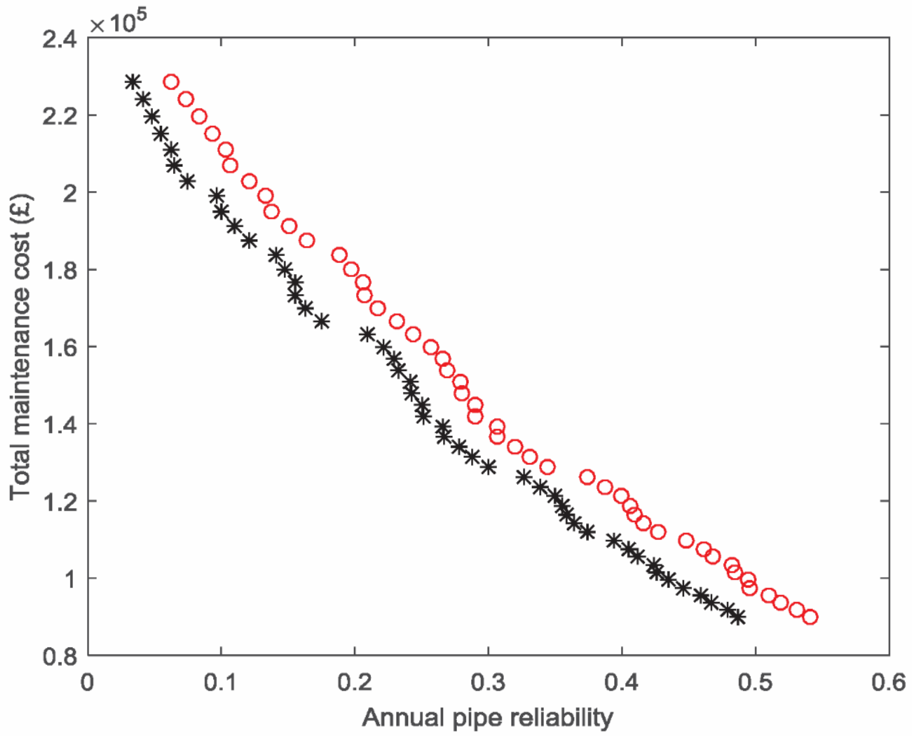


Figure 7.4: Reliability-based Pareto front of buried pipe

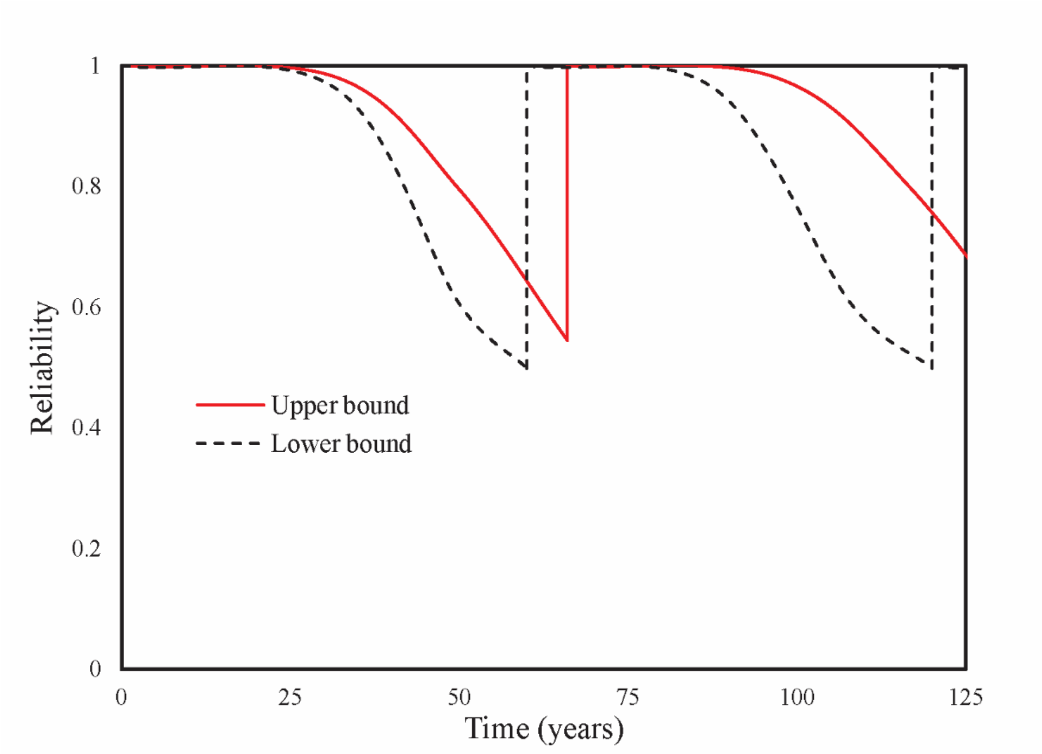


Figure 7.5: Pipe reliability with maintenance action

7.5.2 Annual Risk and Total Cost of Maintenance

The failure of engineering structures are often associated with consequences, and as a result, risk-based assessment becomes necessary, and also, an essential tool for optimisation of maintenance. Ang & Tang (1984) defined risk as the product of the probability of failure and the associated consequences in monetary terms as a result of the failure. Assessment of risk associated with engineering structures can be analysed qualitatively or quantitatively. Qualitative risk assessment of structures deals with simple descriptions of different types of hazards, the associated consequences and likelihood, and reporting all these aspects in a constructive and opportunely built risk matrices (Arunraj & Maiti, 2007; Barone & Frangopol, 2014b). However, a quantitative risk assessment is considered in this study and Figure 7.6, illustrates a flowchart of the computational process used for the risk assessment of buried pipe considering thickness reduction due to corrosion. The quantitative risk assessment associated with the failure of pipe is defined as the product of the failure probability for each pipe segment at time t and the associated consequences due to failure.

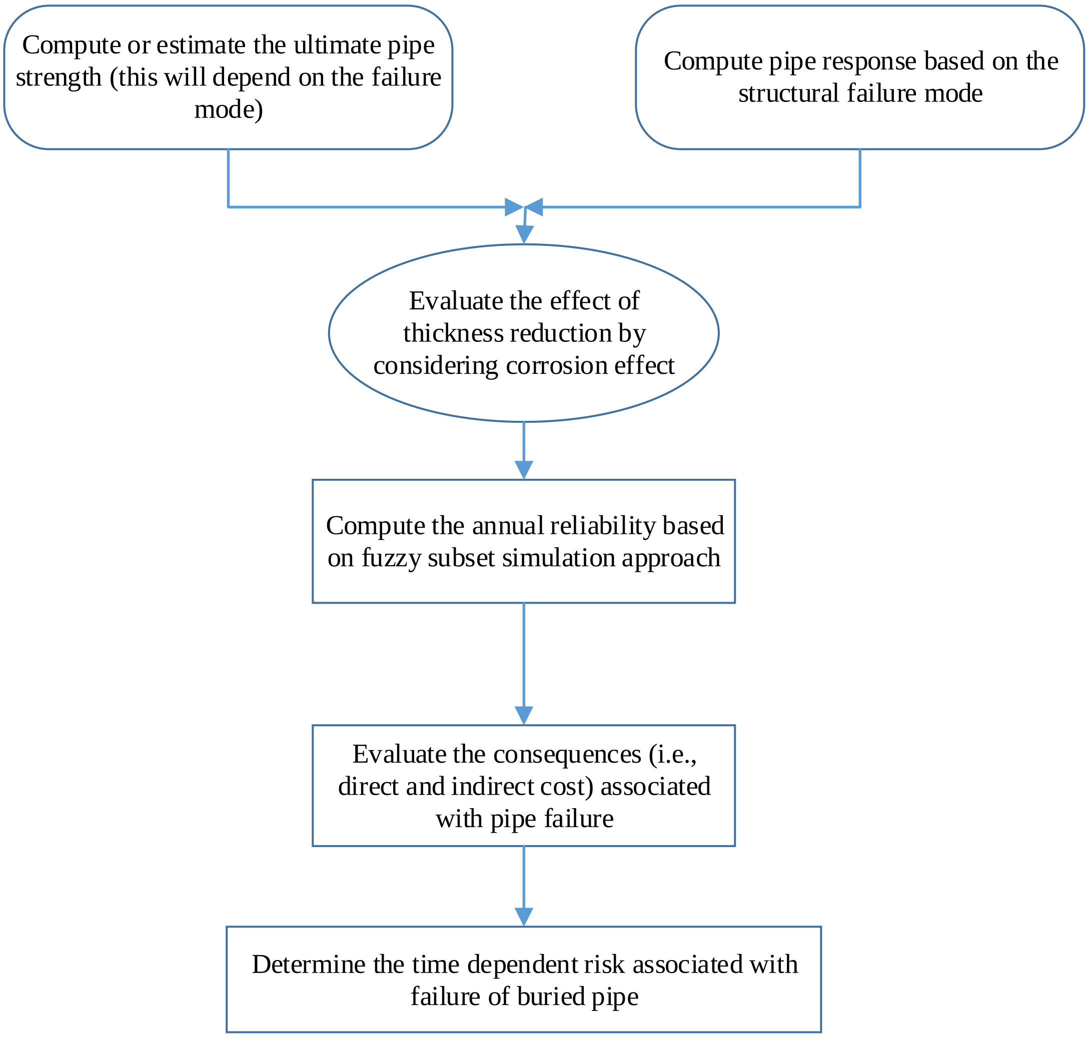


Figure 7.6: Framework for risk assessment of buried pipe considering thickness reduction

The fuzzy annual failure probability and fuzzy annual reliability do not have or contain information concerning the consequences or severity associated with the pipe failure. But considering the risk related to the likelihood of failure, more detailed information for decision-makers or managers when dealing with issues concerning pipe performance over the design life is provided. The most common way of quantifying consequences associated with pipe failure risk is to evaluate the losses associated with the failure regarding cost. The cost related to structural failure can be a direct cost, e.g., cost of replacing the failed part or indirect cost, e.g., environmental contaminations cost. Barone & Frangopol (2014a) suggested that the direct consequences of failure are often associated with repair/replacement cost of the structural component while the indirect consequence is the estimation cost derived from failure, which may not strictly be related to rebuilding the structure. In this case, the indirect effects of pipe failure may contain, for example, injuries, fatalities or environmental contaminations as a result of the structural failure of the buried pipe. With regards to any segment of the pipe network, the risk associated with the possibility of pipe failure is expressed in Eq. (7.13).

$$R(T) = P_f C^{dir}(T) + C^{indir}(T) \tag{7.13}$$

Where P_f denotes the failure probability of the pipe segment, $C^{dir}(T)$ represents the direct cost of replacing the pipe segment and $C^{indir}(T)$ is the indirect cost.

Indirect consequences for failure of buried pipe network are estimated as the sum of three different losses. These include the cost of injuries and fatalities, environmental damages and cost of deferred supply during the pipe maintenance. By making allowance for the discount rate of money, the direct and indirect present cost of pipe maintenance can be obtained using Eq. (7.14) and (7.15).

$$C^{dir}(T) = \frac{C_r}{(1+r)^T} \tag{7.14}$$

$$C^{indir}(T) = \frac{C_i + C_e + C_d}{(1+r)^T} \tag{7.15}$$

Where C_r denotes the direct cost of replacing a pipe segment, C_i represents the cost of injuries, C_s is the cost of environmental damages and C_d is the cost of deferred supply during maintenance.

The total annual pipe risk (i.e., the sum of direct and indirect risks) for the buried pipeline structure when there is no maintenance action is shown in Figure 7.7. As observed in Figure 7.7, the risk associated with pipe failure increases as time increases since maintenance action is not applied. However, to ensure that the structural performance is above the recommended safety level during the service life, it is crucial to reduce the risk associated with pipe failure. Similar to what was used for the reliability case in Section 7.4.1, a multi-objective optimisation procedure is proposed for the determination of optimal maintenance plan for buried pipe using the same constraints. However, in this investigation, replacement of pipe segment would be performed on the segment associated with the highest risk. Therefore, the optimisation problem is as follows:

Given: $g(T), C,\ r,$ (7.16)

Find $T_{opt} = \{T_1, \ldots, T_n\}$ (7.17)

To minimise: $\begin{cases} R^L_{max}(\mathrm{T}) \\ C_{To} \end{cases} \quad 0 \leq \mathrm{T} \leq 125 \text{ years}$ (7.18)

And

$\begin{cases} R^U_{max}(\mathrm{T}) \\ C_{To} \end{cases} \quad 0 \leq \mathrm{T} \leq 125 \text{ years}$ (7.19)

Such that: $\{0 \text{ years} \leq \mathrm{T_{opt}} \leq 125 \text{ years}\}$ (7.20)

Where $R^L_{max}(\mathrm{T})$ is the maximum lower bound value of the annual risk and $R^U_{max}(\mathrm{T})$ is the maximum upper bound value of the annual risk over the considered designed life of the pipe network.

For the risk analysis, the design variable changes during the optimisation, and a Pareto front, as shown in Figure 7.8, are obtained, containing the dominating solutions for the various possible time of repairs. Also, the fuzzy risk profile associated with maintenance action as shown in Figure 7.8 is, instead, shown in Figure 7.9. In this case, two repair actions are provided for the maintenance of pipe network, which corresponds to the lower and upper risk. The optimal time for the lower and upper risk happened at 62 years and 69 years and the corresponding cost of carrying out the maintenance is approximately £85,340 and £98,028 respectively.

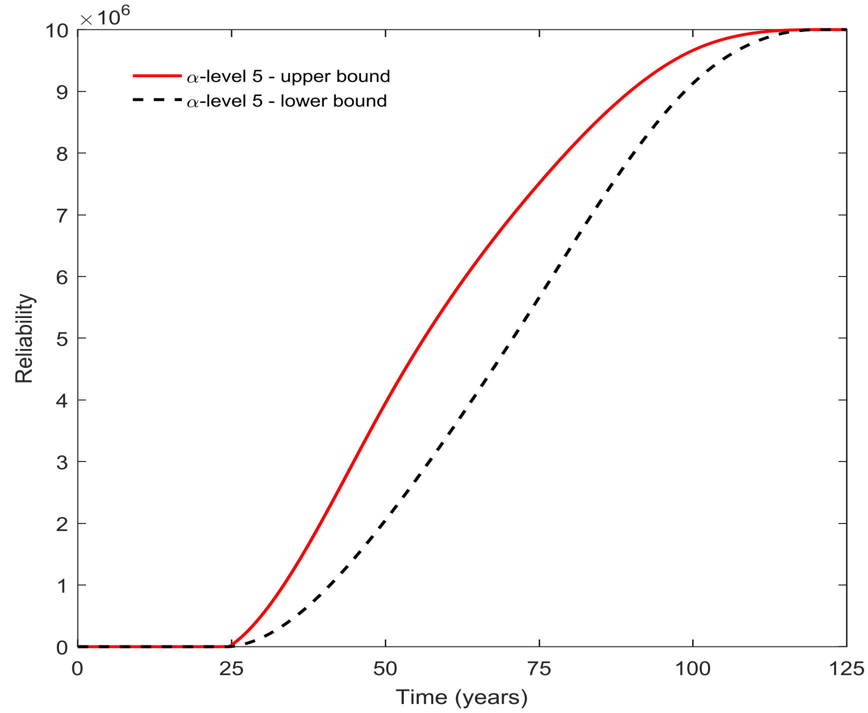


Figure 7.7: Annual risk of buried pipe with no maintenance action

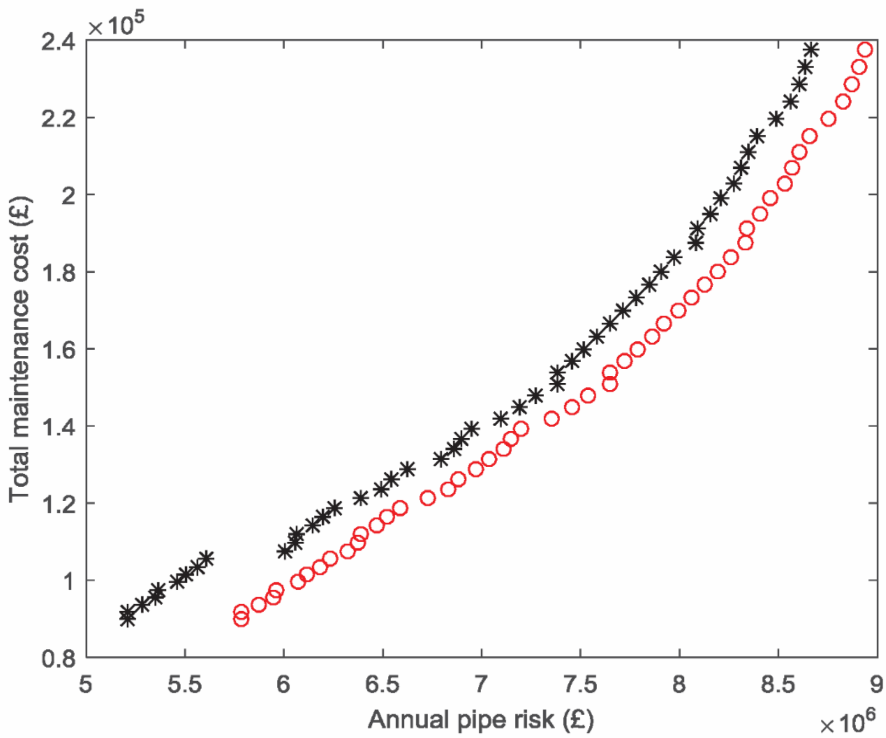


Figure 7.8: Risk-based Pareto front of buried pipe

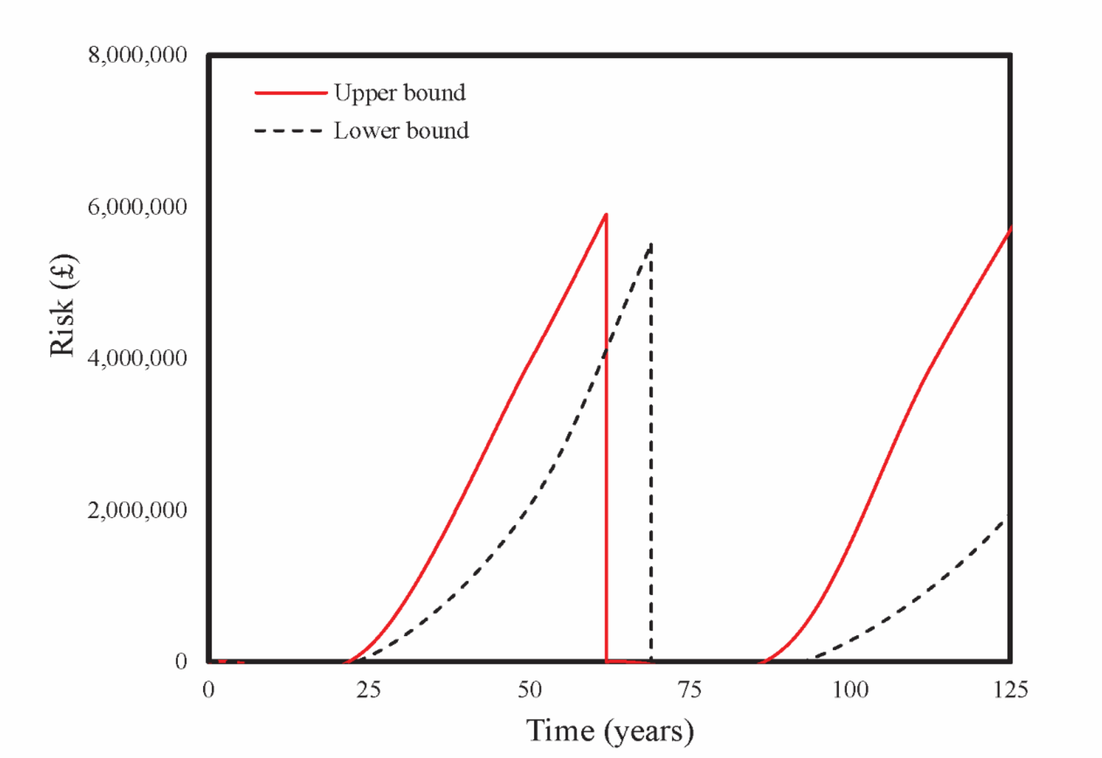


Figure 7.9: Risk-based assessment of buried pipe with maintenance action

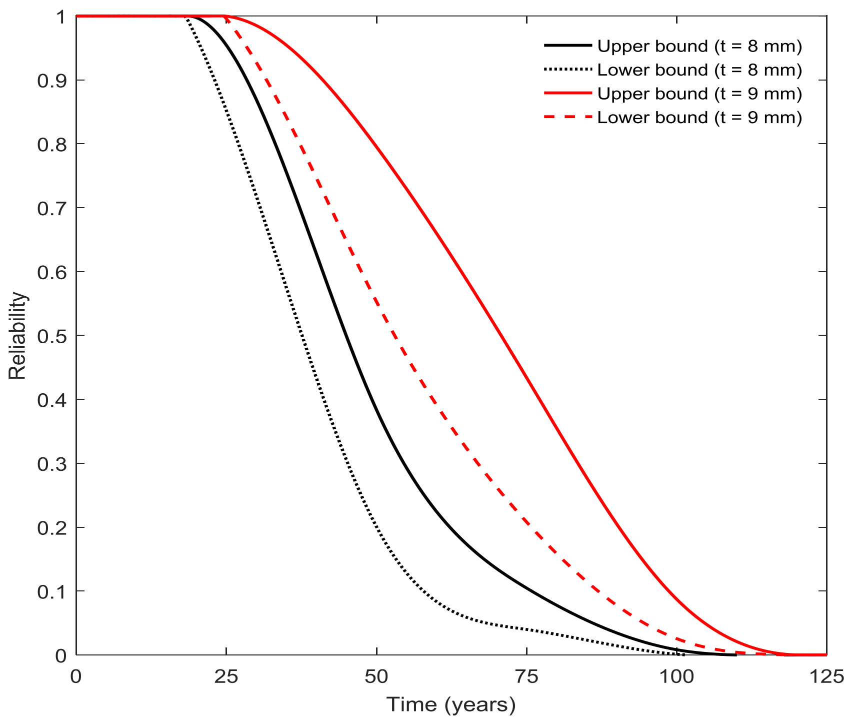


Figure 7.10: Pipe reliability by varying pipe thickness

7.6 Parametric Study

7.6.1 The Effect of Pipe Design Variables on Pipe Reliability and Risk

In this study, the parameters of pipe are considered as deterministic, random and fuzzy variables as defined in Table 7.1, Table 7.2 and Eq. (7.4) to Eq. (7.6). Figure 7.10 and Figure 7.11, shows the effect of pipe wall thickness and the yield stress due to pipe thickness reduction, and with respect to pipe reliability for the service life of 125 years. The result shows that both can affect pipe reliability, the optimal time for maintenance and the associated risk. This is demonstrated by varying the mean values of the input parameters. The increase in pipe thickness and the yield stress increases pipe reliability and the optimal time for maintenance and the associated risk is reduced. The outcome also shows that pipe thickness has a significant impact on pipe reliability compared to the yield stress. This demonstrates the importance of pipe wall thickness in the safety of the buried pipeline. Also, it could be that the outcome of the thickness reduction of pipe wall due to corrosion defects that produce the sudden decrease of pipe capacity. Based on this result, it is important to note that the pipe reliability, risk and optimal time for maintenance can be influenced significantly by a thickness reduction of the pipe wall.

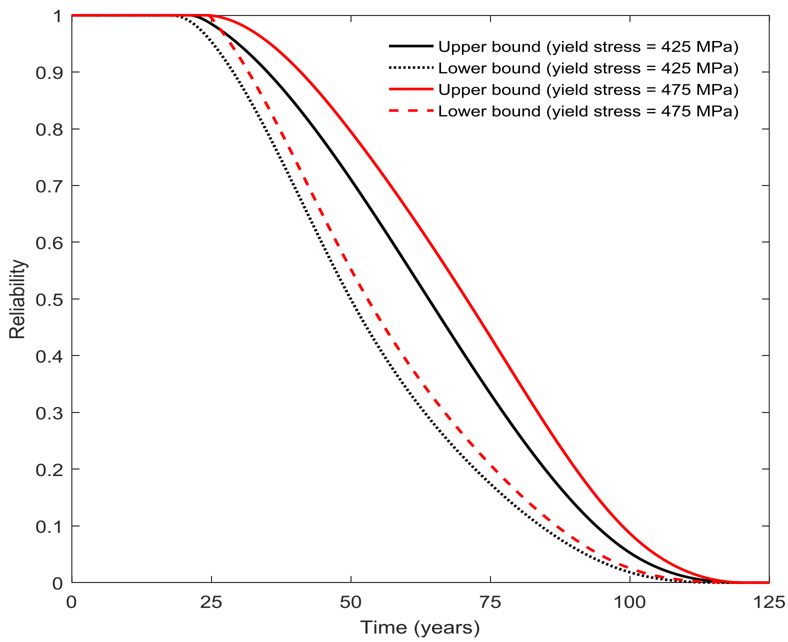


Figure 7.11: Pipe reliability by varying pipe yield stress of pipe material

7.6.2 The Effect of Cost Ratio (Direct and Indirect Cost)

As explained in Section 7.5.2, the direct cost of pipe failure is the cost associated with the replacement of structural component or segment and the indirect cost involves the cost of injuries, fatalities or environmental contaminations. Since the risk associated with pipe failure includes direct and indirect cost, then, their effect including the failure probability can be analysed with regards to the time of maintenance. Based on Eq. (7.13) and to keep the buried pipeline safe during the design life, Eq. (7.21) is proposed to minimise the risk function.

$$R(T_{op}) = P_f(T_{op})C^{dir} + \frac{T_d}{T_{op}}C^{indir} \tag{7.21}$$

Where T_{op} represents the optimised time required for the replacement or maintenance to be conducted; T_d denotes the designed life.

The relationship $\frac{T_d}{T_{op}}$ represents the frequency of maintenance required during the designed life. From Eq. (7.21), an optimal time for maintenance can be found as the minimum of the risk function with respect to optimal time T_{op}.

$$T_{op}: R(T_{op}) \rightarrow \min_{T_{op}}. \tag{7.22}$$

Therefore, the function $R(T_{op})$ is differentiable at any time T_{op}, where the residual pipe thickness is less than the pipe wall thickness and this is expressed in Eq. (7.23).

$$R'_{T_{op}} = P'_{f(T_{op})}C^{dir} + \left(-\frac{T_d}{(T_{op})^2}\right)C^{indir} \tag{7.23}$$

From Eq. (7.23), the optimal time for maintenance or replacement of pipe segment can be determined based on the risk function and numerical solution of the equation. Also, the expression shows that the optimal time for maintenance will depend on the direct and indirect cost, the designed life and probability of failure. However, the maintenance of buried pipe by replacing the failed pipe segment is ideal when it is performed before failure. This will help to save the indirect cost associated with the failure of the pipe. In Figure 7.12, it can be deduced that as the optimal time required for maintenance increases, the cost ratio with the probability of failure increases over the designed life. Based on this, it is crucial to quantify efficiently all the aspect of risk that may influence negatively on the performance of buried pipe.

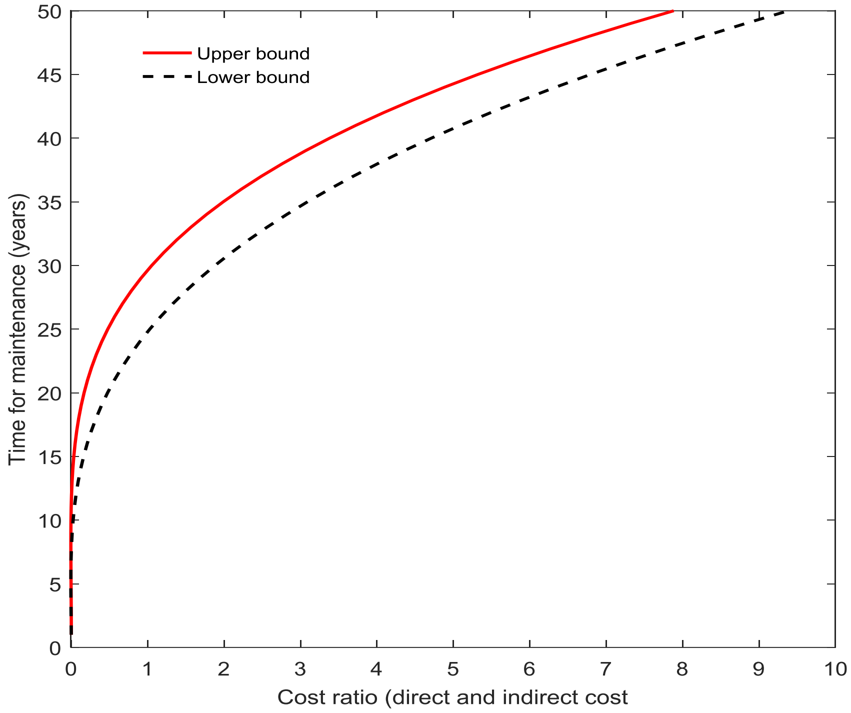


Figure 7.12: Optimal pipe maintenance time using cost ratio and the probability of failure

7.7 Chapter Summary

Structural deterioration of buried pipeline due to adverse corrosion effect is among the leading causes of increasing possibility of pipe failure. As a result, maintenance intervention becomes a fundamental task for good engineering management programme. In this Chapter, a new maintenance technique is developed to determine the optimal time for the maintenance of buried pipeline using the fuzzy-based approach as a non-probabilistic method for computing pipe reliability and risk, based on $\alpha -$ level cut. The strategy aimed at assessing the cost-efficiency required for the determination of the optimal time for maintenance using multi-objective optimisation based on the fuzzy annual reliability, risk, and total maintenance cost. The time for essential maintenance schedules are obtained based on a particular performance indicator (annual fuzzy reliability or risk), and the optimisation is performed using a GA.

The applicability is demonstrated with a case study as reported in the literature, and the method provides engineering technicians with the needed tools for the determination of optimal time interval required to carry out maintenance of buried pipeline. The optimisation of the time for maintenance due to corrosion-induced failure has been analysed using two different multi-objective approaches. In both investigations, annual performance indicators such as annual reliability and risk based on fuzzy approach with lower and upper bound are considered. The purpose of the optimisation is aimed to minimise the total cost of the maintenance and the associated risk. The outcome of the Pareto fronts obtained using the fuzzy-based reliability and fuzzy-based risk assessment techniques are marginally different. Although, the same optimisation constraints, maintenance (replacement) costs and the optimisation method have been considered in the optimisation process. Therefore, this could mean that the incorporation of consequences of structural failure plays a vital role in decision making for the determination of the optimal time for maintenance.

The use of risk as a performance indicator can provide comprehensive and better understanding of the probability of pipe failure and the associated consequences. Therefore, the use of risk in the managing pipe systems is imperative and critical to successful management. The optimal time interval can be determined based on the proposed optimisation strategy. This would provide the opportunity to have a targeted maintenance plan with various trade-offs, which will assist maintenance engineers in taking the needed decision at a point when maintenance is required. However, the fuzzy risk-based approach requires an initial estimation of the present or future direct and indirect consequences of failure cost. This additional task increases slightly the computational effort needed to carry out the optimisation, and this will depend on the number of the failed pipe segment. A parametric study was carried out on the design parameters, and the outcome shows that thickness reduction can significantly reduce the reliability of the buried pipe over the designed life.

CHAPTER EIGHT

8 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

8.1 Conclusions

The reliability analysis of buried pipeline is usually performed to evaluate the structural response defined using the limit state function based on the failure modes. Based on this, there is a need to make informed decisions from the outcome of the buried pipe analysis to ensure an optimal time for maintenance. In the literature, reliability analysis of buried pipe system has been presented by a number of published works using probabilistic methods and considering randomness associated with the input parameters in the performance assessment. These input parameters are related to the pipe and soil materials and are associated with uncertainties, particularly in the process of estimating or determining the values of the parameters. However, the statistical data to determine the PDFs of some of the input parameter may not be available to define the parameter. Hence, the presences of fuzziness or vagueness associated with pipe or soil parameters are often not considered in most computational modelling of buried pipe. Also, the computational capabilities of some of the existing models require an enormous computational cost in estimating the reliability of the structure. Therefore, the purpose of this research is to develop a framework for analysing the reliability and robustness of buried pipe structure in order to promote safety in reliability-based design and robust assessment for the buried pipeline.

8.1.1 Reliability of Buried Pipe using a Combination of LS and IS Method

First, this study presents a time-dependent reliability analysis of buried pipeline using LS, IS, MCS and a combination of LS and IS methods while considering aleatory uncertainties associated with the input parameters. The structural failure modes of total axial stress and through-wall bending stress due to concentrated point load and the adverse effect of active corrosion were considered for the analysis. The outcome based on the reliability methods demonstrates that the combination of LS and IS shows better sampling efficiency compared to the other methods. Also, the effect of groundwater table located below and above the buried pipe was investigated, and the results show that undermining this effect can affect its performance by increasing the probability of failure. Furthermore, a situation where the buried pipe is jacked into an undisturbed soil as an alternative to being placed in a trench is analysed, and the result shows a significant reduction in the probability of failure. For the parametric study, the corrosion empirical constant shows their variable and dynamic nature. Therefore, a good understanding of the corrosion parameters can provide a useful and better analysis of the reliability of a buried pipe.

8.1.2 Fuzzy-based Robustness Assessment of Buried Pipe

As a result of the variabilities and vagueness associated with the input parameters of the buried pipe, a methodological approach for the assessment of robustness behaviour of the buried pipe is presented. The robustness of the buried pipe is formulated based on the pipe failure modes, which include pipe deflection, wall thrust, buckling pressure, and bending strain using the principles of fuzzy set, Shannon's entropy, and interval arithmetic. The entropy-based robustness measure is considered because it provides a potential to assess the robustness in the form of a function, which depends on the magnitude of uncertainty that exists in the structure. The modelling of the failure modes based on fuzzy sets considers the various levels of uncertainties concerning the corrosion pit depth and other input variables. The outcome shows that as the number of pipe service years increases, the pipe robustness behaviour tends to normalise and shows a similar trend, which illustrates the ductility nature of the pipe material. Also, the outcome shows that the values evaluated for the pipe robustness measure would continue to decrease as the number of pipe service years continues to increase. By evaluating the performance of buried steel pipe using the fuzzy-based robustness measure, a wide-ranging understanding concerning the adverse effect of corrosion uncertainty to the examined pipe failure problems can be determined. This result can lead to optimal decision making concerning buried pipe structures and where a degree of accuracy is needed.

8.1.3 Multi-objective Optimisation of Buried Pipe

For optimum design of buried pipes involving design variable and fuzzy variables, a new approach is presented considering multi-objective optimisation based on the expected value of a fuzzy output variable for the pipe failure modes. The concepts and the processes of the proposed algorithm are introduced, and a numerical example is used to demonstrate its applicability and usefulness. The outcome demonstrates that the uncertainty of the fuzzy variables for the input parameters could be propagated for the optimal design of buried pipe by employing a multi-objective optimisation algorithm to find the optimal solution set. The fuzzy-based multi-objective design optimisation problem has been expressed by considering the expected value of a fuzzy output variable for the pipe failure modes. The outcome of the expected value controls the performance of the optimal solution and the entropy deals with the variability of the structural problem. The first extreme value of the optimal solution set is characterised by less performance, less robustness, and more significant variability while the second value characterised with the best performance, greater robustness, and lower variability. The investigated pipe failure conditions give a small value of the fuzzy output as against the second extreme value, but also a substantial value of the fuzzy entropy for buckling pressure. Therefore, comparing the results of the fuzzy-based multi-objective design optimisation for different years of fuzzy variables and their corresponding impact on the failure conditions, the designer would be able to gauge the negative impact on the safety of the structure. Furthermore, a multi-objective optimisation is considered because it offers the potential to consider several mutually conflicting design requirements that are associated with the failure of the buried pipe. Based on this, it is essential to locate the Pareto optimal set which plays a vital role for decision-makers concerning the design of buried pipe.

8.1.4 Reliability of Buried Pipe Considering Random and Fuzzy Variable

Due to the presences of both epistemic and aleatory type of uncertainties in the design of buried pipe, an optimisation based fuzzy-subset simulation approach for estimating the reliability of a buried pipe structure is proposed. The purpose is to develop a framework that is robust and capable of estimating the reliability of buried pipe having parameters that are random and fuzzy. The underlying ideas behind the proposed framework are explained, and a numerical example is used to analyse the applicability and efficiency of the method. The approach shows that the fuzzy uncertainty of the input variables can be propagated to determine the fuzzy reliability of the membership function of a buried pipe system. The result shows that as the $\alpha - level$ increases, the corresponding failure probability for the lower and upper bound increases. This outcome demonstrates how sensitive the interval-based reliability analysis is with respect to the level of imprecision of the input variables. The $\alpha - level$ gains its effectiveness by scrutinising the reliability of the structure at a various level that could represent a different degree of imprecision. As a result, a better understanding of the impact of uncertainty associated with the failure of buried pipe can be evaluated. This feature aids to capture and quantify the adverse effects of uncertain variables on the performance of buried pipeline with regards to estimating the reliability. Moreover, for the evaluation of the failure probability, the approach utilised the efficiency and capability of subset simulation. The developed model can accommodate various types of uncertainty in the computation of fuzzy reliability and can easily be applied to other engineering structures.

8.1.5 Maintenance Optimisation of Deteriorating Buried Pipe

The reliability of buried pipe based on fuzzy approach has been extended to estimate the optimal time interval to carry out maintenance using multi-objective optimisation. The purpose of the optimisation is aimed to minimise the total cost of the maintenance and the associated risk. The outcome of the Pareto fronts obtained using the fuzzy-based reliability and fuzzy risk-based techniques are marginally different. Although, the same optimisation constraints, maintenance (replacement) costs and the optimisation method have been considered in the optimisation process. Therefore, this could mean that the incorporation of consequences of structural failure plays a vital role in decision making for the determination of the optimal time for maintenance. The use of risk as a performance indicator can provide comprehensive and better understanding of the probability of pipe failure and the associated consequences. Therefore, the use of risk in the managing pipe systems is imperative and critical to successful management. Also, the outcome of a parametric study shows that thickness reduction can significantly reduce the reliability of the buried pipe over time.

8.1.6 Concluding Statement

In summary, the above-proposed framework can serve as a prudent tool to evaluate and analyse the performance of buried pipeline efficiently and also, serves as a managerial tool for design engineers in assessing and maintaining the performance of buried pipe. Based on the proposed framework, the reliability and robustness behaviour of buried pipeline considering uncertainties that exist in the input parameters can be determined. Also, the influence of design parameters can be analysed through sensitivity and parametric studies. The proposed framework for the maintenance of a deteriorating buried pipe will enable the decision-makers to select appropriate time interval to repair or replace a particular pipe segment.

8.2 Recommendations for Future Work

The applicability and effectiveness of the presented methods have been exemplified with numerical examples, and the outcomes demonstrate that these techniques are effective to perform reliability and robustness analysis of buried pipe considering aleatory and epistemic uncertainties. However, there are other possible areas for improvement and extension of this study and here are some of the exciting areas for potential future research.

The presented framework for the reliability analysis of buried pipe is based on a corrosion model proposed by Rajani et al. (2000) and the general power law model. However, the corrosion model relies heavily on the corrosion data, which is highly non-linear and can be affected by the environmental conditions. Therefore, it is suggested to use an inline inspection data to quantify the values of corrosion and develop a specific corrosion model that can be used in conjunction with the proposed framework. This will help to model the deterioration process of the buried pipe due to corrosion with better precision because of the data that is tailored to a particular pipeline problem.

It is suggested that more advanced structural failure modes of the buried pipeline should be investigated using finite element analysis software (e.g., ABAQUS) and experiment. Practical experience shows that some of the currently available models involve a considerable model uncertainty. This uncertainty affects the outcome of the existing structural failure modes, which propagates into the evaluated probability of failure and can result in over conservative estimate.

The characterisation of the uncertainties associated with the input parameters of the buried pipeline considering various failure modes is essential because it dictates the accuracy of the results generated from the methods used in the analysis. Therefore, the need to carry out an experimental update on the data used to model the PDFs of the uncertain parameters are recommended. This is an important area for future research.

The damage of buried pipe due to the third party is one of the primary causes of pipeline failure. It is suggested that the damage of buried pipe due to the third party should be investigated and quantified using structural reliability methods. Also, the preventive measures used against the damage should be included in the multi-objective optimisation based maintenance framework.

REFERENCES

Abdoun, T. H., Ha, D., O'Rourke, M. J., Symans, M. D., O'Rourke, T. D., Palmer, M. C., & Stewart, H. E. (2009). Factors influencing the behavior of buried pipelines subjected to earthquake faulting. *Soil Dynamics and Earthquake Engineering*, *29*(3), 415–427.

Ahammed, M. (1998). Probabilistic estimation of remaining life of a pipeline in the presence of active corrosion defects. *International Journal of Pressure Vessels and Piping*, *75*, 321–329.

Ahammed, M., & Melchers, R. E. (1994). Reliability of Underground Pipelines Subject to Corrosion. *Journal of Transportation Engineering*, *120*(6), 989–1002.

Ahammed, M., & Melchers, R. E. E. (1997). Probabilistic analysis of underground pipelines subject to combined stresses and corrosion. *Engineering Structures*, *19*(12), 988–994.

Alliance A. L. (2001). *Guidelines for the Design of Buried Steel Pipe*. Reston VA: American Society of Civil Engineers.

American Water Works Association. (1977). American National standard for thickness design of cast-iron pipe (ANSI/AWWA C101-67). *AWWA Standards*, 1–78.

Amirat, A., Mohamed-Chateauneuf, A., & Chaoui, K. (2006). Reliability assessment of underground pipelines under the combined effect of active corrosion and residual stress. *International Journal of Pressure Vessels and Piping*, *83*(2), 107–117.

Ang, A.H. & Tang, W.H., (1984). *Probability concepts in engineering planning and design, vol. 2: Decision, risk, and reliability*. John Wiley & Sons, Inc., 605 Third Ave., New York, NY 10158, USA, 1984, 608.

Ang, A. H. S., & Tang, W. H. (2007). *Probability Concepts in Engineering: Emphasis on Applications to Civil and Environmental Engineering*. Hoboken, New Jersey: John Wiley & Sons, Inc.

Anoop, M. B., & Balaji Rao, K. (2007). Application of Fuzzy Sets for Remaining Life Assessment of Corrosion Affected Reinforced Concrete Bridge Girders. *Journal of Performance of Constructed Facilities*, *21*(2), 166–171.

Apostolakis, G. (1990). The concept of probability in safety assessments of technological systems. *Science (New York, N.Y.), 250*(4986), 1359–1364.

Arunraj, N. S., & Maiti, J. (2007). Risk-based maintenance-Techniques and applications. *Journal of Hazardous Materials*, *142*(3), 653–661.

Au, S. K., & Beck, J. L. (2001). Estimation of small failure probabilities in high dimensions by subset simulation. *Probabilistic Engineering Mechanics, 16*(4), 263–277.

Au, S., & Wang, Y. (2014). *Engineering Risk Assessment with Subset Simulation.* John Wiley & Sons.

AWWA (American water works association). 1999. Buried pipe design, Fiberglass pipe design. *AWWA Manual* M45, 35–53, Denver, USA.

Babu, G. L. S., & Srivastava, A. (2010). Reliability Analysis of Buried Flexible Pipe-Soil Systems. *Journal of Pipeline Systems Engineering and Practice*, *1*(1), 33–41.

Baecher, G. B., & Christian, J. T. (2005). *Reliability and Statistics in Geotechnical Engineering*. John Wiley & Sons.

Barone, G., & Frangopol, D. M. (2014a). Life-cycle maintenance of deteriorating structures by multi-objective optimization involving reliability, risk, availability, hazard and cost. *Structural Safety*, *48*, 40–50.

Barone, G., & Frangopol, D. M. (2014b). Reliability, risk and lifetime distributions as performance indicators for life-cycle maintenance of deteriorating structures. *Reliability Engineering and System Safety*, *123*, 21–37.

Beck, J. L., & Katafygiotis, L. S. (1998). Updating models and their uncertainties. I: bayesian statistical framework. *Journal of Engineering Mechanics*, *124*(4), 463–467.

Beck, J.L. & Zuev, K.M., (2017). Rare-Event Simulation. *Handbook of uncertainty quantification*, pp.1075-1100.

Beer, M., Ferson, S., & Kreinovich, V. (2013a). Imprecise probabilities in engineering analyses. *Mechanical Systems and Signal Processing*, *37*(1–2), 4–29.

Beer, M., & Liebscher, M. (2008). Designing robust structures - A nonlinear simulation based approach. *Computers and Structures*, *86*(10), 1102–1122.

Beer, M., Zhang, Y., Quek, S. T., & Phoon, K. K. (2013b). Reliability analysis with scarce information: Comparing alternative approaches in a geotechnical engineering context. *Structural Safety*, *41*, 1–10.

Berardi, L., Giustolisi, O., Kapelan, Z. & Savic, D.A., (2008). Development of pipe deterioration models for water distribution systems using EPR. *Journal of Hydroinformatics*, *10*(2), pp.113-126.

Beyer, H. G., & Sendhoff, B. (2007). Robust optimization - A comprehensive survey. *Computer Methods in Applied Mechanics and Engineering*, *196*(33–34), 3190–3218.

Bhaskaran, R., Palaniswamy, N., Rengaswamy, N.S. & Jayachandran, M. (2005). Global cost of corrosion - A historical review. *Corrosion: Materials*, *13*, 621–628.

Biondini, F., & Frangopol, D. M. (2009). Lifetime reliability-based optimization of reinforced concrete cross-sections under corrosion. *Structural Safety*, *31*(6), 483–489.

Biondini, F., Frangopol, D.M. & Restelli, S., (2008). On structural robustness, redundancy, and static indeterminacy. In *Structures Congress 2008: Crossing Borders* (pp. 1-10).

Brown, G.K., (2014). Appendix–internal corrosion monitoring techniques for pipeline systems. *Pipeline integrity handbook. Boston: Gulf Professional Publishing*, pp.255-92.

BS 9295:2010. 2010. Guide to the structural design of buried pipelines. *British Standard Institution*, UK.

BS EN 1295:1-1997. Structural design of buried pipelines under various conditions of loading - General requirements. *British Standards Institution*, UK.

Bucher, C. & Frangopol, D.M., (2006). Optimization of lifetime maintenance strategies for deteriorating structures considering probabilities of violating safety, condition, and cost thresholds. *Probabilistic Engineering Mechanics*, *21*(1), pp.1-8.

Caleyo, F., Velázquez, J. C., Valor, A., & Hallen, J. M. (2009). Probability distribution of pitting corrosion depth and rate in underground pipelines: A Monte Carlo study. *Corrosion Science*, *51*(9), 1925–1934.

Cameron DA. (2005). Analysis of buried flexible pipes in granular backfill subjected to construction traffic. *PhD Thesis, University of Sydney, Department of Civil Engineering, Australia.*

Chankong, V. & Haimes, Y.Y., (1983). *Multiobjective decision making: theory and methodology*. Courier Dover Publications.

Cheng, F. Y., & Le, D. (1997). Multiobjective optimization design with pareto genetic algorithm. *Journal of Structural Engineering*, *9*(2), 1252–1261.

Chughtai, F. & Zayed, T., (2008). Infrastructure condition prediction models for sustainable sewer pipelines. *Journal of Performance of Constructed Facilities*, *22*(5), pp.333-341.

Coello, C. A. C. (2000). Handling preferences in evolutionary multiobjective optimization: A survey. In *Proceedings of the 2000 Congress on Evolutionary Computation, CEC 2000* (Vol. 1, pp. 30–37).

Dandy, G.C. % Engelhardt, M.O., (2006). Multi-objective trade-offs between cost and reliability in the replacement of water mains. *Journal of water resources planning and management*, *132*(2), pp.79-88.

Dash, S.R. & Jain, S.K., (2007). IITK-GSDMA Guidelines for seismic design of buried pipelines: provisions with commentary and explanatory examples. *National Information Center of Earthquake Engineering, Kanpur, India*.

Datta, T. (1999). Seismic response of buried pipelines: a state-of-the-art review. *Nuclear Engineering and Design*, *192*(2–3), 271–284.

Datta, T. K. (2010). *Seismic Analysis of Structures*. John Wiley & Sons (Asia) Pvt. Ltd.

Davies, J. P., Clarke, B. A., Whiter, J. T., & Cunningham, R. J. (2001). Factors influencing the structural deterioration and collapse of rigid sewer pipes. *Urban Water*, *3*(1–2), 73–89.

Davies, J. P., Clarke, B. A., Whiter, J. T., Cunningham, R. J., & Leidi, A. (2001). The structural condition of rigid sewer pipes: A statistical investigation. *Urban Water*, *3*(4), 277–286.

Deb, K. (2001). Multi-Objective Optimization Using Evolutionary Algorithms. *John Wiley & Sons*.

Der Kiureghian, A., Lin, H., & Hwang, S. (1987). Second-Order Reliability Approximations. *Journal of Engineering Mechanics*, *113*(8), 1208–1225.

Doltsinis, I., & Kang, Z. (2004). Robust design of structures using optimization methods. *Computer Methods in Applied Mechanics and Engineering*, *193*(23–26), 2221–2237.

Dong, Y., & Frangopol, D. M. (2015). Risk-informed life-cycle optimum inspection and maintenance of ship structures considering corrosion and fatigue. *Ocean Engineering*, *101*, 161–171.

Earthquake Engineering Research Institute (1999). "Kocaeli, Turkey Earthquake of August 17", EERI Special Earthquake Report.

Echard, B., Gayton, N., Lemaire, M., & Relun, N. (2013). A combined Importance Sampling and Kriging reliability method for small failure probabilities with time-demanding numerical models. *Reliability Engineering and System Safety*, *111*, 232–240.

Eldred, M. S., Swiler, L. P., & Tang, G. (2011). Mixed aleatory-epistemic uncertainty quantification with stochastic expansions and optimization-based interval estimation. *Reliability Engineering and System Safety*, *96*(9), 1092–1113.

Engelhardt, G., & Macdonald, D. D. (2004). Unification of the deterministic and statistical approaches for predicting localized corrosion damage. I. Theoretical foundation. *Corrosion Science*, *46*(11), 2755–2780.

Estes, A.C. & Frangopol, D.M., (2001). Bridge lifetime system reliability under multiple limit states. *Journal of bridge engineering*, 6(6), pp.523-528.

European Commitee for Standardization. (2004). Eurocode 8: Design of structures for earthquake resistance - Part 1 : General rules, seismic actions and rules for buildings. *European Committee for Standardization*.

Faber, M.H., Kroon, I.B. and Sørensen, J. D. (1996). Sensitivities in structural maintenance planning. *Reliability Engineering and System Safety*, *51*(3), 317–329.

Fang, Y., Tee, K.F. & Chen, J. (2016). Structural dynamic reliability evaluation under consideration of fuzzy strength and fuzzy stress. *Journal of Vibration Engineering and Technologies*, *4*(1), 53–58.

Fares, H. & Zayed, T., (2010). Hierarchical fuzzy expert system for risk of failure of water mains. *Journal of Pipeline Systems Engineering and Practice*, *1*(1), pp.53-62.

Farshad, M., (2011). *Plastic pipe systems: Failure investigation and diagnosis* (Vol. 407). Elsevier.

Fenner, R.A., Sweeting, L. & Marriott, M.J., (2000). A new approach for directing proactive sewer maintenance. In *Proceedings of the Institution of Civil Engineers-Water and Maritime Engineering* (Vol. 142, No. 2, pp. 67-77). Thomas Telford Ltd.

Fetz, T. & Tonon, F., (2008). Probability bounds for series systems with variables constrained by sets of probability measures. *International Journal of Reliability and Safety*, *2*(4), pp.309-339.

Fornasini, P., (2008). *The uncertainty in physical measurements: an introduction to data analysis in the physics laboratory*. Springer Science & Business Media.

Fonesca, C.M. and Fleming, P.J. (1993), July. Genetic algorithms for multiobjective optimization: formulation, discussion and generalization. In *Proc of the Fifth Int. Conf. On genetic Algorithms, Forrest S.(Ed.), San Mateo, CA, Morgan Kaufmann* (pp. 415-423).

Frangopol, D.M. & Curley, J. P. (1987). Effects of damage and redundancy on structural reliability. *Journal of Structural Engineering*, *113*(7), 1533–1549.

Gabriel, L. H. (2011). Corrugated polyethylene pipe design manual and installation guide. *Plastic Pipe Institute, USA.*

Gomes, W. J. S., & Beck, A. T. (2014). Optimal inspection and design of onshore pipelines under external corrosion process. *Structural Safety*, *47*, 48–58.

Halfawy, M. R., Dridi, L., & Baker, S. (2008). Integrated Decision Support System for Optimal Renewal Planning of Sewer Networks. *Journal of Computing in Civil Engineering*, *22*(6), 360–372.

Hand, D. J., & Walley, P. (1993). Statistical Reasoning with Imprecise Probabilities. *Applied Statistics*.

Hanss, M., & Turrin, S. (2010). A fuzzy-based approach to comprehensive modeling and analysis of systems with epistemic uncertainties. *Structural Safety*, *32*(6), 433–441.

Hastings, W. K. (1970). Monte carlo sampling methods using Markov chains and their applications. *Biometrika*, *57*(1), 97–109.

Haupt, R. L., & Haupt, S. E. (2004). *Practical Genetic Algorithm*. John Wiley & Sons.

Hong, H. P. (1999). Inspection and maintenance planning of pipeline under external corrosion considering generation of new defects. *Structural Safety*, *21*(3), 203–222.

Huang, B., & Du, X. (2006). A robust design method using variable transformation and Gauss-Hermite integration. *International Journal for Numerical Methods in Engineering*, *66*(12), 1841–1858.

Jayaram, N. & Srinivasan, K., (2008). Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing. *Water Resources Research*, 44(1).

Ji, J., Robert, D. J., Zhang, C., Zhang, D., & Kodikara, J. (2017). Probabilistic physical modelling of corroded cast iron pipes for lifetime prediction. *Structural Safety*, *64*, 62–75.

Karamanos, S.A., Keil, B. & Card, R.J., (2014). Seismic design of buried steel water pipelines. In *Pipelines 2014: From Underground to the Forefront of Innovation and Sustainability* (pp. 1005-1019).

Khan, L.R. & Tee, K.F., (2016). Risk-cost optimization of buried pipelines using subset simulation. *Journal of Infrastructure Systems*, *22*(2), p.04016001.

Khemis, A., Chaouche, A.H., Athmani, A. & Tee, K.F., (2016). Uncertainty effects of soil and structural properties on the buckling of flexible pipes shallowly buried in Winkler foundation. *Structural Engineering and Mechanics*, *59*(4), pp.739-759.

Kleiner, Y., Adams, B.J. & Rogers, J. S. (2001). Water distribution network renewal planning. *Journal of Computing in Civil Engineering*, *15*(1), 15–26.

Kleiner, Y., & Rajani, B. (2001a). Comprehensive review of structural deterioration of water mains: physically based models. *Urban Water*, 3(3), 151-164.

Kleiner, Y., & Rajani, B. (2001b). Comprehensive review of structural deterioration of water mains: statistical models. *Urban Water*, *3*(3), 131–150.

Kleiner, Y., Rajani, B. & Sadiq, R., (2004). Management of failure risk in large-diameter buried pipes using fuzzy-based techniques. *In 4th International Conference on Decision Making in Urban and Civil Engineering*. Porto Portugal.

Klir, G.J. & Yuan, B., (1995). Fuzzy sets and fuzzy logic: theory and applications. *Possibility Theory versus Probab. Theory, 32*(2).

Klir, G.J., (2006). *Uncertainty and information: foundations of generalized information theory*. John Wiley & Sons.

Kouretzis, G. P., Bouckovalas, G. D., & Gantes, C. J. (2006). 3-D shell analysis of cylindrical underground structures under seismic shear (S) wave action. *Soil Dynamics and Earthquake Engineering*, *26*(10), 909–921.

Koutsourelakis, P. S., Pradlwarter, H. J., & Schuëller, G. I. (2004). Reliability of structures in high dimensions, part I: Algorithms and applications. *Probabilistic Engineering Mechanics*, *19*(4), 409–417.

Kroese, D. P., & Chan, J. C. C. (2014). *Statistical Modeling and Computation*. New York: Springer.

Kulhawy, F. H., & Trautmann, C. H. (1996). Estimation of in situ test uncertainty. *Proceedings of uncertainty in the geologic environment: from theory to practice*, ASCE, Reston, VA, pp. 269–286.

Lacasse S, & Nadim F. (1996). Uncertainties in characterizing soil properties. *Proceedings of uncertainty in the geologic environment: from theory to practice*, ASCE. Reston, VA pp. 49–75.

Laggoune, R., Chateauneuf, A., & Aissani, D. (2010). Impact of few failure data on the opportunistic replacement policy for multi-component systems. *Reliability Engineering and System Safety*, *95*(2), 108–119.

Leis, B.N. & Parkins, R. N. (1998). Mechanics and materials aspects in predicting serviceability limited by stress-corrosion cracking. *Fatigue Fract Eng Mater Struct*, *21*(5), 583–601.

Li, H.S., Zhao, A.L. & Tee, K. F. (2016). Structural reliability analysis of multiple limit state functions using multi-input multi-output support vector machine. *Advances in Mechanical Engineering*, *8*(10).

Li, L., & Lu, Z. (2014). Interval optimization based line sampling method for fuzzy and random reliability analysis. *Applied Mathematical Modelling*, *38*(13), 3124–3135.

Liang, J. & Sun, S. (2000). Site effects on seismic behavior of pipelines: a review. *Journal of Pressure Vessel Technology*, *122*(4), pp.469-475.

Limpert, E., Stahel, W. a., & Abbt, M. (2001). Log-normal Distributions across the Sciences: Keys and Clues. *BioScience*, *51*(5), 341.

Lind, N. C. (1995). A measure of vulnerability and damage tolerance. *Reliability Engineering and System Safety*, *48*(1), 1–6.

Liu, B. (2004). *Uncertainty Theory - An Introduction to its Axiomatic Foundations.* New York: Springer-Verlag Berlin Heidelberg.

Liu, B. (2007). A survey of entropy of fuzzy variables. *Journal of Uncertain Systems*, *1*(1), 4–13.

Liu, B., & Liu, Y. K. (2002). Expected value of fuzzy variable and fuzzy expected value models. *IEEE Transactions on Fuzzy Systems*, *10*(4), 445–450.

Mahmoodian, M., & Li, C. Q. (2017). Failure assessment and safe life prediction of corroded oil and gas pipelines. *Journal of Petroleum Science and Engineering*, *151*(December 2016), 434–438.

Marano, G. C., & Quaranta, G. (2008). Fuzzy-based robust structural optimization. *International Journal of Solids and Structures*, *45*(11–12), 3544–3557.

Marano, G. C., Quaranta, G., & Mezzina, M. (2008). Fuzzy Time-Dependent Reliability Analysis of RC Beams Subject to Pitting Corrosion. *Journal of Materials in Civil Engineering*, *20*(9), 578–587.

Marshall, P. (2001). The residual structural properties of cast iron pipes: structural and design criteria for linings for water mains. *UK Water Industry Research, UK*.

McDonald, S. & Zhao, J., (2001). Condition assessment and rehabilitation of large sewers. In *Proceedings of International Conference on Underground Infrastructure Research* (pp. 361-369). Waterloo, Canada: University of Waterloo.

Melchers, R. E. (1999). *Structural reliability analysis and prediction* (Second ed.). New York: John Wiley & Sons.

Melchers, R.E., (2003). Probabilistic models for corrosion in structural reliability assessment—Part 1: empirical models. *Journal of Offshore Mechanics and Arctic Engineering*, *125*(4), pp.264-271.

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of State Calculations by Fast Computing Machines. *The Journal of Chemical Physics*, *21*(6), 1087–1092.

Mohr, W., (2003). Strain-based design of pipelines. *Edison Welding Institute, Columbus, OH, Project Report*, (45892GTH).

Möller, B. & Beer, M. (2004). Fuzzy randomness: uncertainty in civil engineering and computational mechanics. New York: Springer.

Möller, B., & Beer, M. (2008). Engineering computation under uncertainty - Capabilities of non-traditional models. *Computers and Structures*, *86*(10), 1024–1041.

Möller, B., Graf, W., & Beer, M. (2003). Safety assessment of structures in view of fuzzy randomness. *Computers and Structures*, *81*(15), 1567–1582.

Möller, B. & Reuter, U., (2007). Uncertain Forecasting in Engineering and Environmental Science. *Uncertainty Forecasting in Engineering*, pp.153-191.

Moneim MA. (2011). Modelling reliability based optimisation design for water distribution networks. Holding Company for Water and Wastewater. Arab Republic of Egypt.

Moser, A. P., & Folkman, S. L. (2001). *Buried Pipe Design*. New York: McGraw-Hill.

Nadim, F., (2015), October. Accounting for uncertainty and variability in geotechnical characterization of offshore sites. In *Proc. of the 5th International Symposium on Geotechnical Safety and Risk* (pp. 23-35).

Najafi M. (2011). Pipeline rehabilitation for service life extension. In: Karbhari VM, Lee LS, editors. Service life estimation and extension of civil engineering structures. Abington Hall, Cambridge: Woodhead Publishing Limited; pp. 262–89.

Newmark, N. M., (1967). Problems in Wave Propagation in Soil and Rocks. *Proceedings of International Symposium on Wave Propagation and Dynamic Properties of Earth Materials*, Albuquerque, NM, pp. 7-26.

O'Rourke, M.J., Liu, X. (2012). Seismic Design of Buried and Offshore Pipelines. Multidisciplinary Centre for Earthquake Engineering Research, University at Buffalo.

O'Rourke MJ, Liu X. (1999). Response of buried pipelines subject to earthquake effects. Monograph Series, Multidisciplinary Centre for Earthquake Engineering Research (MCEER), University at Buffalo.

Ogawa, Y., & Koike, T. (2001). Structural design of buried pipelines for severe earthquakes. *Soil Dynamics and Earthquake Engineering*, *21*(3), 199–209.

Okasha, N.M. & Frangopol, D.M., (2009). Lifetime-oriented multi-objective optimization of structural maintenance considering system reliability, redundancy and life-cycle cost using GA. *Structural Safety*, *31*(6), pp.460-474.

Olsson, a., Sandberg, G., & Dahlblom, O. (2003). On Latin hypercube sampling for structural reliability analysis. *Structural Safety*, *25*(1), 47–68.

Onoufriou, T. & Frangopol, D.M., 2002. Reliability-based inspection optimization of complex structures: a brief retrospective. *Computers & structures*, *80*(12), pp.1133-1144.

Ossai, C. I., Boswell, B., & Davies, I. J. (2015). Pipeline failures in corrosive environments - A conceptual analysis of trends and effects. *Engineering Failure Analysis*, *53*, 36–58.

Phoon, K., & Kulhawy, F. H. (1999a). Characterization of geotechnical variability. *Canadian Geotechnical Journal*, *36*(4), 612–624.

Phoon, K., & Kulhawy, F. H. (1999b). Evaluation of geotechnical property variability. *Canadian Geotechnical Journal*, *36*(4), 625–639.

Piratla, K.R., Ariaratnam, S.T. & Cohen, A., (2012). Estimation of CO 2 emissions from the life cycle of a potable water pipeline project. *Journal of Management in Engineering*, *28*(1), pp.22-30.

Pradlwarter, H. J., Pellissetti, M. F., Schenk, C. A., Schuëller, G. I., Kreis, A., Fransen, S., Klein, M. (2005). Realistic and efficient reliability estimation for aerospace structures. *Computer Methods in Applied Mechanics and Engineering*, *194*(12–16), 1597–1617.

Pradlwarter, H. J., Schuëller, G. I., Koutsourelakis, P. S., & Charmpis, D. C. (2007). Application of line sampling simulation method to reliability benchmark problems. *Structural Safety*, *29*(3), 208–221.

Rahman, S. & Vanier, D. J. (2004). Life cycle cost analysis as a decision support tool for managing municipal infrastructure. In *CIB 2004 triennial congress* (Vol. 2, pp. 11–8). Ottawa: National Research Council (NRC).

Rajani, B., Zhan, C. & Kuraoka, S. (1996). Pipe soil interaction analysis of jointed water mains. *Canadian Geotechnical Journal*, *33*(3), 393–404.

Rajani, B. & Makar, J. (2000). A methodology to estimate remaining service life of grey cast iron water mains. *Canadian Journal of Civil Engineering*, *27*(6), 1259–1272.

Rajani, B. & Zhan, C. (1996). On the estimation of frost loads. *Canadian Geotechnical Journal*, *33*(4), 629–641.

Rajeev, P., Kodikara, J., Robert, D., Zeman, P., & Rajani, B. (2014). Factors contributing to large diameter water pipe failure. *Water Asset Management International*, *10*(3), 9–14.

Robert, C. P., & Casella, G. (2004). Monte Carlo Statistical Methods. Springer, New York. Sanso, B. and Guenni, L (Vol. 95).

Ross, T.J., (2009). *Fuzzy logic with engineering applications*. John Wiley & Sons.

Røstum, J. (2000). Statistical Modelling of Pipe Failures in Water Networks (Ph.D. thesis). Norwegian University of Science and Technology NTNU.

Sadiq, R., Rajani, B., & Kleiner, Y. (2004). Probabilistic risk analysis of corrosion associated failures in cast iron water mains. *Reliability Engineering & System Safety*, *86*(1), 1–10.

Scheidegger, A., Leitão, J. P., & Scholten, L. (2015). Statistical failure models for water distribution pipes - A review from a unified perspective. *Water Research*, *83*, 237–247.

Schuëller, G. I., & Jensen, H. A. (2008). Computational methods in optimization considering uncertainties – An overview. *Computer Methods in Applied Mechanics and Engineering*, *198*(1), 2–13.

Schuëller, G. I., Pradlwarter, H. J., & Koutsourelakis, P. S. (2004). A critical appraisal of reliability estimation procedures for high dimensions. *Probabilistic Engineering Mechanics*, *19*(4), 463–474.

Sivakumar Babu, G.L., Srinivasa Murthy, B.R. & Seshagiri Rao, R. (2006). Reliability analysis of deflection of buried flexible pipes. *Journal of Transportation Engineering*, *132*(10), 829–836.

Sivakumar Babu, G.L. & Rao, R.S., (2005). Reliability measures for buried flexible pipes. *Canadian geotechnical journal*, *42*(2), pp.541-549.

Sriramula, S. and Chryssanthopoulos, M.K., (2009). Probabilistic models for spatially varying mechanical properties of in-service GFRP cladding panels. *Journal of Composites for Construction*, *13*(2), pp.159-167.

St. Clair, A.M. & Sinha, S., (2014). Development of a standard data structure for predicting the remaining physical life and consequence of failure of water pipes. *Journal of Performance of Constructed Facilities*, *28*(1), pp.191-203.

Starossek, U. & Haberland, M., (2011). Approaches to measures of structural robustness. *Structure and Infrastructure Engineering*, *7*(7-8), pp.625-631.

Tang, X. G., Rezoug, M., Hamzaoui, R., Bassir, D., El Meouche, R., Khreim, J. F., & Feng, Z. Q. (2011). Multiobjective Optimization on Urban Flooding Using RSM and GA. *Advanced Materials Research*, *255–260* (June 2015), 1627–1631.

Tee, K.F., Ebenuwa, A.U. & Zhang, Y., (2018). Fuzzy-based robustness assessment of buried pipelines. J*ournal of Pipeline Systems Engineering and Practice*, 9(1), p.06017007.

Tee, K. F., & Khan, L. R. (2014). Reliability analysis of underground pipelines with correlations between failure modes and random variables. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, *228*(4), 362–370.

Tee, K.F., Khan, L.R. & Chen, H.P., (2013). Probabilistic failure analysis of underground flexible pipes. *Structural engineering and mechanics*, *47*(2), pp.167-183.

Tee, K.F., Khan, L.R., Chen, H.P. & Alani, A.M., (2014). Reliability based life cycle cost optimization for underground pipeline networks. *Tunnelling and Underground Space Technology*, *43*, pp.32-40.

Tee, K. F., Khan, L. R., & Li, H. (2014). Application of subset simulation in reliability estimation of underground pipelines. *Reliability Engineering & System Safety*, *130*, 125–131.

Vazouras, P., Karamanos, S. A., & Dakoulas, P. (2012). Mechanical behavior of buried steel pipes crossing active strike-slip faults. *Soil Dynamics and Earthquake Engineering*, *41*, 164–180.

Velazquez, J.C., Caleyo, F., Valor, A. & Hallen, J.M., (2009). Predictive model for pitting corrosion in buried oil and gas pipelines. *Corrosion*, *65*(5), pp.332-342.

Wang, H., Yajima, A., Liang, R. Y., & Castaneda, H. (2015). Bayesian modeling of external corrosion in underground pipelines based on the integration of markov chain monte carlo techniques and clustered inspection data. *Computer-Aided Civil and Infrastructure Engineering*, *30*(4), 300–316.

Wang, H., Yajima, A., Liang, R. Y., & Castaneda, H. (2016). Reliability-based temporal and spatial maintenance strategy for integrity management of corroded underground pipelines. *Structure and Infrastructure Engineering*, *12*(10), 1281–1294.

Water Research Centre, (2001). *Sewerage rehabilitation manual* (Vol. 1). WRC Publications.

Watkins, R.K. & Anderson, L. R. (1999). *Structural mechanics of buried pipes*. CRC press.

Whidden, W. R. (2009). *Buried flexible steel pipe: Design and structural analysis*. American Society of Civil Engineers.

Yeh, G.C., (1974). Seismic analysis of slender buried beams. *Bulletin of the Seismological Society of America*, 64(5), pp.1551-1562.

Yin, H., Yu, D., Yin, S., & Xia, B. (2018). Possibility-based robust design optimization for the structural-acoustic system with fuzzy parameters. *Mechanical Systems and Signal Processing*, *102*, 329–345.

Zadeh, L.A., (1965). Fuzzy sets. *Information and control*, *8*, p.3.

Zhang, J., & Du, X. (2010). A Second-Order Reliability Method With First-Order Efficiency. *Journal of Mechanical Design*, *132*(10), 101006.

Zhang, M. Q., Beer, M., Koh, C. G., & Jensen, H. A. (2015). Nuanced Robustness Analysis with Limited Information. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *2*(3), B4015001.

Zhang, M. Q., Beer, M., Quek, S. T., & Choo, Y. S. (2010). Comparison of uncertainty models in reliability analysis of offshore structures under marine corrosion. *Structural Safety*, *32*(6), 425–432.

Zhang, Y., Kim, C.W., Tee, K.F. and Lam, J.S.L., 2017. Optimal sustainable life cycle maintenance strategies for port infrastructures. *Journal of cleaner production*, *142*, pp.1693-1709.

Zimmermann, H. J. (2001). *Fuzzy Set Theory and Its Applications*. *London Kluwer Academic Publishers*.

Zio, E. (2009). Reliability engineering: Old problems and new challenges. *Reliability Engineering and System Safety*, *94*(2), 125–141.

Zio, E. (2013). The Monte Carlo Simulation Method for System Reliability and Risk Analysis. London: Springer.

Zio, E., & Pedroni, N. (2009). Functional failure analysis of a thermal-hydraulic passive system by means of Line Sampling. *Reliability Engineering and System Safety*, *94*(11), 1764–1781.

Zio, E., & Pedroni, N. (2010). An optimized Line Sampling method for the estimation of the failure probability of nuclear passive systems. *Reliability Engineering & System Safety*, *95*(12), 1300–1313.

Zuev, K. (2015). Subset Simulation Method for Rare Event Estimation: An Introduction. *Encyclopedia of Earthquake Engineering*, 1–26.

LIST OF PUBLICATIONS

Ebenuwa, A.U. & Tee, K.F., (2019). Fuzzy-based optimised subset simulation for reliability analysis of engineering structures. *Structure and Infrastructure Engineering*, pp.1-13.

Ebenuwa, A.U. & Tee, K.F., (2017). Reliability analysis of buried pipes with corrosion and seismic impact. *Geo-Risk 2017* (pp. 424-433).

Tee, K.F., **Ebenuwa, A.U.** & Zhang, Y., (2018). Fuzzy-based robustness assessment of buried pipelines. *Journal of Pipeline Systems Engineering and Practice*, *9*(1), p.06017007.

Tee, K.F. & **Ebenuwa, A.U.**, (2018). Combination of line sampling and important sampling for reliability assessment of buried pipelines. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, p.1748006X18764986.

Ebenuwa, A.U. & Tee, K.F., (2016). Reliability Assessment of Buried Pipeline under Seismic Action. *9th IMA International Conference on Modelling in Industrial Maintenance and Reliability (MIMAR)*. London, UK, July 12-14, 2016.

Ebenuwa, A.U. Tee, K.F. & Zhang, Y., (2016). Structural robustness assessment of corroded buried pipes. *High Performance and Optimum Design of Structures and Materials II*, 166, pp.81-92.

Ebenuwa, A.U. & Tee, K.F., (2017). Reliability assessment of buried pipelines for through-wall bending stress. In *14th International Probabilistic Workshop* (pp. 377-387). Springer, Cham.

Ebenuwa, A.U. & Tee, K.F. Fuzzy-based Multi-Objective Design Optimisation of Buried Pipelines. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems (Under review)*

Ebenuwa A.U. & Tee, K.F. Reliability-based maintenance of buried pipeline using multi-objective optimisation involving fuzzy reliability, risk, and cost. *Journal of Infrastructure System (Under review)*

Ebenuwa, A.U. and Tee, K.F. Assessment of Buried Pipes under Seismic Action using Line Sampling. *International Journal of Pressure Vessels and Piping (Under review)*